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Explaining Job Polarization: Routine-Biased Technological Change and Offshoring

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This paper documents the pervasiveness of job polarization in 16 Western European countries over the period 1993-2010. It then develops and estimates a framework to explain job polarization by the recent processes of routine-biased technological change and offshoring. This model can explain much of both total job polarization and the split into within-industry and between-industry components.

JEL: J21, J23, J24
Keywords: Labor Demand, Technology, Globalization, Polarization

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I. Appendix A: Data

In this section we describe in more detail the data sources of our measures of employment and wages, the routineness and offshorability of occupations as well as our measures of industry output and costs.

A. Employment

The European Union Labour Force Survey (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. 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 use the latter definition in our analyses.

Occupations are coded with the two-digit 1988 International Standard Classification for Occupations (ISCO1988) and industries with the Nomenclature Statistique des Activités Economiques dans la Communauté Européenne (NACE) revision 1. For 2008-2010, the NACE code changes from revision 1 to revision 2, and we assign revision 1 codes to individual observations from these years by using our own software program Mapper98 (available upon request) and the official Eurostat crosswalk between the two codes as mapping matrix.

We supplement the ELFS with German employment data from the SIAB dataset– a 2% random sample of social security records covering 1993-2008. We retain only full-time employed workers who are subject to social security contributions. Since the 2-digit industry code used in the SIAB (classified by the 2003 Industrial Classification of Economic Activities) differs somewhat from NACE and no crosswalk was available, we matched them manually. Due to anonymization, industry codes in the SIAB are no more disaggregate than the ones in the ELFS**,** and as a result we were not able to find a match for each NACE: specifically, there were no separate equivalents NACE D and E in the SIAB. Instead, employment in these industries are taken together: however, none of our analyses are sensitive to the exclusion of Germany. Lastly, prior to 2003, a different industry classification was used (the 1973 Industrial Classification of Economic Activities): because this classification is more difficult to reconcile with NACE, we assign the 2003 industry code to these years instead. This is possible using Mapper98 since both codes are reported for 2003-2008.

For the occupation code used in the SIAB data, several steps are required to assign

ISCO1988 codes. Since the SIAB occupational code is based on the German KldB1988 code, we use an available crosswalk to KldB2010, from which there is a crosswalk available to ISCO2008, which then can be converted to ISCO1988. Since these conversions are not one-to-one, we retain the multiple-to-multiple crosswalk between the SIAB code and ISCO1988, and use Mapper98 to assign ISCO1988 codes to individual observations in the SIAB data.

Tables A1 and A2 provide an overview of the 26 2-digit ISCO1988 occupations and 17 NACE revision 1 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 the coverage of German data is not complete 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, we adjust occupational employment for several breaks apparent at the level of our three occupational groups (see Table 2 in the main text). When an occupation's employment jumps up or down in any one particular year, we apply (to all occupations) the post-break year-to-year employment growth to the employment level before the break. This is the case for the following countries and years: Austria 2004, Finland 2002, France 1995 and 2003, Italy 2004, Luxembourg 2009, Portugal 1998, UK 2001.

Table A3 presents, for each country we use, the years for which full data (i.e. employed individuals for whom hours worked, as well as a 2-digit occupation and a major industry group is known) is available. The employment dataset is created by summing the individual hours worked data by country, industry, occupation, and year – Table A3 also shows the number of year-occupation-industry cell observations by country.

B. Routineness

To capture the impact of RBTC, we use the five original task measures from Autor, Levy and Murnane (2003) based on the Dictionary of Occupational Titles (DOT). Following Autor, Katz and Kearney (2006, 2008), Autor and Dorn (2012) and Autor, Dorn and Hanson (2013), we collapse the original five task measures of Autor, Levy and Murnane (2003) to three task aggregates: the Manual task measure corresponds to the DOT variable measuring an occupation's demand for 'eye-hand-foot coordination'; the Routine task measure is a simple average of two DOT variables, 'set limits, tolerances and standards' measuring an occupation's demand for routine cognitive tasks, and 'finger dexterity', measuring an occupation's use of routine motor tasks; and the Abstract task measure is the average of two DOT variables: 'direction control and planning', measuring managerial and interactive tasks, and 'GED Math', measuring mathematical and formal reasoning requirements. Further details on these variables are found in Appendix Table 1 of Autor, Levy and Murnane (2003). From this, we construct the Routine Task Intensity (RTI) index used in Autor and Dorn (2013) as the difference between the log of Routine tasks and the sum of the log of Abstract and the log of Manual tasks, which we normalize to have mean zero and unit standard deviation across our occupations. To obtain these measures at the level of ISCO1988 occupations, several crosswalks are necessary. Firstly, we convert the Census occupations to SOC occupations. Then, we use the crosswalk between SOC and ISCO2008, and subsequently the crosswalk between ISCO2008 and ISCO1988.

C. Offshorability

Blinder and Krueger (2013) construct three measures of offshorability from the individual level Princeton Data Improvement Initiative (PDII) dataset (the PDII survey data can be downloaded from Alan Krueger's web-page): 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. For our analyses, we apply this preferred measure after using the crosswalk between SOC and ISCO2008, and subsequently the crosswalk between ISCO2008 and ISCO1988 and normalizing it to have mean zero and unit standard deviation across our occupations. The resulting BK values are reported in column (2) of Table A4.

Firpo, Fortin and Lemieux (2011), on the other hand, construct three task-based offshorability measures from the O*NET database: they argue that occupations are more offshorable, the less face-to-face communication (FFL1), on-site presence (FFL2), or decision-making (FFL3) they require. We use the O*NET database to exactly replicate those measures, use the crosswalk between SOC and ISCO2008, and subsequently the crosswalk between ISCO2008 and ISCO1988 and normalize to have mean zero and unit standard deviation across our occupations. The resulting numbers for FFL1 are reported in column (3), for FFL2 in column (4) and for FFL3 in column (5) of Table A4.

Finally, we also use data on *actual* instances of offshoring by European companies compiled in the European Restructuring Monitor (ERM) from the European Foundation for Improvement of Living and Working Conditions.[1] ERM contains summaries of news reports about cases of actual 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.

[1] See http://www.eurofound.europa.eu/emcc/erm/index.htm.

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 offshoring and normalize this sum to have mean zero and unit standard deviation across our occupations: this is the ERM measure of actual offshoring reported in column (1) of Table A4.

To see how the measures of *offshorability* discussed above (BK, FFL1, FFL2, FFL3) are related to *actual offshoring* (ERM), we regress ERM onto BK, FFL1, FFL2 and FFL3. This is done in Table A5. Columns (1) to (4) include the BK, FFL1, FFL2 and FFL3 measures of offshorability separately, suggesting that BK (column (1)) and FFL1 (column (2)) are most strongly correlated with actual offshoring. The coefficient in column (3) suggests that FFL2 is, if anything, negatively related to actual offshoring and the coefficient on FFL3 in column (4) is positive but not significant at the 5 percent level. Columns (5) to (8) of Table A4 always include the BK measure and one of FFL1, FFL2 or FFL3. The point estimates in column (5) show that BK and FFL1 are related to actual offshoring but, by and large, for similar occupations – although Table A4 shows that BK is relatively higher for some high-paid occupations such as physical, mathematical and engineering professionals (21) whereas FFL1 is relatively higher for some low-paid occupations such as sales and service elementary occupations (91). The point estimates in column (6) show that FFL2 is independent of ERM conditional on BK and, if taken at face value, negatively related to it perhaps because the requirement of on-site presence does not preclude offshoring if the whole site can be offshored. Finally, the point estimates in column (7) show that BK and FFL3 are both related to actual offshoring but that BK is relatively higher for some high-paid occupations whereas FFL3 is relatively higher for some low-paid occupations such as personal and protective service workers (52) and models, salespersons and demonstrators (52). However, column (8) of Table A5 shows that none of the three FFL measures is a significant predictor of the ERM measure in a multivariate analysis so we exclude the FFL measures from the analysis in the main text.

