Explaining Job Polarization: The Roles of Technology, Offshoring and Institutions

Appendices - for online publication

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This paper develops a simple and empirically tractable model of labor demand to explain recent changes in the occupational structure of employment as a result of technology, offshoring and institutions. This framework takes account not just of direct effects but indirect effects through induced shifts in demand for different products. Using data from 16 European countries, we find that the routinization hypothesis of Autor, Levy and Murnane (2003) is the most important factor behind the observed shifts in employment but that offshoring does play a role. We also find that shifts in product demand are acting to attenuate the impacts of recent technological progress and offshoring and that differences or changes in wage-setting institutions play little role in explaining job polarization in Europe.

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Appendix A: Employment data

A1. ELFS and IABS

The ELFS contains data for 29 European countries which is collected on a national level. The same set of characteristics is recorded in each country, common classifications and definitions are used, and data are processed centrally by Eurostat. We limit our analyses to the fifteen countries that made up the European Union previous to the 2004 enlargement, plus Norway and minus Germany. These countries are the ones for which the most years of data are available, and we suspect them to be more similar in terms of access to technology or impact of offshoring than the newer EU members. We retain only individuals who are employed according to the ILO definition of employment (the ELFS variable *ilostat*) and then eliminate a very small number of unpaid family workers using a variable classifying professional status (*stapro*) – our analyses are not sensitive to this.

Table A1 presents, for each ELFS country we use, the years for which full data (i.e. employed individuals for whom a 2-digit occupation and a major industry group is known) is available. Employment is measured either by thousands of persons employed (given by the ELFS survey weights) or by thousands of weekly hours worked (ELFS survey weights multiplied by usual weekly hours).

We supplement the ELFS with German employment data from the IABS – a 2% random sample of social security records covering 1993-2004. Since the 2-digit occupation and industry codes used in the IABS differ somewhat from ISCO and NACE and no crosswalk was available, we matched them manually. Due to anonymization, occupation and industry codes in the IABS are no more disaggregate than the ones in the ELFS, and as a result we were not able to find a match for each ISCO and NACE: specifically, there were no separate equivalents of ISCO 13 and 74, and NACE E, H, N, and P in the IABS. Instead, employment in these occupations and industries is included in other ISCO and NACE categories: however, none of our analyses are sensitive to the exclusion of Germany. Lastly, the IABS industry classification changes in 2003: this classification is somewhat easier to reconcile with NACE, but since it covers only 2 years and no crosswalk exists between the IABS industry classifications before and after 2003, we drop years 2003 and 2004.

Tables A2 and A3, below, provide an overview of the 26 2-digit ISCO occupations and 17 NACE major group industries available in the ELFS. In our analyses, we drop several occupations and industries. The following occupations are dropped: legislators and senior officials (ISCO 11); teaching professionals and teaching associate professionals (ISCO 23 and 33); skilled agricultural and fishery workers (ISCO 61); and agricultural, fishery and related laborers (ISCO 92). We also drop the following industries: agriculture, forestry and hunting (NACE A); fishing (NACE B); mining and quarrying (NACE C); public administration and defense, compulsory social security (NACE L); education (NACE M); and extra territorial organizations and bodies (NACE Q).

These occupations and industries were dropped because German data is not random for workers who are not legally obliged to make social security contributions and because the OECD STAN data, especially the net operating surplus data, covering several public industries is unreliable (particularly, NACE L and M, and by association, ISCO 23 and 33). Others were eliminated because the data appears unreliable: employment in these occupations or industries occurs only in a small number of country-year cells, suggesting classification problems (ISCO 11, 92, and ISCO 61 by association through ISCO 92; NACE A, B, C, Q). However, our results are qualitatively identical when we do not drop these occupations and industries.

Lastly, the ELFS sometimes contains 1-digit ISCO codes such as 20 and 30: since they appear only sporadically we treat them as measurement error and delete them. Our results are unaffected if we instead assign 2-digit ISCO codes based on information about gender, age, and education level. The ELFS employment dataset is created by collapsing the individual employment data by country, industry, occupation, and year. Table A4 shows the number of observations (individual and by country-year-occupation-industry cells) we have left.

The ELFS is also the source of our education information. For this, we use a three-level education variable (*hatlev1d*) classified with ISCED: the lowest level of education corresponds to ISCED 0, 1, and 2 (pre-primary education; primary and lower secondary education); the middle level to ISCED 3 and 4 (upper secondary and post-secondary non-tertiary education); and the highest level to ISCED 5 and 6 (tertiary and postgraduate education). This variable is available for all countries, and cross-country correlations in average educational attainment by occupation are very high, as shown in Table A5.

Lastly, Table A6 gives an idea of the absolute and relative employment sizes of the 16 European countries in our restricted sample.

A2. Polarization is not cyclical

One might be concerned that 1993 is a recession and 2006 a boom so that the changes in Table 1 are cyclical not trends. To examine this, for each country in each year, we group the occupations listed in Table 1 into three groups: the four lowest paid occupations (service and elementary occupations), nine middling occupations (craft and related trade workers, plant and machine operators and assemblers) and the eight highest paying occupations (managers, professionals and associate professionals). Figure A1 then plots the cumulative percentage change in employment for the group of highest-paid and lowest-paid occupations relative to middling occupations averaged across countries. If polarization exists and is invariant to the business cycle we would expect to see two time series with positive constant slopes. Figure A1 shows that the time series are primarily trends and that the polarization found in Table 1 is not sensitive to endpoints.

Appendix B: Testing the assumptions of the model using ANOVA

B1. Testing the assumptions of the model using ANOVA

Albeit less informative, a less data demanding alternative to test for the assumptions in equation (7) would be to estimate ANOVA models. Note that the first row on the right-hand side of equation (7) is occupation-country-year specific capturing variation in employment related to wages, the second and third rows are occupation-year specific capturing (part of) the employment impacts of technological progress and offshoring whereas the last row captures variation in employment that is industry-occupation-country and industry-country-year specific. One way to see this is true in the data is to construct ANOVA F-test statistics.

Column (1) of Table B1 presents ANOVA F-test statistics (with p-values in brackets) for this model.[1] As we would expect from equation (7), F-test statistics are significant for industry-country-year, industry-occupation and occupation-year effects. If there is a country-specific component to technological change or offshoring, we would expect to see that occupation-country-year effects have significant extra explanatory power – the F-test statistic of 0.93 with a p-value of 1 in column 1 shows they do not. It should be noted that in our model wages are allowed to vary at the country-occupation-year level and the finding that such effects are not very significant suggests that either country-specific changes in relative occupational wages are not very important (i.e. there is little change in wage inequality in most countries in our sample period so that differences in relative wages across countries are approximately constant) or that the occupational wage is not very important. The significance of occupation-year effects suggests pervasive effects across countries and industries, which indicates scope for the importance of factors that vary at this level, such as technological change and offshoring.

Now consider how we can use this set-up to further test our identifying assumptions. The variation in employment that remains unaccounted for in column (1) of Table B1 is industry-occupation-year, industry-occupation-country or industry-occupation-country-year specific. Column (2) therefore adds an industry-occupation-year effect. This effect does not have significant explanatory power, which is inconsistent with task-biased technological change or offshoring having an industry-occupation specific component.

