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Article (Published version) (Refereed)

Original citation:
Michaels, Guy, Natraj, Ashwini and Van Reenen, John (2014) *Has ICT polarized skill demand? Evidence from eleven countries over 25 years.* Review of Economics and Statistics, 96 (1). pp. 60-77. ISSN 0034-6535 DOI: 10.1162/REST_a_00366

HAS ICT POLARIZED SKILL DEMAND? EVIDENCE FROM ELEVEN COUNTRIES OVER TWENTY-FIVE YEARS

Guy Michaels, Ashwini Natraj, and John Van Reenen*

Abstract—We test the hypothesis that information and communication technologies (ICT) polarize labor markets by increasing demand for the highly educated at the expense of the middle educated, with little effect on low-educated workers. Using data on the United States, Japan, and nine European countries from 1980 to 2004, we find that industries with faster ICT growth shifted demand from middle-educated workers to highly educated workers, consistent with ICT-based polarization. Trade openness is also associated with polarization, but this is not robust to controlling for R&D. Technologies account for up to a quarter of the growth in demand for highly educated workers.

I. Introduction

THE demand for more highly educated workers has risen for many decades across OECD countries. Despite a large increase in the supply of such workers, the return to college education has not fallen. Instead, it has risen significantly since the early 1980s in the United States, United Kingdom, and many other nations (Acemoglu & Autor, 2010). The consensus view is that this increase in skill demand is linked to technological progress (Goldin & Katz, 2008) rather than increased trade with low-wage countries (although see Krugman, 2008, for a more revisionist view).[1]

Recent analyses of data through the 2000s, however, suggest a more nuanced view of the change in demand for skills. Autor, Katz, and Kearney (2006, 2008) use U.S. data to show that although upper-tail inequality (between the 90th and 50th percentiles of the wage distribution) has continued to rise in an almost secular way over the past thirty years, lower-tail inequality (between the 50th and 10th percentiles of the distribution) increased during the 1980s but has stayed relatively flat from around 1990. They also show a related pattern for different education groups, with the hourly wages of college graduates rising relative to high school graduates since 1980 and high school graduates gaining relative to high school dropouts during the 1980s but not since then. When considering occupations rather than education groups, Goos and Manning (2007) describe a polarization of the workforce. In the United Kingdom, middle-skilled occupations have declined relative to both the high-skilled and low-skilled occupations. Spitz-Oener (2006) finds related results for Germany, and Goos, Manning and Salomons (2009) find similar results for almost all OECD countries.[2]

What could account for these trends? One explanation is that new technologies, such as information and communication technologies (ICT), are complementary with human capital, and rapid falls in quality-adjusted ICT prices have therefore increased skill demand. A large body of literature is broadly consistent with this notion.[3] A more sophisticated view has been offered by Autor, Levy, and Murnane (2003) who emphasize that ICT substitutes for routine tasks but complements nonroutine cognitive tasks.

Many routine tasks were traditionally performed by less educated workers, such as assembly workers in a car factory, and many of the cognitive nonroutine tasks are performed by more educated workers such as consultants, advertising executives, and physicians. However, many routine tasks are also performed in occupations employing middle-educated workers, such as bank clerks, and these groups have found demand for their services falling as a result of computerization. Similarly, many less educated workers are employed in nonroutine manual tasks such as janitors or cab drivers, and these tasks are much less affected by ICT. Since the number of routine jobs in the traditional manufacturing sectors (like car assembly) declined substantially in the 1970s, subsequent ICT growth may have primarily increased demand for highly educated workers at the expense of those in the middle of the educational distribution and left the least educated (mainly working in nonroutine manual jobs) largely unaffected.

Although this seems intuitive, we first corroborate the view that workers of different educational background cluster into occupations along the task-based view of the world. Using data from the U.S. Census and the Dictionary of Occupational Titles, we show that the most educated workers do indeed disproportionately move into occupations that require relatively little routine cognitive or manual tasks. Middle-educated workers, by contrast are overrepresented in occupations that require routine tasks, especially cognitive ones. The least educated workers are in between when it comes to routine tasks; their work involves less nonroutine cognitive tasks than the others but more nonroutine manual tasks. The task-based theory predicts that ICT improvements increase demand for the most educated (complementing their nonroutine cognitive

Received for publication March 23, 2011. Revision accepted for publication September 18, 2012.