Finally, Table A6 shows the correlation coefficients between the RTI and the different offshorability measures. For example, the coefficient of correlation between RTI and BK is 0.46 and is statistically significant as was mentioned in the main the text.

D. Industry output, prices and costs

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 omitted 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.

We use a measure of 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. To obtain a measure of output, we deflate production using industry-country-year specific price deflators – also taken from STAN. To obtain a measure of industry marginal costs, we use STAN's net operating surplus data in addition to production and output, and take the difference between production and net operating surplus and divide this difference by output.

E. Wages

We obtain wages from the European Community Household Panel (ECHP) and European Union Statistics on Income and Living Conditions (EU-SILC), since the ELFS does not contain any earnings information. The ECHP contains individual gross monthly wages for the period 1994-2001, whereas the EU-SILC reports individual gross monthly wages for the period 2004-2010. For Germany, we again use the superior SIAB dataset. For the UK, we use the gross weekly wage from the UK Labour Force Survey because it contains many more observations and is available for 1993-2010. All wages were converted into 2000 Euros using harmonized price indices and real exchange rates. The ranking of occupations used Tables 1, 2 and 4 in the main text and Table A4 is then obtained by averaging wages for each occupation-country cell across all years and then averaging these occupational wages across countries.

An operative assumption in our main text is that skills or tasks are roughly comparable within occupations across countries in the sample. Table A7 makes this case by showing pairwise Spearman correlations between countries across occupational wage levels. All correlations are very high and significant at the 1% level. We can also show the similarity of occupations across countries by using the education level of workers: the ELFS is the source of 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 Spearman correlations in average educational attainment by occupation are all significant and very high, as shown in Table A8.

F. Employment share changes for all years

One might be concerned that cyclical fluctuations rather than trends drive the long differences in employment shares reported in Table 1 and Table 2 in the main text. To examine this, for each country in each year, we group the occupations listed in Table 1 into three groups: the 4 lowest-paid occupations, 9 middling occupations and the 8 highest-paying occupations, as is done in Table 2 in the main text. 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. Indeed, Figure A1 shows that the time series are primarily trends and that the polarization found in Table 1 is not sensitive to endpoints.

Figure A2 makes an adjustment to this picture by filtering out the impact of an unbalanced country-year panel due to incomplete data spans (see Table A3). This is done by running a regression of log hours worked onto a set of occupation group dummies interacted with year dummies (these coefficients, multiplied by 100, are reported in the figure), while controlling for country-year dummies. This confirms the conclusion drawn above, that the majority of the observed patterns are trends not cycle.

Table A1. 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 A2. 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 A3. Data availability for number of weekly hours worked

	Years covered	*Total nr of obs*	*Total nr of obs in ind-occ-year cells*
Austria	1995-2010	648,808	2,846
Belgium	1993-2010	361,315	3,434
Denmark	1993-2010	300,808	3,139
Finland	1997-2010	184,490	2,328
France	1993-2010	689,567	3,339
Germany	1993-2008	8,283,986	3,360
Greece	1993-2010	844,880	3,355
Ireland	1998-2010	501,175	2,603
Italy	1993-1999, 2004-2010	1,583,339	2,337
Luxembourg	1993-2010	128,757	2,742
Netherlands	1993-2010	593,040	3,594
Norway	1996-2010	174,291	2,631
Portugal	1993-2010	517,899	2,954
Spain	1993-2010	830,467	3,678
Sweden	1997-2001; 2004-2010	821,751	2,239
UK	1993-2010	900,406	3,560

Sources: ELFS and SIAB (for Germany).

Table A4. Offshorability measures for occupations ranked by their mean European wage

Occupations ranked by mean European wage	ISCO code	(1) ERM	(2) Blinder-Krueger (BK)	(3) No Face-to-Face (FFL1)	(4) No On-Site (FFL2)	(5) No Decision-Making (FFL3)
Corporate managers	12	-0.59	-0.32	-1.43	0.80	-1.66
Physical, mathematical and engineering professionals	21	-0.37	1.05	0.39	0.80	-1.48
Life science and health professionals	22	-0.64	-0.76	-1.92	0.54	-1.70
Other professionals	24	-0.51	0.21	-0.89	1.56	-1.18
Managers of small enterprises	13	-0.59	-0.63	-0.94	0.27	-1.19
Physical, mathematical and engineering associate professionals	31	-0.27	-0.12	0.12	-0.39	-0.43
Other associate professionals	34	-0.12	0.10	-0.40	1.11	-0.30
Life science and health associate professionals	32	-0.64	-0.75	-1.58	0.19	-0.63
Stationary plant and related operators	81	1.63	1.59	0.99	-1.41	0.31
Metal, machinery and related trade work	72	0.29	-0.45	0.79	-1.58	0.06
Drivers and mobile plant operators	83	-0.63	-1.00	0.40	-1.37	0.70
Office clerks	41	1.21	0.40	0.30	1.26	0.91
Precision, handicraft, craft printing and related trade workers	73	-0.62	1.66	0.59	-0.56	0.01
Extraction and building trades workers	71	-0.59	-0.93	0.60	-1.23	0.01
Customer service clerks	42	-0.27	-0.25	-0.69	1.23	0.75
Machine operators and assemblers	82	3.18	2.35	1.66	-1.02	0.99
Other craft and related trade workers	74	-0.27	1.15	1.49	-0.45	1.07
Laborers in mining, construction, manufacturing and transport	93	0.87	-0.66	0.65	-1.02	0.64
Personal and protective service workers	51	-0.64	-0.94	-0.91	0.31	0.24
Models, salespersons and demonstrators	52	-0.64	-0.89	0.06	0.91	1.34
Sales and service elementary occupations	91	-0.37	-0.81	0.73	0.05	1.52

Notes: Occupations are ordered by their mean wage across the 16 European countries across all years. All measures are rescaled to have mean 0 and standard deviation 1, a higher value means an occupation is more offshorable.

Table A5. Estimating offshoring
Dependent variable: ERM

Standardized offshoring measure:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blinder-Krueger (BK)	0.614*** (0.176)	–	–	–	0.444** (0.201)	0.579*** (0.173)	0.588*** (0.166)	0.649** (0.245)
No Face-to-Face (FFL1)	–	0.555*** (0.186)	–	–	0.316 (0.201)	–	–	-0.183 (0.397)
No On-Site (FFL2)	–	–	-0.333 (0.212)	–	–	-0.253 (0.173)	–	-0.247 (0.238)
No Decision-Making (FFL3)	–	–	–	0.365* (0.209)	–	–	0.315* (0.166)	0.357 (0.269)
R^2	0.391	0.319	0.115	0.138	0.464	0.455	0.493	0.527
Adj R^2	0.358	0.283	0.0685	0.0926	0.404	0.395	0.436	0.409

Notes: 21 observations for each regression. *** p<0.01, ** p<0.05, * p<0.1.