Finally, column (3) of Table B1 adds an industry-occupation-country instead of an industry-occupation-year effect to the ANOVA. The F-test statistic of 15.39 is statistically significant. One possible explanation could be that the technology to combine tasks in production varies across countries (that is, varies with country but not time). Our preferred interpretation for the significance of the industry-occupation-country effect is that our industries and occupations are quite aggregated and that the product mix within aggregate industry groups differs across countries – for evidence in support of this hypothesis, see Appendix B2 below. If, for example, the single industry 'manufacturing' that we observe in our data in one country mainly consists of the manufacture of textiles and in another country mainly consists of the manufacture of chemical products, one would expect to see significant industry-occupation-country variation in employment even if countries use the same technologies. To account for this where relevant, the regression results presented in the main text always control for industry-occupation-country fixed effects rather than only an industry-occupation fixed effect. Finally note

[1] Note that because each ANOVA also includes industry, occupation, country, year and occupation-country controls, all the interactions listed in the table are exactly identified except for the term industry-country-year which additionally contains industry-country, industry-year and country-year variation. For instance, because the ANOVA controls for occupation and year effects separately, the F-test statistic on occupation-year only tests for the significance of occupation-year specific variation.

from column (3) that the inclusion of an industry-occupation-country effect increases the F-test statistic for the occupation-country-year interaction, which – although it remains relatively small – becomes statistically significant. Also note from column (4) that the inclusion of an industry-occupation-country effect increases the F-test statistic on the industry-occupation-year interaction slightly.

B2. Explaining the industry-occupation-country variation in the ANOVA decomposition

Columns (3) and (4) of Table B1 find significant industry-occupation-country specific variation in our employment data. Although this is not in contrast with the assumptions that allow us to identify the impact of technological progress and offshoring and although we do control for this variation in our empirical analysis where relevant, an important question is where this variation is coming from.

We can show that the significance of the industry-occupation-country effect mainly captures the fact that the product mix within aggregate industry groups differs between countries. To this end we use data from the ELFS that are not in the anonymized version and where the industry dimension is 2-digit rather than 1-digit. However, these data cannot be published and we can only report a more general analysis here.

We constructed predicted employment at the 1-digit industry-occupation-country level as follows:

$$\widehat{E}_{(i1)jc} = \sum_{(i2)\in(i1)} E_{(i2)c} \times \overline{E}_{j|(i2)}$$

where $(i1)$ is the 1-digit industry level; $(i2)$ is the 2-digit industry level, j is occupation, and c is country. That is, we predict employment at the 1-digit industry-occupation-country level, $E_{(i1)jc}$, by summing employment over 2-digit sub-industries while restricting the distribution of occupations in each 2-digit sub-industry to be identical across countries – or, $\overline{E}_{j|(i2)}$ is the average share of occupation j in industry $(i2)$. We then plot the 1-digit industry-occupation-country specific variation in the logarithm of this predicted employment series against the 1-digit industry-occupation-country specific variation in the actual log employment data[2] – it can be seen that all data points lie very close to a 45-degree line: the coefficient in a bivariate regression is 0.992 with a standard error of 0.003 and an R^2 of 0.96.

APPENDIX C: MEASURING TECHNOLOGICAL PROGRESS

C1. Constructing task content measures using ONET

The ONET database, version 11, contains 161 occupation-specific variables (ordered within a so-called 'content model'), many of which can be seen as representing certain tasks. We use 96 variables from 5 different sections: from Worker Characteristics, we use Abilities (section 1A), from Worker Requirements, we use Basic Skills and Cross-Functional Skills (sections 2A and 2B), and from Occupational Requirements,

[2] This is achieved by taking the residuals from a regression of the constructed or actual log employment series onto a full set of country-year, occupation-year and occupation-country dummies.

we use Generalized Work Activities and Work Context (sections 4A and 4B). Several other sections exist, but they were either not good measures of tasks (sections covering education levels and study specialization such as in section 2D-Education and section 3-Experience Requirements; working conditions and job satisfaction such as in section 4B-Organizational Context); not yet available (ONET is still regularly being updated: e.g. sections 1B-Interests and 1C-Work Styles are not yet available); or did not allow for comparison across occupations (e.g. section 4D-Detailed Work Activities).

All 96 variables we selected have the importance scale, where the respondent and/or occupational expert ranks each task as not important at all (1), somewhat important (2), important (3), very important (4) or extremely important (5). We categorized the variables manually into one of three tasks (Abstract, Routine or Service) based on the ALM-hypothesis of how well technology can substitute for these tasks: this is presented in Table C1. We then calculate 3 principal components (Abstract, Routine, and Service) at the ONET occupational level and the scale reliabilities are reported in the notes to Table C1. We then collapse the principal components to the ISCO level by weighing them by their US occupational employment size in 2005, which we obtain from the Bureau of Labor Statistics. We then have a dataset with ONET task measures at the ISCO level. We rescale the three task content measures such that they have a zero mean and unit standard deviation: these values are reported in Table 3 in the paper. This ONET ISCO-level dataset is merged with the ELFS dataset which has been described in Appendix A.

C2. Dealing with the different occupational classifications

DIFFERENCES BETWEEN ONET OCCUPATIONAL CODES AND SOC 2000

The ONET occupational coding is based on SOC 2000, but differs in that ONET splits up several SOC 2000 occupations into multiple separate occupations. These occupations are different, but related, and should according to the developers of ONET be given a separate SOC 2000 code in the future. For instance, SOC code 13-2011 is accountants and auditors, which ONET divides up into 13-2011.01, accountants; and 13-2011.02, auditors. We have dealt with these ONET categories by taking a simple mean of the importance measure for each task. Although we cannot weigh the task importances because of the lack of employment data for these categories separately, we do not expect them to have a major impact since they are extremely few in comparison to the SOC 2000 codes that ONET does not split up.

MAPPING OF ONET OCCUPATIONAL CODES TO ISCO

For lack of an official crosswalk between SOC 2000 and ISCO, we have mapped ONET occupational codes to ISCO occupations by hand. Since the ONET occupational code is much more disaggregate, this was relatively straightforward in most cases. However, the ONET occupational code does not contain any clear equivalent of the ISCO occupation "managers of small enterprises" (ISCO 13); and does not contain data for the equivalent of "legislators and senior officials" (ISCO 11). Since we drop ISCO 11 (see Appendix A), only ISCO 13 remains: we have recoded it as "corporate managers"

(ISCO 12), and hence assumed that the importance scores for task measures of corporate managers also apply to managers of small enterprises.

C3. Using principle components to construct task content measures

Rather than manually selecting and assigning 96 variables into three task content categories, here we construct alternative task content measures based exclusively on principle components analysis. We perform two analyses here: one where we use the same subsample of 96 ONET variables used in the construction of Abstract, Routine, and Service task content measures above; and one where we use all ONET variables that have an importance scale.

Table C2 reports standardized principal components for occupations ranked by the mean European wage. The principal components reported in panel A are constructed from the 96 ONET task measures used above whereas those in panel B are constructed from all 161 ONET task measures that have the importance scale. Within each panel, the first two columns show 'unweighted' principal components that were calculated across SOC 2000 occupations, and then averaged to ISCO occupations using US employment in SOC 2000 occupations. The last two columns in each panel show 'weighted' principal components that have been calculated using US employment in SOC 2000 occupations. We refer to this first type as 'unweighted' principal components, and the second as 'weighted' ones, since only the latter has been weighted at the level of SOC 2000 occupations, but it is worth stressing that both are weighted when aggregating into ISCO occupations.