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We thank David Autor, Tim Brenahan, David Dorn, Liran Einav, Maarten Goos, Larry Katz, Paul Krugman, Alan Manning, Denis Nekipelov, Stephen Redding, Anna Salomons, and seminar participants at the AEA, Imperial, LSE, NBER, SOLE-EALE meetings and Stanford for extremely helpful comments. David Autor kindly provided the data on routine tasks. Finance was provided by the ESRC through the Centre for Economic Performance.

A supplemental appendix is available online at http://www.mitpressjournals.org/doi/suppl/10.1162/REST_a_00366.

[1] Throughout the paper, we follow the literature by referring to "education" and "skills" interchangeably; thus "high skilled" refers to "highly educated," "middle skilled" refers to those with intermediate levels of education, and "low skilled" refers to those with lower levels of education. For more details on how the variables are constructed for each country, see below.

[2] See also Dustmann, Ludsteck, and Schonberg (2009) and Smith (2008).

[3] See Bond and Van Reenen (2007) for a survey. Industry-level data are used by Berman, Bound, and Griliches (1994), Autor, Katz, and Krueger (1998), and Machin and Van Reenen (1998). Krueger (1993) and DiNardo and Pischke (1997) use individual data.

tasks), reduce demand for the middle educated (as it substitutes for routine tasks), and has ambiguous effects for the least educated.

There is currently little direct international evidence that ICT causes a substitution from middle-skilled workers to high-skilled workers. Autor et al. (2003) show some consistent trends, and Autor and Dorn (2009) exploit spatial variation across to show that the growth in low-skilled services has been faster in areas where initially there were high proportions of routine jobs. But these are solely within one country: the United States.[4]

In this paper, we test the hypothesis that ICT may be behind the polarization of the labor market by implementing a simple test using 25 years of international cross-industry data. If the ICT-based explanation for polarization is correct, then we would expect that industries and countries that had a faster growth in ICT also experienced an increase in demand for college-educated workers, relative to workers with intermediate levels of education, with no clear effect on the least educated. We show that this is indeed a robust feature of the international data.

We exploit the new EUKLEMS database, which provides data on college graduates and disaggregates noncollege workers into two groups: those with low education and those with middle-level education.[5] For example, in the United States, the middle education group includes those with some college and high school graduates but excludes high school dropouts and GEDs (see Timmer et al., 2007, table 5.3, for the country-specific breakdown). The EUKLEMS database covers eleven developed economies (the United States, Japan, and nine countries in Western Europe) from 1980 to 2004 and also contains data on ICT capital. In analyzing the data, we consider not only the potential role of ICT but also several alternative explanations. In particular, we examine whether the role of trade in changing skill demand could have become more important in recent years (most of the early studies predated the growth of China and India as major exporters).

The idea behind our empirical strategy is that the rapid fall in quality-adjusted ICT prices will have a greater effect in some country-industry pairs that are more reliant on ICT. This is because some industries are (for technological reasons) inherently more reliant on ICT than others. We have no compelling natural experiment, however, so our results should be seen primarily as conditional correlations. We do, however, implement some instrumental variable strategies using the industry-specific initial levels of U.S. ICT intensity and routine tasks as an instrument for subsequent ICT increases in other countries (these are the sectors that stood to gain the most from the rapid fall of ICT prices). These support the OLS results. We conclude that technical change has raised relative demand for college-educated workers, and, consistent with the ICT-based polarization hypothesis, this increase has come mainly from reducing the relative demand for middle-skilled workers rather than low-skilled workers.

Our approach of using industry and education is complementary to the alternative approach of using occupations and their associated tasks. Goos, Manning, and Salomons (2010) use wage and employment changes in occupations based on task content, for example, to show that routine occupations are in decline and that these are in the middle of the wage distribution. In order to examine ICT-based theories of polarization, however, we believe it is useful to have direct measures of ICT capital. Such data are not generally available for individuals consistently across countries and years, which is why using the EUKLEMS data is so valuable. As noted above, however, we do use the occupational information to confirm that educational groups cluster into routine and nonroutine tasks in a systematic way and to construct instrumental variables for the growth of ICT.