Table A6. Correlations between RTI and offshorability measures

	(1)	(2)	(3)	(4)	(5)	(6)
(1) RTI	1.00					
(2) ERM offshoring	0.41*	1.00				
	0.07					
(3) Blinder-Krueger (BK)	0.46**	0.63***	1.00			
	0.04	0.00				
(4) No Face-to-Face (FFL1)	0.48**	0.57***	0.54**	1.00		
	0.03	0.01	0.01			
(5) No On-Site (FFL2)	-0.03	-0.34	-0.1395	-0.61***	1.00	
	0.89	0.13	0.55	0.00		
(6) No Decision-Making (FFL3)	0.58***	0.37*	0.08	0.67***	-0.30	1.00
	0.01	0.10	0.72	0.00	0.18	

Notes: 21 observations. Correlation coefficients and p-values reported. *** p<0.01, ** p<0.05, * p<0.1.

Table A7. Pairwise Spearman correlations of occupational wages for 16 European countries

	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxemb.	Netherl.	Norway	Portugal	Spain	Sweden	UK
Austria	1.00															
Belgium	0.92	1.00														
Denmark	0.92	0.85	1.00													
Finland	0.93	0.93	0.92	1.00												
France	0.88	0.86	0.94	0.90	1.00											
Germany	0.93	0.91	0.87	0.89	0.85	1.00										
Greece	0.95	0.94	0.87	0.96	0.88	0.86	1.00									
Ireland	0.89	0.87	0.92	0.96	0.91	0.86	0.89	1.00								
Italy	0.94	0.94	0.80	0.91	0.84	0.88	0.96	0.85	1.00							
Luxemb.	0.95	0.95	0.87	0.95	0.90	0.92	0.95	0.93	0.97	1.00						
Netherl.	0.93	0.93	0.94	0.95	0.90	0.90	0.92	0.90	0.85	0.91	1.00					
Norway	0.92	0.95	0.92	0.97	0.92	0.89	0.95	0.92	0.91	0.94	0.95	1.00				
Portugal	0.92	0.90	0.79	0.89	0.82	0.86	0.91	0.85	0.97	0.95	0.84	0.89	1.00			
Spain	0.94	0.96	0.88	0.95	0.92	0.91	0.97	0.91	0.96	0.98	0.92	0.96	0.95	1.00		
Sweden	0.93	0.96	0.93	0.98	0.94	0.91	0.95	0.95	0.91	0.96	0.97	0.98	0.88	0.96	1.00	
UK	0.89	0.90	0.93	0.95	0.91	0.89	0.87	0.95	0.84	0.91	0.94	0.95	0.83	0.91	0.97	1.00

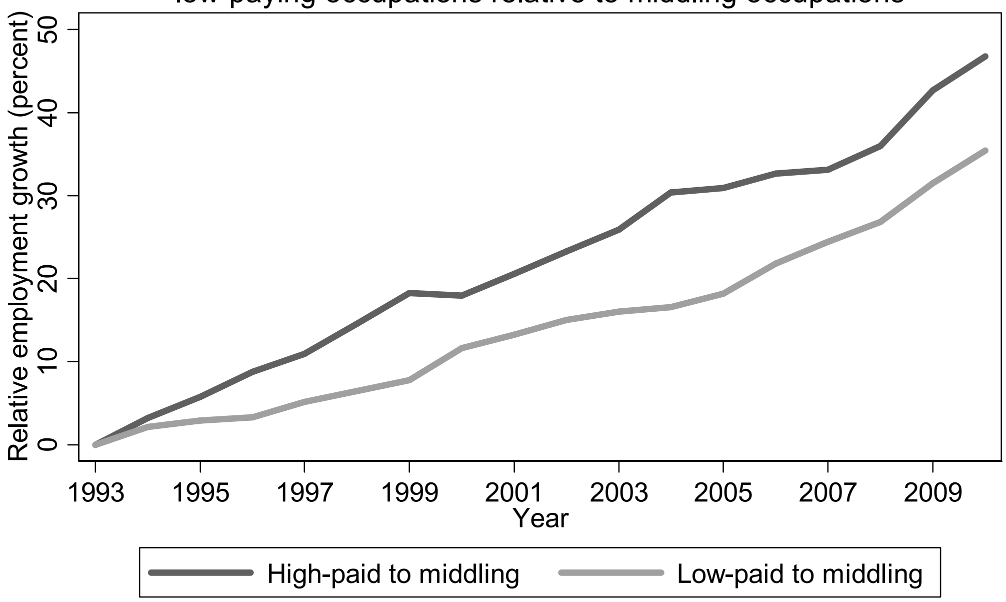
Notes: All correlations significant at the 1% level. Occupational wage level weighted by occupational hours worked, averaged across all years. 21 ISCO occupations included, see Table A1.

Table A8. Pairwise Spearman rank correlations of occupational education levels for 16 European countries

	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxemb.	Netherl.	Norway	Portugal	Spain	Sweden	UK
Austria	1.00															
Belgium	0.94	1.00														
Denmark	0.94	0.90	1.00													
Finland	0.91	0.91	0.80	1.00												
France	0.93	0.95	0.95	0.84	1.00											
Germany	0.91	0.86	0.94	0.75	0.93	1.00										
Greece	0.91	0.95	0.84	0.89	0.91	0.80	1.00									
Ireland	0.96	0.98	0.90	0.94	0.93	0.85	0.95	1.00								
Italy	0.91	0.94	0.83	0.93	0.88	0.79	0.97	0.95	1.00							
Luxemb.	0.90	0.90	0.91	0.80	0.94	0.95	0.84	0.88	0.83	1.00						
Netherl.	0.94	0.97	0.92	0.87	0.95	0.92	0.93	0.95	0.93	0.94	1.00					
Norway	0.92	0.95	0.95	0.84	0.96	0.90	0.92	0.94	0.90	0.90	0.97	1.00				
Portugal	0.91	0.95	0.84	0.90	0.89	0.78	0.99	0.94	0.98	0.83	0.94	0.91	1.00			
Spain	0.88	0.92	0.80	0.92	0.87	0.75	0.95	0.95	0.93	0.84	0.90	0.88	0.94	1.00		
Sweden	0.94	0.94	0.90	0.91	0.91	0.83	0.89	0.96	0.91	0.83	0.92	0.92	0.90	0.87	1.00	
UK	0.96	0.91	0.97	0.85	0.93	0.92	0.85	0.93	0.84	0.92	0.93	0.93	0.84	0.86	0.93	1.00