Table C3 shows that these various principal components are closely related to our manually constructed task content measures of Abstract, Routine and Service. The first principal component, $PC1$, whether weighted or unweighted, constructed from the 96 or 161 measures, is highly positively correlated to our Service and Abstract task measures (and negatively to the Routine measure) and the second principal component $PC2$ is highly negatively correlated with our Routine task measure (and positively to the Abstract and Service measures).

For example, Table C4 uses specifications similar to those used in the last two columns of Table 6 in the paper but now using the various principal components as task content measures for technological progress rather than our manually composed Abstract, Routine and Service measures – as before, the task measures are interacted with a linear timetrend to capture secular changes in employment. As before, Panel A uses principal components constructed from 96 ONET task measures whereas panel B uses those from 161 ONET task measures and within each panel, results using weighted and unweighted principal components are reported. This table shows faster (slower) employment growth associated with the first (second) principal component, which Table C3 showed to be positively correlated with the Abstract and Service (Routine) task measures. The point estimates on these task measures are similar in magnitude to the ones reported in the main text, as is the point estimate we find on the measure of offshoring.

All in all, these results suggest our results are not driven by the manual categorization of tasks into aggregate task content measures: when we mechanically construct principal components instead, these are found to be highly correlated to the ones we constructed and have similar predictive power over recent occupational employment changes in our sample of European countries.

Appendix D: Offshoring

D1. Constructing a measure of offshoring using ERM

The European Restructuring Monitor (ERM) contains summaries of news reports about cases of offshoring by companies located in Europe. Started in May 2002, 460 reports were available up to June 20th, 2008. From these news reports, called fact sheets, we abstracted information about the occupations that were being offshored. Some fact sheets explicitly stated the occupations being offshored (e.g. call centre workers; back office workers; assembly line workers; R&D workers; accountants), whereas in other cases, we deduced the affected occupations based on the description. For instance, the first case concerns a factory in Austria where car-seatbelt production done by low-skilled women is offshored to the Czech Republic and Poland. Based on this description, we classified the affected occupations as Stationary Plant and Related Operators (ISCO 81); Machine Operators and Assemblers (ISCO 82); and Laborers in Mining, Construction, Manufacturing and Transport (ISCO 93). This assigning of occupations was relatively straightforward in most cases, both because the reports are quite extensive and because our occupational classification is very aggregated. Whenever it was not possible to deduce the offshored occupation(s) from the fact sheet, we turned to the original news report provided in the fact sheet, and if that was not sufficient, looked on the company's website. Maximizing information in this way, we were able to obtain offshored occupations for 415 of the 460 fact sheets.

We then count the number of cases by ISCO occupation as a measure for that occupation's offshorability: this is reported in Table D1. This table shows that apart from the manufacturing occupations (a combined 532 counts), office occupations (141 counts) and (associate) professional occupations (a combined 111 counts) are also being offshored relatively often.

A weakness of this approach is that it does not take into account how many jobs of an occupation are being offshored, although this number may vary significantly among occupations. While the number of lost jobs per case of offshoring is provided in the fact sheets, we chose not to use this information for two reasons. Firstly, there is no meaningful reference to compare these job losses to: the 'total employment' figure documented in some 350 fact sheets is not uniformly defined. In some cases (particularly for manufacturing), total employment refers to the number of workers in that particular plant and since it is often the case that an entire plant is closed, the percentage of offshored manufacturing jobs is close to 100, even though the firm retains workers of the same occupations in other plants in the same country. In other cases, most notably in the financial sector, total employment is measured as nation- or even EU-wide employment in that firm, leading to very small percentages for occupations like call centre workers. Secondly, since one fact sheet usually refers to several offshored occupations, the job losses should somehow be divided up between these occupations, but there is no way to do this.

D2. Using the Blinder and Krueger (2009) measures of offshorability

To assess the sensitivity of our findings concerning offshoring to the use of the ERM dataset, we redo some of our estimations using Blinder and Krueger (2009) offshoring measures derived from the individual level Princeton Data Improvement Initiative (PDII) dataset. Blinder and Krueger (2009) construct three measures of offshoring: one self-reported, one a combination of self-reported questions made internally consistent, and the last one which is based on the assessment of coders that have been trained by the authors. The authors conclude that their third measure – constructed by professional coders based on a worker's occupational classification – is preferred.

Specifically, we take their table that reports the percent of jobs that can be offshored within 10 broad occupational groups – these occupational groups correspond well to our ISCO occupations, although some ISCOs are assigned the same offshorability since we have more ISCO codes than Blinder and Krueger (2009) have occupations. The correlation between our offshorability measure and the measures reported in Blinder and Krueger (2009) are given in Table D2. Table D2 shows that our measure is quite highly positively correlated with Blinder and Krueger's (2009) preferred measure, the offshorability of occupations as determined by trained coders.

Note that these correlations are based on the full sample of occupations, whereas the Blinder and Krueger (2009) measures do not vary between several of our ISCO occupations. To correct for this, we group employment in our occupations together such that they match the occupational groups in Blinder and Krueger (2009). Table D3 shows that this increases the strength of the correlation between our offshoring measure and the preferred measure in Blinder and Krueger (2009).

To check for robustness of our results, we illustrate by estimating specifications in line with the last column of Table 5 in the paper using these alternative measures – both for the complete set of occupations and for the one where several occupations have been taken together. Table D4 shows the first of these estimation results – in this table, the full set of ISCO occupations is used for identification. It can be seen that a one standard deviation more offshorability according to Blinder and Krueger's (2009) preferred measure (reported in the column labeled 'coders') is associated with 0.23 percentage points slower employment growth, very similar in size to the impact we find for our ERM measure of -0.21 percentage points. Also note that the estimated impacts of technological change are also very similar in both regressions. When we use Blinder and Krueger's less-preferred measures (columns 'self' and 'infer'), we find (statistically insignificant) positive employment effects for occupations that can be offshored with more ease. In other words, it seems that our ERM measure performs very similarly to the measure preferred by Blinder and Krueger (2009). Table D5 shows that this conclusion is not qualitatively affected when we reduce the number of occupational groups to fit the Blinder and Krueger (2009) data.

Appendix E: Occupational wages

We obtain wage data at the occupation-country-year level from the European Community Household Panel (ECHP) and the European Union Statistics on Income and Living Conditions (EU-SILC). The ECHP started in 1994 and lasted until 2001 and reports wages in national currencies, while the EU-SILC covers 2004-2006 and contains wages in euros. For the UK, we rely on the UK Labour Force Survey which does contain wages, unlike the ELFS.

We use the gross monthly (weekly for the UK) wage, and weight it by persons employed and hours worked to obtain two wage measures. Table E1 shows how many individual observations we have for each country-year cell summed over all occupations, whereas Table E2 shows the average number of observations for each country-occupation cell across years. Although sample sizes are small (except for the UK), we find that the wage ranking of occupations is very stable both across time within a country – see Table 4 in the paper – as well as across countries over time – see Table E3.

Since we need to control for the country-occupation-year specific wages in our regressions, we would lose some 35% of our data due to missing wage cells. Therefore, we impute missing country-occupation-year cells as described in the paper. Lastly, the ECHP and EU-SILC do not contain wage data for Finland and Sweden. For Finland and Sweden, we use aggregate OECD data to construct occupational wages using the following formula:

$$w_{jct} = \overline{w}_{ct} + \frac{\sigma_{ct}}{\sigma_{(DE)t}}(w_{j(DE)t} - \overline{w}_{(DE)t})$$

where w_{jct} is the average wage in occupation j, in country c (in this case, Finland or Sweden) at time t; $\overline{w}_{ct}$is the median wage in country c at time t; and σ_{ct} is a measure of wage inequality in country c at time t (specifically the ratio of the 90th to the 10th percentile derived from the OECD). The variables with the subscript (DE) refer to the value of those variables for Germany. Two implicit assumptions underlie the validity of this construction: that occupational wage structures are very highly correlated across countries; and that the level of occupational wage differentials is related to wage inequality in the country.

Appendix F: Industry marginal costs and industry output

STAN uses a standard industry list for all countries based on the International Standard Industrial Classification of all Economic Activities, Revision 3 (ISIC Rev.3). The first two digits of ISIC Rev.3 are identical to the first two digits of NACE Rev.1, the industry classification used in the ELFS. Since the ELFS only contains major groups for NACE, this is identical to ISIC. However, in the STAN database, data on NACE industry P (Private households with employed persons) is often missing or not reliable – we have therefore dropped it altogether except for France, Portugal, Spain and the UK, where it is included in NACE industry O (Other community, social and personal service activities). Although this ommited industry mainly employs low-paid service elementary workers and its employment share has increased from 0.82% in 1993 to 0.90% in 2006, it is too small to be important.

The measure of output we use in the paper is production, defined as the value of goods or services produced in a year, whether sold or stocked. We use production to account for the fact that intermediate goods are part of production costs – in fact, the STAN methodology counts any capital costs from equipment that is rented (rather than owned) by a firm and any costs of offshoring as intermediate goods. However, our results are robust to using STAN's value added series instead. We deflate production using industry-country-year specific price deflators – also taken from STAN – and 2000 real exchange rates taken from the ECB's web-page.

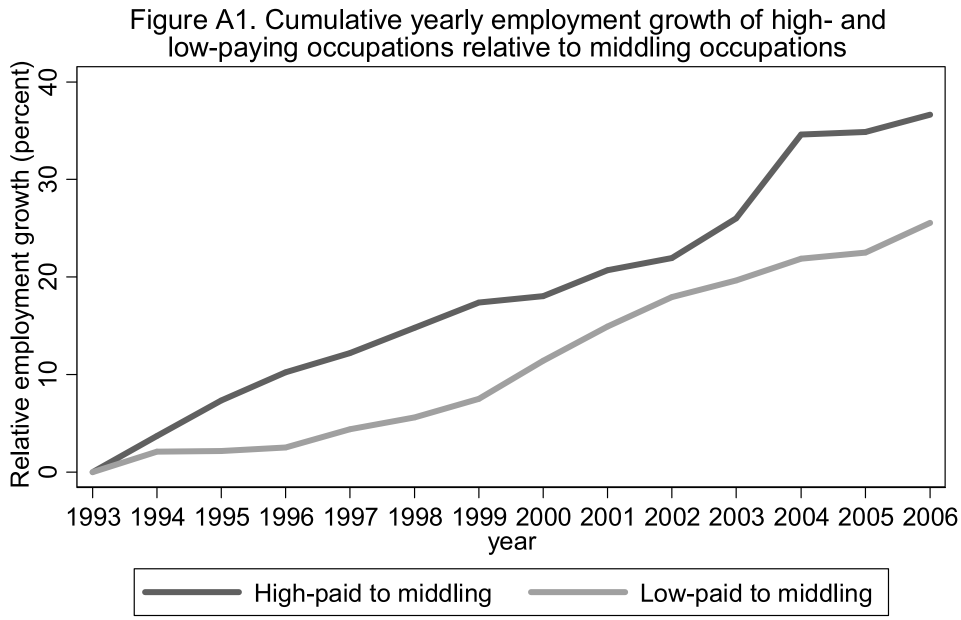
APPENDIX G: COUNTRY AND INDUSTRY HETEROGENEITY IN THE IMPACTS OF TECHNOLOGICAL PROGRESS AND OFFSHORING

In the paper we assume that technological progress and offshoring have the same impact in all 16 countries and that the effect is the same for all industries. If all countries and industries in our sample can be assumed to be equally affected by similar changes in the within-industry demand for occupations, an additional test would be to see whether point estimates do not differ significantly between countries or industries. That is what we do here.

For example, Table G1 shows F-test statistics (with p-values in brackets) for the interactions with country or industry dummies of the technology and offshorability specific time trends estimated in the last two columns of Table 5 in the paper. Column (1) of Table G1 shows that country heterogeneity only exists for growth in abstract intense occupations which also explains the significance of the country dummy interactions in column (2) where the task measures have been replaced by the RTI index. The F-test statistic for the impact of offshoring, however, is statistically significant in both columns (1) and (2). This suggests that the impact of offshoring is generally less pervasive compared to technological progress. Columns (3) and (4) of Table G1 interact the technological progress and offshoring specific time trends with industry instead of country dummies. The reported p-values of the F-test statistics show that none of the industry specific time trends are different at less than the 5% significance level. In sum, Table G1 shows that the impact of technological progress on the within-industry demand for occupations is pervasive across countries and industries and that there is some country heterogeneity in the impact of offshoring.

APPENDIX H: OCCUPATIONAL EMPLOYMENT CHANGES WITHIN- AND BETWEEN-INDUSTRIES

That industry shifts can be quantitatively important also follows from Table H1 showing the result of decomposing aggregate occupational employment share changes into within- and between-industry components. As our model suggests, one sees large negative within-industry components for some occupations such as office clerks (ISCO 41), building workers, craft and related trades workers (ISCO 71-74), stationary plant and related operators (ISCO 81) and machine operators and assemblers (ISCO 82) and large positive effects for others, e.g. managers (ISCO 12,13) and some (associate) professional occupations (ISCO 21,31,34). However, Table H1 also shows that the between-industry component may be important – in particular, it suggests an increase in the demand for industry output intense in life science and health (associate) professionals (ISCO 22,32), other (associate) professionals (ISCO 24,34) and some low-paid service (elementary) workers (ISCO 51,91) at the expense of demand for manufactured goods which use operators, assemblers and other production occupations (ISCO 72,74,81,82) intensively.



Note: Employment growth averaged across countries, no imputation for countries with shorter data spans.

Table A1. Data availability for number of persons employed and number of weekly hours worked

	Years covered	*Total nr of obs*	*Total nr of obs in ind-occ-year cells*
Austria	1995-2006	340,772	3,498
Belgium	1993-2006	264,107	4,064
Denmark	1993-2006	133,390	3,592
Finland	1997-2006	153,989	2,743
France	1993-2006	632,257	4,625
Germany	1993-2002	8,011,935	2,270
Greece	1993-2006	593,992	3,984
Ireland	1998-2006	338,153	3,191
Italy	1993-1999, 2004-2006	811,788	3,232
Luxembourg	1993-2006	114,472	3,351
Netherlands	1993-2006	472,050	4,424
Norway	1996-2006	149,679	3,013
Portugal	1993-2006	332,552	4,341
Spain	1993-2006	833,596	4,774
Sweden	1997-2001; 2004-2006	260,905	2,246
UK	1993-2006	865,284	5,086

Notes: Number of observations with non-missing ISCO and NACE codes. We dropped years 1993-1997 for Ireland and 2002-2003 for Sweden because an industry (NACE code P) is missing and years 2000-2003 for Italy because an occupation (ISCO code 13) is missing. We excluded Iceland altogether since only two years of complete data (2002 and 2003) are available. The same number of observations is available for the number of persons employed and the number of weekly hours worked, except for Germany, where there are 7,481,352 individual observations for hours worked.