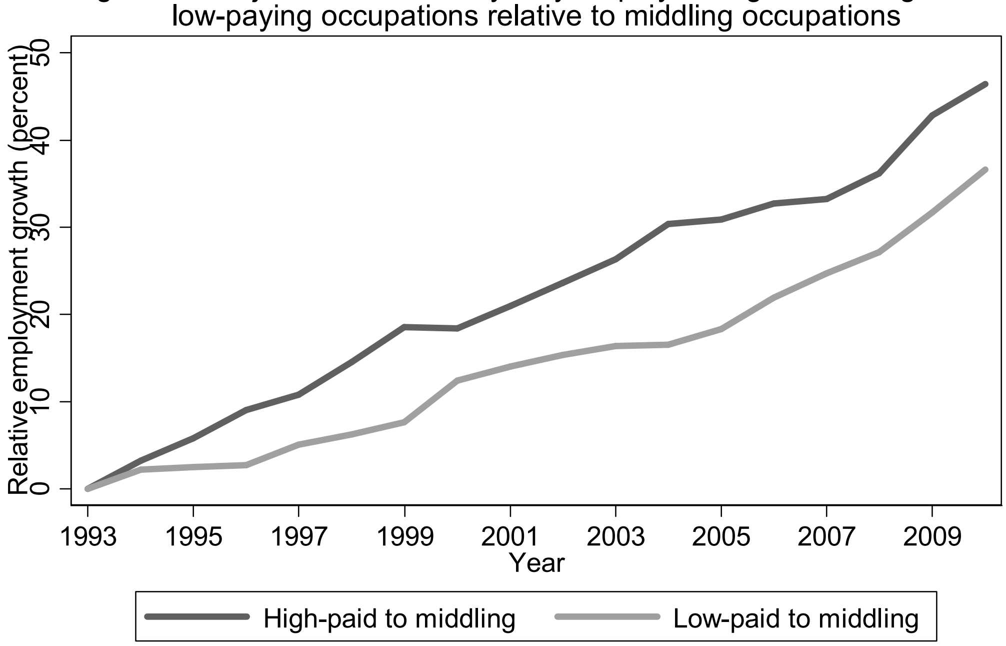
Notes: All correlations significant at the 1% level. Occupational education level weighted by occupational hours worked. 21 ISCO occupations included, see Table A1.

Figure A1. Cumulative yearly employment growth of high- and low-paying occupations relative to middling occupations



Note: Employment growth averaged across countries, no adjustment for countries with incomplete data spans.

Figure A2. Adjusted cumulative yearly employment growth of high- and low-paying occupations relative to middling occupations



Note: Employment growth averaged across countries, adjusted for countries with incomplete data spans.

II. Appendix B: CES Task Production Technologies

In the main text we assume that output of task j is produced using labor of occupation j and some other input, K_{ij}, according to a Cobb-Douglas production function that is common across industries:

$$T_{ij}(N_{ij}, K_{ij}) = N_{ij}^{\kappa} K_{ij}^{1-\kappa} \text{ with } 0 < \kappa < 1 \tag{1}$$

Assuming that task production technologies are CES instead, we get that:

$$T_{ij}(N_{ij}, K_{ij}) = \left[\kappa N_{ij}^{\frac{\rho-1}{\rho}} + (1-\kappa) K_{ij}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \text{ with } \rho > 0 \tag{2}$$

where ρ is the elasticity of substitution between N_{ij} and K_{ij} in task production. Assuming that $\rho \to 1$ gives equation (1). The expression for the log demand for occupation j in industry i conditional on industry output and marginal costs (and adding country and time subscripts) is given by:

$$\begin{aligned} \log N_{ijct} \quad = \quad & -[(1-\kappa)\rho + \kappa\eta] \log w_{jct} \\ & + [\rho - \eta][1-\kappa] \left[\gamma_R R_j + \gamma_F F_j \right] \times time \\ & + \eta \log c_{ict}^I + \log Y_{ict} + (\eta - 1) \log \beta_{ijc} + \varepsilon_{ijct} \end{aligned} \tag{3}$$

Table B1 reports estimates of equation (3). Column (1) gives estimates of $[\rho - \eta][1 - \kappa]\gamma_R$ as the coefficient on R_j interacted with a linear time trend (the row RTI); of $[\rho - \eta][1 - \kappa]\gamma_F$ as the coefficient on F_j interacted with a linear time trend (the row Offshorability); of the elasticity of labor demand using the wages discussed in Online Appendix A which is an estimate of $-[(1-\kappa)\rho + \kappa\eta]$; and of the coefficient on industry marginal costs which is an estimate of η. Column (2) repeats the regression in column (1) but constrains the coefficient on $\log Y_{ict}$ to be unity to impose the assumption of constant returns to scale. The coefficients on RTI, Offshorability and log industry marginal costs are comparable to those reported in Table 3 in the main text. The estimated labor demand elasticity suggests an estimate for $-[(1-\kappa)\rho + \kappa\eta]$ of -0.72 with a standard error of 0.05 in column (1) or of -0.63 with a standard error of 0.04 in column (2).

For an assumed value of κ, it is possible from the point estimates in Table B1 to impute an estimate for ρ. For example, assume $\kappa = 0.50$ and $\eta = 0.66$ with a standard error of 0.14. We then get from $[(1-\kappa)\rho + \kappa\eta] = 0.72$ with a standard error of 0.05 that $\rho = 0.78$ with a standard error of 0.16. Assuming $\kappa = 0.40$ gives an estimate for ρ of 0.76 with a standard error of 0.12; and assuming $\kappa = 0.60$ gives an estimate for ρ of 0.81 with a standard error of 0.23. If we set κ equal to 0.54 which is the share of labor costs in value added in our STAN data, we get an estimate of ρ of 0.79 with a standard error of 0.19. In sum, we find estimates for ρ that are relatively close to unity which justifies the Cobb-Douglas simplification in the main text. Moreover, it can be shown that allowing for a more general CES task production function makes little difference to the conclusions in the shift-share analysis in Section V of the main text.

Table B1. Assuming CES task production
Dependent variable: Log(hours worked/1000)

Linear time-trend interacted with :	(1)	(2)
RTI	-1.064***	-1.068***
	(0.158)	(0.159)
Offshorability	0.179	0.167
	(0.187)	(0.188)
Log wage	-0.723***	-0.630***
	(0.045)	(0.041)
Log industry marginal costs	0.659***	0.668***
	(0.136)	(0.136)
Log industry output	0.930***	1
	(0.013)	_
Observations	*48,139*	44,062
R^2	0.832	_

Notes: Point estimates (and standard errors in parentheses) on RTI and Offshorability have been multiplied by 100. Regressions include occupation-industry and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1

III. Appendix C: Heterogeneity in the impacts of RBTC and offshoring

Table 3 in the main text assumes that RBTC and offshoring have the same impact in all 16 countries, that the effect is the same within all industries and across different time periods. If all countries, industries and time periods in our sample can be assumed to be equally affected, an additional test would be to see whether the point estimates reported in Table 3 of the main text do not differ significantly between groups of countries, industries or across decades. That is what we do in this appendix.