Table A2. Overview of ISCO occupation codes available in the ELFS and their description

ISCO code	*Occupation*
11	Legislators and senior officials
12	Corporate managers
13	Managers of small enterprises
21	Physical, mathematical and engineering professionals
22	Life science and health professionals
23	Teaching professionals
24	Other professionals
31	Physical, mathematical and engineering associate professionals
32	Life science and health associate professionals
33	Teaching associate professionals
34	Other associate professionals
41	Office clerks
42	Customer service clerks
51	Personal and protective service workers
52	Models, salespersons and demonstrators
61	Skilled agricultural and fishery workers
71	Extraction and building trades workers
72	Metal, machinery and related trade work
73	Precision, handicraft, craft printing and related trade workers
74	Other craft and related trade workers
81	Stationary plant and related operators
82	Machine operators and assemblers
83	Drivers and mobile plant operators
91	Sales and service elementary occupations
92	Agricultural, fishery and related labourers
93	Laborers in mining, construction, manufacturing and transport

Note: In our analyses, we exclude occupations 11, 23, 33, 61, and 92.

Table A3. Overview of NACE industry codes available in the ELFS and their description

NACE code	*Industry*
A	Agriculture, forestry and hunting
B	Fishing
C	Mining and quarrying
D	Manufacturing
E	Electricity, gas and water supply
F	Construction
G	Wholesale and retail
H	Hotels and restaurants
I	Transport, storage and communication
J	Financial intermediation
K	Real estate, renting and business activity
L	Public administration and defense, compulsory social security
M	Education
N	Health and social work
O	Other community, social and personal service activities
P	Private household with employed persons
Q	Extra territorial organizations and bodies

Note: In our analyses, we exclude industries A, B, C, L, M, and Q.

Table A4. Data availability for number of persons employed and number of weekly hours worked

	Years covered	*Total nr of obs*	*Total nr of obs in ind-occ-year*
Austria	1995-2006	280,886	2,246
Belgium	1993-2006	206,525	2,600
Denmark	1993-2006	105,508	2,345
Finland	1997-2006	125,318	1,802
France	1993-2006	497,324	2,870
Germany	1993-2002	7,201,954	1,520
Greece	1993-2006	447,781	2,577
Ireland	1998-2006	274,954	1,799
Italy	1993-1999, 2004-2006	653,617	1,924
Luxembourg	1993-2006	85,106	2,261
Netherlands	1993-2006	386,307	2,797
Norway	1996-2006	118,066	1,934
Portugal	1993-2006	252,315	2,626
Spain	1993-2006	672,604	2,885
Sweden	1997-2001; 2004-2006	209,252	1,446
UK	1993-2006	712,893	2,924

Sources: ELFS and IABS (for Germany). Notes: Number of observations in the restricted sample: occupations 11, 23, 33, 61 and 92 and industries A, B, L, M and Q are dropped. The same number of observations is available for the number of persons employed and the number of weekly hours worked, except for Germany, where there are 6,705,421 individual observations for hours worked.

Table A5. Pairwise correlations of occupational education levels for 16 European countries

	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxemb.	Netherl.	Norway	Portugal	Spain	Sweden
Austria	1.00														
Belgium	0.90	1.00													
Denmark	0.90	0.93	1.00												
Finland	0.90	0.92	0.86	1.00											
France	0.90	0.97	0.98	0.89	1.00										
Germany	0.92	0.90	0.93	0.87	0.92	1.00									
Greece	0.90	0.98	0.93	0.94	0.97	0.91	1.00								
Ireland	0.89	0.98	0.94	0.92	0.96	0.91	0.98	1.00							
Italy	0.95	0.94	0.88	0.96	0.91	0.90	0.95	0.93	1.00						
Luxemb.	0.91	0.92	0.90	0.92	0.93	0.96	0.92	0.92	0.92	1.00					
Netherl.	0.94	0.96	0.95	0.93	0.96	0.95	0.96	0.96	0.96	0.96	1.00				
Norway	0.89	0.95	0.98	0.87	0.98	0.90	0.96	0.96	0.91	0.89	0.96	1.00			
Portugal	0.95	0.95	0.90	0.94	0.93	0.91	0.96	0.92	0.98	0.92	0.95	0.92	1.00		
Spain	0.90	0.96	0.91	0.95	0.95	0.89	0.98	0.97	0.95	0.91	0.95	0.94	0.96	1.00	
Sweden	0.87	0.94	0.96	0.87	0.97	0.88	0.95	0.95	0.88	0.87	0.93	0.97	0.91	0.93	1.00
UK	0.88	0.94	0.99	0.87	0.98	0.91	0.94	0.96	0.88	0.90	0.95	0.98	0.90	0.93	0.98

Notes: All correlations significant at the 1% level. Occupational education level weighted by occupational hours worked. 21 ISCO occupations included, see Table A2.

Table A6. Employment compared across 16 European countries

	Persons employed in thousands	% of total nr of persons employed	Weekly hours worked in thousands	% of total nr of hours worked
Austria	3,150	2.27%	121,687	2.37%
Belgium	2,857	2.06%	106,846	2.08%
Denmark	2,205	1.59%	77,284	1.50%
Finland	1,994	1.44%	75,188	1.46%
France	18,108	13.06%	688,902	13.39%
Germany	34,519	24.89%	1,192,070	23.18%
Greece	3,172	2.29%	140,049	2.72%
Ireland	1,458	1.05%	53,284	1.04%
Italy	17,978	12.96%	708,214	13.77%
Luxembourg	135	0.10%	5,048	0.10%
Netherlands	6,255	4.51%	194,819	3.79%
Norway	1,855	1.34%	62,107	1.21%
Portugal	3,796	2.74%	153,666	2.99%
Spain	15,457	11.15%	615,678	11.97%
Sweden	3,510	2.53%	127,206	2.47%
UK	22,223	16.03%	821,410	15.97%

Note: 2002 for Germany, 2006 for all other countries.

Table B1. Analysis of variance models

Dependent variable: log(hours worked/1000)

F-statistics for interactions:	df	(1)	(2)	(3)	(4)
Industry*Country*Year	2,087	3.73	3.43	4.01	3.77
		(0.000)	(0.000)	(0.000)	(0.000)
Industry*Occupation	200	601.95	574.83	1192.99	1084.27
		(0.000)	(0.000)	(0.000)	(0.000)
Occupation*Year	260	2.26	2.27	5.26	4.93
		(0.000)	(0.000)	(0.000)	(0.000)
Occupation*Country	298	37.70	36.69	69.71	62.38
		(0.000)	(0.000)	(0.000)	(0.000)
Occupation*Country*Year	3,322	0.93	0.89	1.99	_
		(1.000)	(1.000)	(0.000)	
Industry*Occupation*Year	2,556	_	0.80	_	1.41
			(1.000)		(0.000)
Industry*Occupation*Country	2,745	_	_	15.39	14.18
				(0.000)	(0.000)
F-statistic (model)		58.49	41.01	98.18	99.96
		(0.000)	(0.000)	(0.000)	(0.000)
R^2		0.92	0.93	0.97	0.97

Notes: All countries; 36,556 observations for each ANOVA. F-statistics reported, corresponding p-values in brackets. All specifications control for industry, occupation, country and year effects. All interactions in the table are therefore exactly identified, except for industry*country*year, which additionally contains industry*country, industry*year and country*year variation.

Table C1. ONET task measures categorized into Abstract, Routine, or Service task importance measures

ARS measure	Dimension	ONET variables
ABSTRACT	Non-routine	Originality; Critical Thinking; Active Learning; Learning Strategies; Monitoring; Coordination; Persuasion; Negotiation; Instructing; Judgment and Decision Making; Systems Analysis; Systems Evaluation; Time Management; Management of Financial Resources; Management of Material Resources; Management of Personnel Resources; Judging the Qualities of Things, Services, or People; Making Decisions and Solving Problems; Thinking Creatively; Developing Objectives and Strategies; Scheduling Work and Activities; Organizing, Planning, and Prioritizing Work; Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment; Interpreting the Meaning of Information for Others; Communicating with Supervisors, Peers, or Subordinates; Communicating with Persons Outside the Organization; Coordinating the Work and Activities of Others; Developing and Building Teams; Training and Teaching Others; Guiding, Directing, and Motivating [illegible] Staffing Organizational Units; Monitoring and Controlling Resources; Oral Comprehension; Written Comprehension; Oral Expression; Written Expression; Fluency of Ideas; Problem Sensitivity; Deductive Reasoning; Inductive Reasoning; Information Ordering; Category Flexibility; Mathematical Reasoning; Number Facility; Speed of Closure; Flexibility of Closure; Perceptual Speed; Visualization; Selective Attention; Time Sharing; Speech Recognition; Speech Clarity; Reading Comprehension; Writing; Speaking; Mathematics; Science; Complex Problem Solving; Operations Analysis; Technology Design; Equipment Selection; Programming; Troubleshooting; Getting Information; Monitor Processes, Materials, or Surroundings; Processing Information; Evaluating Information to Determine Compliance with Standards; Analyzing Data or Information; Updating and Using Relevant Knowledge; Interacting With Computers
ROUTINE	Routine	Operation Monitoring; Operation and Control; Equipment Maintenance; Quality Control Analysis; Inspecting Equipment, Structures, or Material; Estimating the Quantifiable Characteristics of Products, Events, or Information; Arm-Hand Steadiness; Manual Dexterity; Finger Dexterity; Reaction Time; Wrist-Finger Speed; Speed of Limb Movement; Static Strength; Explosive Strength; Dynamic Strength; Trunk Strength
SERVICE	Non-Routine	Social Perceptiveness; Service Orientation; Assisting and Caring for Others; Establishing and Maintaining Interpersonal Relationships; Resolving Conflicts and Negotiating with Others; Selling or Influencing Others; Active Listening; Performing for or Working Directly with the Public

Notes: All 96 variables are taken from the ONET database 11, sections 1A, 2A, 2B, 4A and 4B, and have the Importance scale, ranging from 1 (not important) to 5 (extremely important). We calculate the average US employment-weighted value for each ISCO occupation after calculating a principal component of each measure at the ONET SOC level. Scale reliability coefficients are 0.9848 for Abstract, 0.9310 for Routine and 0.9398 for Service.

Table C2. Principal components, Abstract, Routine and Service task importance for occupations ranked by their mean European wage

ISCO code	*Occupation*	A. Principal components from 96 task measures: PC1	PC2	weighted PC1	weighted PC2	B. Principal components from 161 task measures: PC1	PC2	weighted PC1	weighted PC2
12	Corporate managers	1.10	−0.46	1.44	−0.29	1.02	−0.66	1.38	−0.49
21	Physical, mathematical and engineering professionals	0.86	0.34	1.24	0.47	0.81	−0.19	1.21	0.06
22	Life science and health professionals	1.01	0.22	1.42	0.32	1.05	−0.04	1.49	0.19
24	Other professionals	0.76	−0.97	0.97	−0.66	0.65	−1.05	0.95	−0.72
13	Managers of small enterprises	1.10	−0.46	1.44	−0.29	1.02	−0.66	1.38	−0.49
31	Physical, mathematical and engineering associate professio	0.29	0.72	0.53	0.94	0.40	0.61	0.65	0.84
34	Other associate professionals	0.49	−0.78	0.61	−0.55	0.39	−0.83	0.56	−0.60
32	Life science and health associate professionals	0.36	0.08	0.55	0.30	0.40	0.02	0.61	0.27
83	Drivers and mobile plant operators	−0.69	0.36	−0.80	0.86	−0.57	1.01	−0.68	1.32
81	Stationary plant and related operators	−0.61	0.93	−0.59	1.50	−0.49	1.02	−0.50	1.42
72	Metal, machinery and related trade work	−0.42	1.03	−0.35	1.51	−0.30	1.12	−0.25	1.46
73	Precision, handicraft, craft printing and related trade worker	−1.19	0.45	−1.43	1.20	−1.14	0.26	−1.38	0.77
41	Office clerks	−0.04	−1.00	−0.14	−0.74	−0.17	−1.04	−0.22	−0.81
42	Customer service clerks	−0.14	−1.29	−0.35	−1.10	−0.23	−1.11	−0.36	−0.93
71	Extraction and building trades workers	−0.94	0.35	−1.11	1.11	−0.91	0.61	−1.08	1.11
82	Machine operators and assemblers	−0.77	1.08	−0.79	1.67	−0.69	0.92	−0.76	1.32
74	Other craft and related trade workers	−1.20	0.24	−1.50	0.94	−1.20	0.08	−1.51	0.58
51	Personal and protective service workers	−0.04	−0.46	−0.06	−0.05	−0.06	−0.21	−0.06	0.10
93	Laborers in mining, construction, manufacturing and transp	−0.77	0.32	−0.90	1.01	−0.71	0.57	−0.85	0.99
52	Models, salespersons and demonstrators	0.08	−1.22	0.00	−0.84	−0.07	−0.98	−0.10	−0.73
91	Sales and service elementary occupations	−0.68	−0.59	−0.91	0.04	−0.73	−0.21	−0.93	0.19

Note: All task importances and principal components standardized to mean zero unit standard deviation. Principal components in panel A are constructed from the same 96 ONET task measures as Abstract, Routine, Service task measures; those in panel B are constructed from all 161 ONET task measures that have the importance scale. In each panel, the first two principal components are unweighted at the level of SOC 2000 occupations, the final two are weighted by US employment in SOC 2000 occupations.

Table C3. Correlations between principal components, Abstract, Routine and Service task importances

		Abstract	Routine	Service	96 ONET measures PC1	96 ONET measures PC2	96 ONET measures weighted PC1	96 ONET measures weighted PC2	161 ONET measures PC1	161 ONET measures PC2	161 ONET measures weighted PC1	161 ONET measures weighted PC2
	Abstract	1.00										
	Routine	−0.49	1.00									
	Service	0.61	−0.68	1.00								
96 ONET measures	PC1	0.90	−0.73	0.80	1.00							
96 ONET measures	PC2	−0.05	0.84	−0.63	−0.37	1.00						
96 ONET measures	weighted PC1	0.93	−0.66	0.76	0.99	−0.27	1.00					
96 ONET measures	weighted PC2	−0.25	0.91	−0.74	−0.56	0.97	−0.47	1.00				
161 ONET measures	PC1	0.93	−0.65	0.77	0.99	−0.27	1.00	−0.47	1.00			
161 ONET measures	PC2	−0.24	0.94	−0.62	−0.53	0.94	−0.44	0.96	−0.43	1.00		
161 ONET measures	weighted PC1	0.94	−0.61	0.74	0.99	−0.22	1.00	−0.42	1.00	−0.39	1.00	
161 ONET measures	weighted PC2	−0.31	0.95	−0.67	−0.60	0.93	−0.51	0.97	−0.51	0.99	−0.46	1.00

Notes: All task importances and principal components standardized to mean zero unit standard deviation. Observation for ISCO 13 (which by construction contains the same task score as ISCO 12) excluded.