Column (1) in Table C1 shows the grand mean effect of RBTC from a regression similar to column (4) in Table 3 in the main text, as well as the deviation from this grand mean for three country groups: Nordic countries (Denmark, Finland, Ireland, Norway, Sweden and the UK), Central countries (Austria, Belgium, France, Germany, Luxembourg and the Netherlands) and Southern countries (Greece, Italy, Portugal and Spain). Column (2) of Table C1 shows the grand mean effect of offshoring from a regression similar to column (5) in Table 3, as well as the deviation from this grand mean for the same three country groups. By and large, there is not much evidence for significant country-group specific impacts from RBTC and offshoring. If taken at face value, the coefficients would indicate that the negative impact of RBTC is largest in Nordic countries and smallest in Central countries, with Southern countries in between. Regarding offshoring, the negative impact of offshoring is larger in Nordic countries and smaller in Southern countries, with Central countries in between.

Table C2 performs a similar exercise, but for five industry groups. None of the industry-specific deviations are significant at the 1% level. If taken at face value, the negative impact of RBTC is stronger for the group of manufacturing, transport, storage and communication and less strong for utilities and construction. Regarding offshoring, the negative employment effect is stronger for financial intermediation, real estate, renting and business activity and less strong for utilities and construction and health, social work, other community, social and personal service activities.

Lastly, Table C3 investigates whether the 1990s and the 2000s have been different in terms of technological change and offshoring: we estimate the mean effect, as well as a deviation from this mean effect for a time trend capturing 2001-2010 (versus 1993-2000). We find no statistically significant evidence of these two decades differing in terms of the impact of RBTC and offshoring. Taken at face value, the estimated difference is economically very small for RBTC whereas there is some evidence that the effects of offshoring have been stronger in the 1990s than in the 2000s.

In sum, we find only limited evidence of significant heterogeneity in the impacts of RBTC and offshoring on the within-industry demand for occupations – most estimates suggest these effects are pervasive across countries, industries and decades.

Table C1. Country heterogeneity in the impacts of RBTC and offshoring
Dependent variable: log(hours worked/1000)

	(1)	(2)
	RTI	*Offshorability*
Mean effect for task measure interacted with timetrend	-0.925***	-0.401**
	(0.129)	(0.169)
Deviation from mean effect for:		
Northern countries	-0.330*	-0.392*
	(0.177)	(0.237)
Central countries	0.411**	0.110
	(0.172)	(0.217)
Southern countries	-0.081	0.282
	(0.197)	(0.251)
Log industry marginal costs	0.895***	0.897***
	(0.160)	(0.161)
Log industry output	1	1
	–	–
Obs	*44,062*	*44,062*

Notes: Point estimates (and standard errors in parentheses) on RTI and offshorability have been multiplied by 100. The regressions include occupation-industry-country and year fixed effects. Northern countries = Denmark, Finland, Ireland, Norway, Sweden and the UK; Central countries = Austria, Belgium, France, Germany, Luxembourg and the Netherlands; Southern countries = Greece, Italy, Portugal and Spain. *** p<0.01, ** p<0.05, * p<0.1

Table C2. Industry heterogeneity in the impacts of RBTC and offshoring
Dependent variable: log(hours worked/1000)

	(1)	(2)
	RTI	*Offshorability*
Mean effect for task measure interacted with timetrend	-0.844***	-0.397**
	(0.132)	(0.172)
Deviation from mean effect for:		
Manufacturing, Transport, Storage & Communication	-0.499**	-0.008
	(0.217)	(0.263)
Utliities & Construction	0.426	0.466
	(0.311)	(0.414)
Hotels, Restaurants, Wholesale & Retail	0.118	-0.301
	(0.258)	(0.288)
Financial Intermediation, Real Estate, Renting & Business Activity	0.016	-0.460
	(0.271)	(0.388)
Health, Social Work, Other Community, Social & Personal Service Activities	-0.060	0.302
	(0.247)	(0.320)
Log industry marginal costs	0.894***	0.898***
	(0.161)	(0.159)
Log industry output	1	1
	–	–
Obs	*44,062*	*44,062*

Notes: Point estimates (and standard errors in parentheses) on RTI and offshorability have been multiplied by 100. The regressions include occupation-industry-country and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table C3. Decade heterogeneity in the impacts of RBTC and offshoring
Dependent variable: log(hours worked/1000)

	(1)	(2)
	RTI	*Offshorability*
Mean effect for task measure interacted with timetrend	-0.810***	-0.260
	(0.153)	(0.185)
Deviation from mean effect for:		
2001-2010	-0.040	-0.084
	(0.070)	(0.084)
Log industry marginal costs	0.895***	0.899***
	(0.161)	(0.161)
Log industry output	1	1
	–	–
Obs	*44,062*	*44,062*

Notes: Point estimates (and standard errors in parentheses) on RTI and offshorability have been multiplied by 100. The regressions include occupation-industry-country and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1

IV. Appendix D: Product Demand

Consumer demands can shift because preferences are non-homothetic since different income elasticities for different goods or services yield structural change even if productivity growth is balanced across tasks or sectors. In particular, job polarization might be caused by increasing inequality leading to increased demand for low-skill service sector jobs from high-wage workers to free up more of their time for market work. That is what we examine in this appendix.

A. Modeling Product Demand

Assume that individual k has income Z_k and that the demand for the output of industry i by individual k is given by:

$$Y_{ik} = Z_k^{\theta_i} P_i^{-\varepsilon} \tag{1}$$

with θ_i the income elasticity of demand for good i which will be unity if preferences are homothetic but not otherwise; P_i the price of good i relative to an aggregate price index; and ε the elasticity of substitution between goods in consumption. Where $\theta_i \neq 1$ for all industries one should acknowledge that this formulation of the demand curve does not satisfy the budget constraint in which case equation (1) is best thought of as a local approximation to the demand curve that will be reasonably accurate if departures from homotheticity are fairly small.

If there are L individuals in the economy and we assume that income has a log-normal distribution with variance σ^2, we can add up the individual demand curves over all individuals in the economy to arrive at the following log aggregate demand equation (also adding time t and country c subscripts and rearranging terms):

$$\log Y_{ict} = -\varepsilon \log P_{ict} + \theta_i \log Y_{ct} + (1-\theta_i) \log L_{ct} + \frac{1}{2}\theta_i(\theta_i - 1) \log \sigma_{ct}^2 \tag{2}$$

with $\log Y_{ict}$ the log of aggregate demand for good i and $\log Y_{ct}$ aggregate income in country c at time t.

Equation (2) shows that there are a number of ways to test for homotheticity – that is, $\theta_i = 1$ – in the data. First, homotheticity implies that the elasticity of industry demand with respect to aggregate income must be unity for each industry because expenditure shares on goods are constant. Secondly, homotheticity implies that, conditional on aggregate income, population size does not affect product demands. The intuition for this is simple: if preferences are non-homothetic and we compare two economies with the same aggregate GDP but with different populations, the economy with the lower population will have a higher demand for luxury goods as GDP per capita is higher. Thirdly, income inequality will not affect product demand if preferences are homothetic. Again the intuition for this is straightforward: if preferences are non-homothetic and we compare two economies with the same average GDP per capita but different income inequality, the economy with more inequality will have a higher demand for luxury goods.