Table C4. Conditional labor demand

Dependent variable: Log(hours worked/1000)

Linear time-trend interacted with:	A. 96 ONET task measures				B. 161 ONET task measures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PC1	1.37*	1.30*	–	–	1.23*	1.16*	–	–
	(0.14)	(0.14)			(0.14)	(0.15)		
PC2	−0.43*	−0.38*	–	–	−0.61*	−0.57*	–	–
	(0.13)	(0.13)			(0.13)	(0.13)		
weighted PC1	–	–	1.36*	1.32*	–	–	1.36*	1.31*
			(0.15)	(0.15)			(0.15)	(0.15)
weighted PC2	–	–	−0.40*	−0.32*	–	–	−0.38*	−0.32*
			(0.15)	(0.15)			(0.14)	(0.14)
Offshorability	–	−0.26	–	−0.26	–	−0.27*	–	−0.28*
		(0.14)		(0.14)		(0.14)		(0.13)
Log industry marginal costs	0.83*	0.83*	0.83*	0.83*	0.83*	0.83*	0.83*	0.82*
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Log industry output	1	1	1	1		1		
	–	–	–	–	–	–	–	–
Log wage	−0.81*	−0.82*	−0.80*	−0.81*	−0.81*	−0.82*	−0.81*	−0.81*
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)

Notes: Years 1993-2006, all countries except Ireland. Each regression constrains the point estimate on log industry output to be equal to 1, includes dummies for industry-occupation-country cells, and has 32,044 observations. Point estimates on the principal components and offshorability have been multiplied by 100. Standard errors clustered by country-industry-occupation. *Significant at the 5% level or better.

Table D1. Number of cases of offshoring by ISCO occupation

Occupation	ISCO	Number of cases	Standardized rank of number of cases
Corporate managers	12	4	−0.57
Managers of small enterprises	13	0	−0.62
Physical, mathematical and engineering professionals	21	23	−0.35
Life science and health professionals	22	0	−0.62
Other professionals	24	11	−0.49
Physical, mathematical and engineering associate professionals	31	32	−0.24
Life science and health associate professionals	32	0	−0.62
Other associate professionals	34	45	−0.09
Office clerks	41	161	1.26
Customer service clerks	42	32	−0.24
Personal and protective service workers	51	0	−0.62
Models, salespersons and demonstrators	52	0	−0.62
Extraction and building trades workers	71	4	−0.57
Metal, machinery and related trade work	72	81	0.33
Precision, handicraft, craft printing and related trade workers	73	2	−0.59
Other craft and related trade workers	74	32	−0.24
Stationary plant and related operators	81	198	1.69
Machine operators and assemblers	82	333	3.27
Drivers and mobile plant operators	83	1	−0.61
Sales and service elementary occupations	91	23	−0.35
Laborers in mining, construction, manufacturing and transport	93	131	0.91

Source: European Restructuring Monitor 2002-2008. Note: Standardized rank of the number of cases of offshoring has mean zero and unit standard deviation.

Table D2. Correlations between our RTI and offshoring measures and Blinder and Krueger's (2009) measures of offshorability

	RTI	ERM offshoring	B&K self reported	B&K inferred	B&K coders*
ERM offshoring	0.38	1.00			
B&K self reported	−0.67	−0.20	1.00		
B&K inferred	−0.43	0.11	0.87	1.00	
B&K coders*	0.23	0.65	0.07	0.43	1.00

Notes: Correlations across all ISCO occupations. *This is the measure preferred by Blinder and Krueger (2009).

Table D3. Correlations between our RTI and offshoring measures and Blinder and Krueger's (2009) measures of offshorability

	RTI	ERM offshoring	B&K self reported	B&K inferred	B&K coders*
ERM offshoring	0.40	1.00			
B&K self reported	−0.80	−0.14	1.00		
B&K inferred	−0.60	0.14	0.91	1.00	
B&K coders*	0.11	0.85	0.12	0.41	1.00

Notes: Correlations across 9 occupation groups as used in Blinder and Krueger (2009). *This is the measure preferred by Blinder and Krueger (2009).

Table D4. Conditional effects of task content and offshorability on employment
Dependent variable: Log(hours worked/1000)

Linear time-trend interacted with:	ERM	Self	Inferred	Coded
RTI	−1.44*	−1.39*	−1.42*	−1.47*
	(0.13)	(0.18)	(0.15)	(0.13)
Offshorability	−0.21	0.19	0.21	−0.23
	(0.13)	(0.17)	(0.15)	(0.13)
Log wage	−0.09	−0.10	−0.10	−0.09
	(0.12)	(0.12)	(0.12)	(0.12)

Notes: All countries; 34,816 observations for each regression; all regressions have an R^2 of 0.96. All regressions include dummies for industry-country-year and industry-occupation-country. Point estimates on RTI and offshorability have been multiplied by 100 to reflect percentage point changes. Standard errors are clustered by industry-occupation-country. *Significant at the 5%

Table D5. Conditional effects of task content and offshorability on employment
Dependent variable: Log(hours worked/1000)

Linear time-trend interacted with:	ERM	Self	Inferred	Coded
RTI	−1.08*	−1.15*	−1.13*	−1.20*
	(0.15)	(0.24)	(0.19)	(0.15)
Offshorability	−0.58*	0.11	0.17	−0.33*
	(0.14)	(0.24)	(0.19)	(0.14)
Log wage	0.05	0.04	0.03	0.05
	(0.18)	(0.18)	(0.18)	(0.18)

Notes: All countries; 17,316 observations for each regression; all regressions have an R^2 of 0.98. All regressions include dummies for industry-country-year and industry-occupation-country. Point estimates on RTI and offshorability have been multiplied by 100 to reflect percentage point changes. Standard errors are clustered by industry-occupation-country. *Significant at the 5%

Table E1. Number of wage observations by country and year

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Austria												3,865	4,548	5,143
Belgium		2,469	2,248	2,119	2,083	1,995	335	322	1,664			3,538	3,319	
Denmark		2,685	2,519	2,268	989	1,925	1,902	1,808	1,802					
France		5,174	5,098	5,016	4,565	4,377	4,168	4,093	4,048					
Germany		8,278	8,578	8,105	8,454	8,012	7,302	7,794	6,907					
Greece		4,131	3,850	3,569	3,618	3,375	3,155	3,171	3,341			3,498	3,029	3,111
Ireland		3,137	2,650	2,361	2,360	2,248	2,003	1,702	1,525			4,009	4,318	3,987
Italy		8,057	7,858	7,642	7,256	6,860	6,600	6,173	5,879			14,470	13,292	13,127
Luxembourg		867	816	789										
Netherlands		5,214	5,641	5,696	5,678	5,523	5,781	5,953	4,838					
Norway												2,829		2,873
Portugal		3,447	3,628	3,642	3,867	3,948	3,994	4,055	4,035			4,189	3,871	3,622
Spain		6,782	6,178	5,969	5,922	5,758	5,838	5,795	5,708			9,661	9,220	9,743
UK	7,592	34,692	33,983	34,189	68,296	67,968	64,562	61,105	60,665	59,032	55,988	53,124	51,018	47,536

Sources: LFS for all years for UK; ECHP for 1994-2001 and EUSILC for 2004-2006 for all other countries. Notes: the ECHP and EU-SILC do not contain any occupational wages for Sweden or Finland: we impute them using the procedure described in the data appendix.