B. Estimating Product Demand Curves

ASSUMING PREFERENCES ARE HOMOTHETIC

Table D1 shows results of estimating a product demand equation that assumes an income elasticity that is the same for each industry (i.e. θ_i in equation (2) is the same for all i):

$$\log Y_{ict} = \delta_0 + \delta_1 \log P_{ict} + F_{ct} + \xi_{ict} \tag{3}$$

where δ_1 is an estimate of $-\varepsilon$; F_{ct} is a country-year fixed effect to capture the impact of variation in $\log Y_{ct}$, $\log L_{ct}$ and $\log \sigma^2_{ct}$; and ξ_{ict} is an error term. As mentioned in the main text, the point estimate for δ_1 is -0.42 with a standard error of 0.07.

TESTING FOR HOMOTHETIC PREFERENCES

Table D2 shows results of estimating the following product demand equation:

$$\log Y_{ict} = \delta_0 + \delta_1 \log P_{ict} + \delta_{2i} \log Y_{ct} + \delta_{3i} \log L_{ct} + \xi_{ict} \tag{4}$$

where $\log Y_{ct}$ is the log of total family consumption expenditure of households in country c at time t taken from the OECD (variable P31DC) and converted into 2000 Euros using harmonized price indices and real exchange rates; $\log L_{ct}$ is the population in country c at time t also taken from the OECD; and ξ_{ict} is an error term. Coefficient δ_1 is again an estimate of $-\varepsilon$ and, under the null hypothesis of homothetic preferences, it must hold that $\delta_{2i} = 1$ and $\delta_{3i} = 0$ and for all i.

Column (1) of Table D2 shows estimates if we assume that for all i we have that $\delta_{2i} = \delta_2$ and $\delta_{3i} = \delta_3$. The point estimate for δ_2 is 1.00 with standard error 0.14 and the point estimate for δ_3 is -0.05 with a standard error of 0.16. Column (2) reports the same grand means for δ_{2i} and δ_{3i}. But column (2) also allows for the industry specific income elasticities to deviate from their grand means by including industry interactions with income and population in the regression equation. Because these interaction coefficients are defined as deviations from their grand means, for any given industry the coefficient on income and population should be the same in absolute value but have opposite signs, which the estimates seem to suggest. Moreover, if preferences are homothetic, these estimates should be insignificant which is the case for most industries. If taken at face value, the income elasticities are higher for electricity, gas and water supply; hotels and restaurants; real estate, renting and business activities; health and social work; and other community, social and personal service activities. In sum, it can be seen that there are some income elasticities that deviate from unitary, but these deviations are generally not statistically significant. Therefore, we do not find strong evidence in our data that non-homotheticity is a good candidate for explaining job polarization.

Table D1. Product demand
Dependent variable: Log(output)

Log price index	-0.422*** (0.071)

Notes: 2,700 observations, 15 countries (no industry-country-year deflated production data available for Ireland). Industry "Private household with employed persons" excluded for all countries, except France, Portugal, Spain and the UK, where it is included in "Other community, social and personal service activities". The regression includes dummies for country-year cells. ***p<0.01.

Table D2. Testing homothetic preferences
Dependent variable: Log(output)

	(1)		(2)	
Log relative price index	-0.514***		-0.546***	
	(0.141)		(0.148)	
Log income	0.999***		0.999***	
	(0.142)		(0.144)	
Log population	-0.050		-0.049	
	(0.162)		(0.163)	
Deviation from mean effect for:		*Log income*		*Log population*
Manufacturing		-0.175		0.216**
		(0.143)		(0.106)
Electricity, gas and water supply		0.339**		-0.312**
		(0.164)		(0.123)
Construction		-0.137		0.109
		(0.129)		(0.094)
Wholesale and retail		-0.089		0.094
		(0.117)		(0.086)
Hotels and restaurants		0.180		-0.187
		(0.309)		(0.230)
Transport, storage and communication		-0.227*		0.181*
		(0.130)		(0.099)
Financial intermediation		-0.173		0.112
		(0.458)		(0.344)
Real estate, renting and business activity		0.025		0.031
		(0.135)		(0.100)
Health and social work		0.073		-0.070
		(0.161)		(0.121)
Other community, social and personal service activities		0.181		-0.174
		(0.146)		(0.108)

Notes: 2,700 observations, 15 countries (no industry-country-year deflated production data available for Ireland). Industry "Private household with employed persons" excluded for all countries, except France, Portugal, Spain and the UK, where it is included in "Other community, social and personal service activities". ***p<0.01, **p<0.05, *p<0.1.

V. Appendix E: Predicting the Impact of RBTC and Offshoring Separately

The predictions in Table 4 and Figure 1 in the main text use, together with an estimate of 0.42 for ε,the coefficients in column (3) of Table 3 where RTI and offshorability are simultaneously added to the regression equation. This appendix provides a separate accounting for the unconditional impacts of RBTC and offshoring using the point estimates in column (4), which excludes offshorability from the regression equation, and column (5), which excludes RTI from the regression equation, of Table 3.

Table E1 replicates Table 4 in the main text while using point estimates from column (4) in Table 3. A comparison of columns (1) and (4) shows that RBTC while not conditioning on offshoring can explain 79 percent (4.46/5.62) of the actual increase in the employment share for the group of 8 highest-paid occupations; 74 percent (6.84/9.27) of the decrease for the group of 9 middling occupations; and 65 percent (2.38/3.65) of the increase for the group of 4 lowest-paid occupations. Columns (2), (3), (5) and (6) of Table E2 show that RBTC while not conditioning on offshoring also predicts job polarization within as well as between industries. In particular, it explains all (3.56/3.11) of the within-industry decrease for the group of 8 highest-paid occupations; 77 percent (3.65/4.77) of the within-industry decrease for the group of 9 middling occupations; 5 percent (0.09/1.66) of the within-industry increase for the group of 4 lowest-paid occupations; 36 percent (0.90/2.51) of the between-industry increase for the group of 8 highest-paid occupations; 71 percent (3.19/4.50) of the between-industry decrease for the group of 9 middling occupations; and all (2.30/1.99) of the between-industry increase for the group of 4 lowest-paid occupations. Figure E1 presents scatter plots by occupation of the actual and predicted overall changes in employment shares (Panel A) as well as their within-industry (Panel B) and between-industry (Panel C) components taken from Table E1. In sum, these numbers are comparable to those presented in Table 4 and Figure 1 in the main text suggesting that RBTC can explain much of job polarization and its within-industry and between-industry components.

Table E2 replicates Table 4 in the main text while using point estimates from column (5) in Table 3. A comparison of columns (1) and (4) shows that offshoring while not conditioning on RBTC can explain 6 percent (0.33/5.62) of the actual increase in the employment share for the group of 8 highest-paid occupations; 28 percent (2.59/9.27) of the decrease for the group of 9 middling occupations; and 62 percent (2.26/3.65) of the increase for the group of 4 lowest-paid occupations. Columns (2), (3), (5) and (6) of Table E2 show that, by and large, offshoring also predicts job polarization within as well as between industries. In particular, it explains 16 percent (0.74/4.77) of the within-industry decrease for the group of 9 middling occupations; 46 percent (0.77/1.66) of the within-industry increase for the group of 4 lowest-paid occupations; 14 percent (0.36/2.51) of the between-industry increase for the group of 8 highest-paid occupations; 41 percent (1.85/4.50) of the between-industry decrease for the group of 9 middling occupations; and 75 percent (1.49/1.99) of the between-industry increase for the group of 4 lowest-paid occupations. Finally, Figure E2 presents scatter plots by occupation of the actual and predicted overall changes in employment shares (Panel A) as well as their within-industry (Panel B) and between-industry (Panel C) components taken from Table

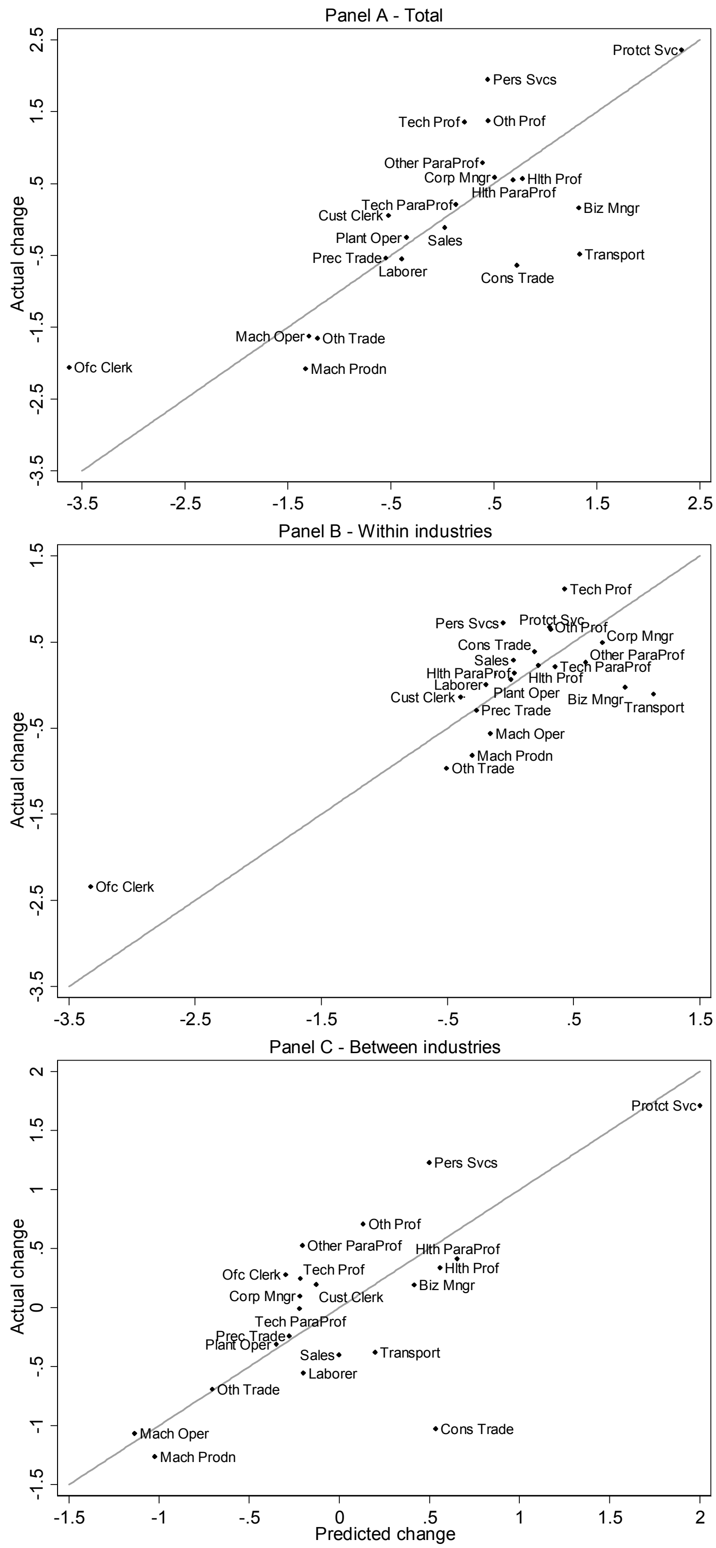
E2. The figure shows, for example, that offshoring has difficulties explaining the large decrease in the employment share of office clerks (41) and the impact this has had within all industries (which is almost all explained by RBTC as is shown in Figure 1 in the main text and Figure E1 above), but for machine operators and assemblers (82) offshoring predicts a sizeable between-industry component. In sum, offshoring goes some distance towards explaining actual changes but is generally less predictive than RBTC.

Table E1. Actual and predicted changes in the shares of hours worked 1993-2010 for occupations ranked by their mean European wage

Occupations ranked by mean European wage	ISCO code	Actual changes (1) Total	(2) Within	(3) Between	Predicted changes, RBTC (4) Total	(5) Within	(6) Between
High-paying occupations		**5.62**	**3.11**	**2.51**	**4.46**	**3.56**	**0.90**
Corporate managers	12	0.59	0.49	0.10	0.51	0.73	-0.22
Physical, mathematical and engineering professionals	21	1.36	1.11	0.25	0.21	0.43	-0.22
Life science and health professionals	22	0.57	0.23	0.34	0.78	0.22	0.56
Other professionals	24	1.38	0.67	0.71	0.44	0.31	0.13
Managers of small enterprises	13	0.17	-0.03	0.19	1.32	0.91	0.41
Physical, mathematical and engineering associate professior	31	0.21	0.22	-0.01	0.13	0.35	-0.22
Other associate professionals	34	0.79	0.27	0.53	0.39	0.59	-0.21
Life science and health associate professionals	32	0.55	0.14	0.41	0.68	0.03	0.65
Middling occupations		**-9.27**	**-4.77**	**-4.50**	**-6.84**	**-3.65**	**-3.19**
Stationary plant and related operators	81	-0.25	0.06	-0.31	-0.35	0.00	-0.35
Metal, machinery and related trade work	72	-2.08	-0.81	-1.26	-1.33	-0.31	-1.02
Drivers and mobile plant operators	83	-0.48	-0.11	-0.38	1.33	1.13	0.20
Office clerks	41	-2.06	-2.34	0.28	-3.63	-3.33	-0.30
Precision, handicraft, craft printing and related trade workers	73	-0.54	-0.30	-0.24	-0.55	-0.27	-0.28
Extraction and building trades workers	71	-0.64	0.39	-1.03	0.72	0.19	0.53
Customer service clerks	42	0.06	-0.14	0.20	-0.52	-0.40	-0.13
Machine operators and assemblers	82	-1.63	-0.56	-1.07	-1.30	-0.16	-1.14
Other craft and related trade workers	74	-1.66	-0.96	-0.69	-1.21	-0.51	-0.71
Low-paying occupations		**3.65**	**1.66**	**1.99**	**2.38**	**0.09**	**2.30**
Laborers in mining, construction, manufacturing and transpor	93	-0.55	0.01	-0.55	-0.40	-0.20	-0.20
Personal and protective service workers	51	2.36	0.65	1.71	2.32	0.32	2.00
Models, salespersons and demonstrators	52	-0.11	0.29	-0.40	0.02	0.02	0.00
Sales and service elementary occupations	91	1.95	0.72	1.23	0.44	-0.06	0.50

Notes: Occupations are ordered by their mean wage across the 16 European countries across all years. Employment pooled across countries; long difference over 1993-2010. Predicted changes are constructed from equation (13) using an estimate of 0.42 for the elasticity of product demand together with point estimates in column (4) of Table 3 accounting for the impact of RBTC unconditional on offshoring.