Table E2. Average number of wage observations by country and occupation

ISCO	Austria	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Luxemb.	Netherl.	Norway	Portugal	Spain	UK
12	85	102	122	229	178	32	180	103	24	339	269	40	96	3,680
13	22	12	17	17	25	28	83	54	19	115	59	46	28	3,402
21	38	71	99	148	278	102	97	129	25	225	130	55	224	2,122
22	35	80	43	40	278	100	107	138	7	225	82	54	238	1,217
24	151	102	120	133	234	103	125	125	27	294	140	79	151	1,782
31	372	63	110	242	406	100	80	439	29	434	148	92	178	1,221
32	83	106	93	169	406	97	33	377	15	434	159	43	153	1,289
34	227	140	195	485	684	142	150	642	74	468	356	179	434	2,745
41	302	448	270	736	677	459	356	1,426	144	583	201	394	593	7,346
42	611	82	43	116	677	357	86	992	25	583	40	108	492	2,096
51	818	129	244	447	367	238	319	490	64	259	429	460	581	5,883
52	217	70	55	176	212	187	193	318	30	167	195	226	352	3,376
71	110	56	89	236	561	311	141	587	82	186	112	356	604	1,293
72	297	74	104	283	543	154	122	553	34	206	137	250	384	2,335
73	21	30	12	12	543	110	23	379	3	206	17	43	261	388
74	362	57	35	95	561	261	40	486	17	186	36	312	486	518
81	41	36	9	133	340	139	25	286	30	166	46	48	241	416
82	81	64	75	290	234	65	165	311	19	101	71	172	211	1,937
83	114	55	75	181	340	193	135	358	48	166	113	218	323	1,789
91	334	127	109	305	171	182	124	458	96	99	102	477	579	3,543
93	198	108	69	94	216	83	173	188	12	100	15	202	352	1,606

Sources: LFS for 1993-2006 for UK; ECHP for 1994-2001 and EUSILC for 2004-2006 for all other countries. Notes: the ECHP and EU-SILC do not contain any occupational wages for Sweden or Finland: we impute them using the procedure described in the data appendix.

Table E3. Pairwise Spearman rank correlations of occupational wage ranks, 1994 and 2001

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Luxemb.	Netherl.	Portugal	Spain
1994											
Belgium	1.00										
Denmark	0.76	1.00									
France	0.86	0.87	1.00								
Germany	0.90	0.90	0.91	1.00							
Greece	0.87	0.83	0.85	0.96	1.00						
Ireland	0.91	0.87	0.94	0.95	0.91	1.00					
Italy	0.93	0.75	0.85	0.92	0.94	0.89	1.00				
Luxembourg	0.90	0.72	0.82	0.86	0.87	0.88	0.95	1.00			
Netherlands	0.69	0.62	0.60	0.75	0.75	0.68	0.73	0.66	1.00		
Portugal	0.87	0.71	0.82	0.92	0.87	0.87	0.91	0.89	0.77	1.00	
Spain	0.91	0.83	0.91	0.95	0.89	0.91	0.91	0.88	0.68	0.95	1.00
UK	0.85	0.89	0.91	0.87	0.84	0.93	0.80	0.81	0.65	0.75	0.79
2001											
Belgium	1.00										
Denmark	0.83	1.00									
France	0.84	0.82	1.00								
Germany	0.85	0.82	0.94	1.00							
Greece	0.86	0.77	0.88	0.93	1.00						
Ireland	0.79	0.92	0.92	0.87	0.79	1.00					
Italy	0.92	0.81	0.85	0.89	0.95	0.80	1.00				
Luxembourg											
Netherlands	0.86	0.88	0.92	0.92	0.87	0.92	0.88		1.00		
Portugal	0.83	0.81	0.82	0.87	0.89	0.85	0.89		0.85	1.00	
Spain	0.91	0.84	0.94	0.95	0.93	0.89	0.95		0.96	0.87	1.00
UK	0.84	0.88	0.95	0.88	0.80	0.93	0.83		0.92	0.81	0.92

Notes: Mean occupational wages in 1994 and 2001, weighted by weekly hours worked, are calculated on the basis of ECHP and EU-SILC wage data, respectively. All correlations significant at the 1% level.

Table G1. Country and industry heterogeneity in the conditional impacts of technological change and offshoring

Dependent variable: Log(hours worked/1000)

A. Country heterogeneity	(1)	(2)	B. Industry heterogeneity	(3)	(4)
F-statistic (p-value) for interaction with a linear timetrend:			F-statistic (p-value) for interaction with a linear timetrend:		
ABSTRACT task importance* country dummies	2.40 (0.00)	–	ABSTRACT task importance* industry dummies	1.63 (0.09)	–
ROUTINE task importance* country dummies	1.00 (0.45)	–	ROUTINE task importance* industry dummies	1.83 (0.05)	–
SERVICE task importance* country dummies	1.19 (0.27)	–	SERVICE task importance* industry dummies	1.34 (0.20)	–
RTI* country dummies	–	2.47 (0.00)	RTI* industry dummies	–	1.87 (0.05)
Offshorability* country dummies	2.29 (0.00)	2.10 (0.01)	Offshorability* industry dummies	1.23 (0.26)	1.06 (0.39)

Notes: All countries; 34,816 observations for each regression. All regressions control for the occupation-country-year specific log wage and dummies for industry-country-year and industry-occupation-country. Standard errors clustered by industry-occupation-country. The null hypothesis is that interactions of the task importances or of offshorability with country or industry dummies are jointly equal to zero.

Table H1. Shiftshare analysis of changes in share of hours worked between and within industries for occupations ranked by the mean 1993 European wage

Occupations ranked by 1993 mean European wage	ISCO code	Total change in occupational employment share	Change in employment share within industries	Change in employment share between industries
Corporate managers	12	1.23	1.26	-0.02
Physical, mathematical and engineering professionals	21	1.02	0.71	0.31
Life science and health professionals	22	-0.12	-0.41	0.29
Other professionals	24	0.65	0.03	0.62
Managers of small enterprises	13	1.25	1.19	0.06
Physical, mathematical and engineering associate professi	31	0.87	0.81	0.06
Other associate professionals	34	2.15	1.37	0.78
Life science and health associate professionals	32	0.69	0.22	0.46
Drivers and mobile plant operators	83	-0.19	0.09	-0.27
Stationary plant and related operators	81	-0.38	-0.02	-0.36
Metal, machinery and related trade work	72	-2.29	-1.13	-1.17
Precision, handicraft, craft printing and related trade worke	73	-0.40	-0.18	-0.22
Office clerks	41	-1.94	-2.26	0.32
Customer service clerks	42	0.18	0.11	0.07
Extraction and building trades workers	71	-0.51	-0.24	-0.27
Machine operators and assemblers	82	-1.96	-0.69	-1.27
Other craft and related trade workers	74	-1.35	-0.75	-0.59
Personal and protective service workers	51	1.11	-0.03	1.14
Laborers in mining, construction, manufacturing and transp	93	0.45	0.80	-0.35
Models, salespersons and demonstrators	52	-1.38	-0.93	-0.45
Sales and service elementary occupations	91	0.89	0.05	0.85

Notes: Years 1993-2006. All 16 countries, pooled. Between and within effects may not exactly add up to the total change due to rounding errors. All numbers are percentage points.