Figure E1: Actual versus predicted employment share changes, RBTC



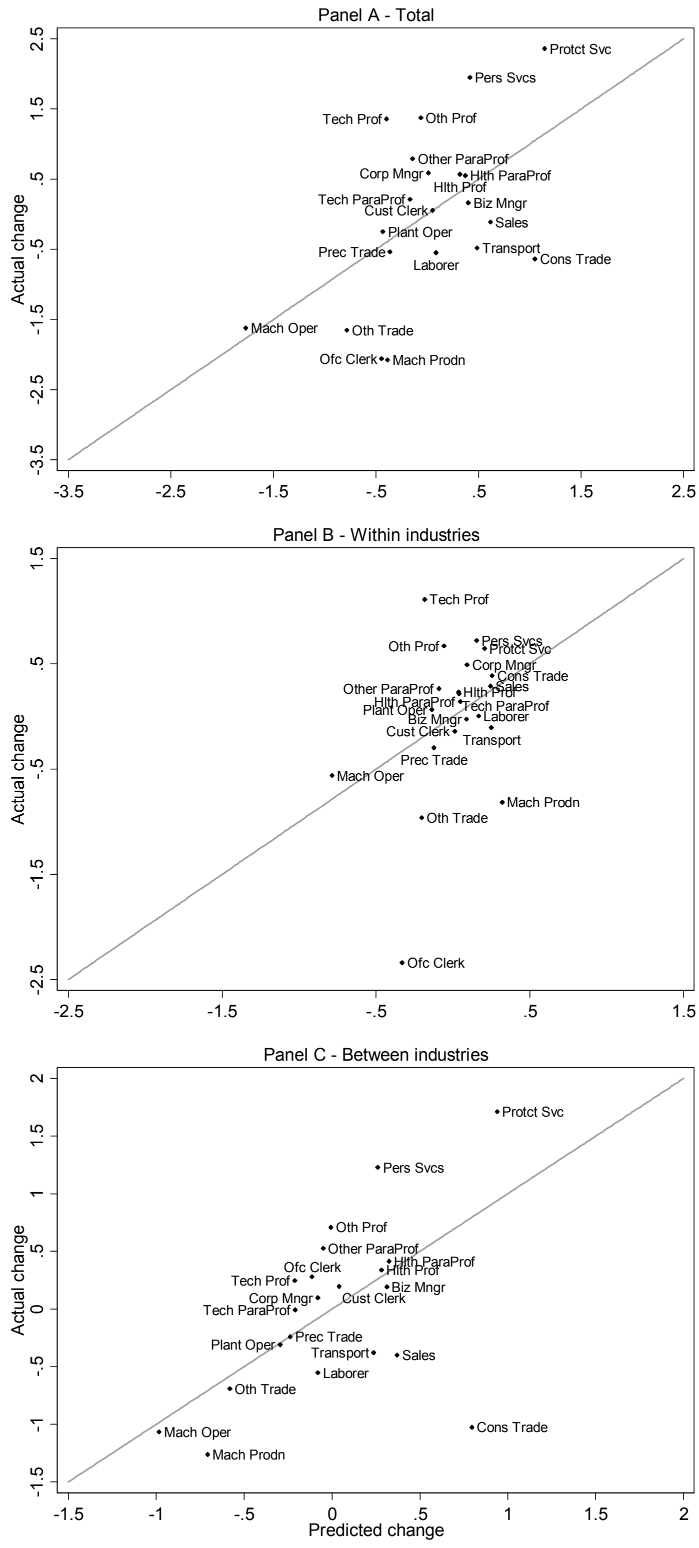
Notes: Data for Panel A are taken from columns (1) and (4); for Panel B from columns (2) and (5); and for Panel C from columns (3) and (6) of Table E1.

Table E2. Actual and predicted changes in the shares of hours worked 1993-2010 for occupations ranked by their mean European wage

Occupations ranked by mean European wage	ISCO code	Actual changes (1) Total	(2) Within	(3) Between	Predicted changes, offshoring (4) Total	(5) Within	(6) Between
High-paying occupations		**5.62**	**3.11**	**2.51**	**0.33**	**-0.03**	**0.36**
Corporate managers	12	0.59	0.49	0.10	0.01	0.09	-0.08
Physical, mathematical and engineering professionals	21	1.36	1.11	0.25	-0.40	-0.18	-0.21
Life science and health professionals	22	0.57	0.23	0.34	0.32	0.04	0.28
Other professionals	24	1.38	0.67	0.71	-0.06	-0.06	-0.01
Managers of small enterprises	13	0.17	-0.03	0.19	0.40	0.09	0.31
Physical, mathematical and engineering associate professior	31	0.21	0.22	-0.01	-0.17	0.04	-0.21
Other associate professionals	34	0.79	0.27	0.53	-0.14	-0.09	-0.05
Life science and health associate professionals	32	0.55	0.14	0.41	0.37	0.05	0.32
Middling occupations		**-9.27**	**-4.77**	**-4.50**	**-2.59**	**-0.74**	**-1.85**
Stationary plant and related operators	81	-0.25	0.06	-0.31	-0.43	-0.14	-0.30
Metal, machinery and related trade work	72	-2.08	-0.81	-1.26	-0.39	0.32	-0.71
Drivers and mobile plant operators	83	-0.48	-0.11	-0.38	0.49	0.25	0.24
Office clerks	41	-2.06	-2.34	0.28	-0.44	-0.33	-0.11
Precision, handicraft, craft printing and related trade workers	73	-0.54	-0.30	-0.24	-0.36	-0.12	-0.24
Extraction and building trades workers	71	-0.64	0.39	-1.03	1.05	0.26	0.80
Customer service clerks	42	0.06	-0.14	0.20	0.05	0.01	0.04
Machine operators and assemblers	82	-1.63	-0.56	-1.07	-1.77	-0.79	-0.98
Other craft and related trade workers	74	-1.66	-0.96	-0.69	-0.78	-0.20	-0.58
Low-paying occupations		**3.65**	**1.66**	**1.99**	**2.26**	**0.77**	**1.49**
Laborers in mining, construction, manufacturing and transpor	93	-0.55	0.01	-0.55	0.09	0.17	-0.08
Personal and protective service workers	51	2.36	0.65	1.71	1.15	0.21	0.94
Models, salespersons and demonstrators	52	-0.11	0.29	-0.40	0.62	0.24	0.37
Sales and service elementary occupations	91	1.95	0.72	1.23	0.42	0.15	0.26

Notes: Occupations are ordered by their mean wage across the 16 European countries across all years. Employment pooled across countries; long difference over 1993-2010. Predicted changes are constructed from equation (13) using an estimate of 0.42 for the elasticity of product demand together with point estimates in column (5) of Table 3 accounting for the impact offshoring unconditional on RBTC.

Figure E2: Actual versus predicted employment share changes, offshoring



Notes: Data for Panel A are taken from columns (1) and (4); for Panel B from columns (2) and (5); and for Panel C from columns (3) and (6) of Table E2.