The paper is laid out as follows. Section II describes the empirical model, section III the data, and section IV the empirical results. Section V offers some concluding comments.

II. Empirical Model

Consider the short-run variable cost function, $CV(.)$:

$$CV(W^H, W^M, W^L; C, K, Q) \tag{1}$$

where W indicates hourly wages and superscripts denote education or skill group S (H = highly educated workers, M = middle-educated workers, and L = low-educated workers), K = non-ICT capital services, C = ICT capital services, and Q = value added. If we assume that the capital stocks are quasi-fixed, factor prices are exogenous and that the cost function can be approximated by a second-order flexible functional form such as the translog, then cost minimization (using Shephard's lemma) implies the following three skill share equations:

$$\begin{aligned} SHARE^H = {} & \phi_{HH}\ln(W^H/W^L) + \phi_{MH}\ln(W^M/W^L) \\ & + \alpha_{CH}\ln(C/Q) + \alpha_{KH}\ln(K/Q) + \alpha_{QH}\ln Q, \end{aligned} \tag{2}$$

$$\begin{aligned} SHARE^M = {} & \phi_{HM}\ln(W^H/W^L) + \phi_{MM}\ln(W^M/W^L) \\ & + \alpha_{CM}\ln(C/Q) + \alpha_{KM}\ln(K/Q) + \alpha_{QM}\ln Q, \end{aligned} \tag{3}$$

$$\begin{aligned} SHARE^L = {} & \phi_{HL}\ln(W^H/W^L) + \phi_{ML}\ln(W^M/W^L) \\ & + \alpha_{CL}\ln(C/Q) + \alpha_{KL}\ln(K/Q) + \alpha_{QM}\ln Q, \end{aligned} \tag{4}$$

where $SHARE^S = \frac{W^S N^S}{W^H N^H + W^S N^M + W^L N^L}$ is the wage bill share of skill group $S = \{H, M, L\}$ and N^S is the number of hours

[4] The closest antecedent of our paper is perhaps Autor, Katz, and Krueger (1998, table V) who found that in the United States, the industry-level growth of demand for U.S. high school graduates between 1993 and 1979 was negatively correlated with the growth of computer use between 1993 and 1984. We find this is a robust feature of eleven OECD countries over a much longer time period. For other related work, see Black and Spitz-Oener (2010) and Firpo, Fortin, and Lemieux (2011), and work surveyed by Acemoglu and Autor (2010).

[5] In the paper we refer to the three skill groups as high skilled (or sometimes as the college group), middle skilled, and low skilled.

worked by skill group S. Our hypothesis of the ICT-based polarization theory is that $\alpha_{CH} > 0$ and $\alpha_{CM} < 0$ (with the sign of α_{CL} being ambiguous).[6]

Our empirical specifications are based on these equations. We assume that labor markets are national in scope and include country-by-year effects (ϕ_{jt}) to capture the relative wage terms. We also check that our results are robust to including industry-specific relative wages directly on the right-hand side of the share regressions. We allow for unobserved heterogeneity between industry-by-country pairs (η_{ij}) and include fixed effects to account for these, giving the following three equations:

$$SHARE^S = \phi_{jt} + \eta_{ij} + \alpha_{CS} \ln(C/Q)_{ijt} + \alpha_{KS} \ln(K/Q)_{ijt} + \alpha_{QS} \ln Q_{ijt}, \quad (5)$$

where i = industry, j = country and t = year. We estimate in long (25-year) differences, Δ, to look at the historical trends and smooth out measurement error. We substitute levels rather than logarithms ($\Delta(C/Q)$ instead of $\Delta \ln(C/Q)$) because of the very large changes in ICT intensity over this time period. Some industry-by-country pairs had close to zero IT intensity in 1980, so their change is astronomical in logarithmic terms.[7] Consequently our three key estimating equations are

$$\Delta SHARE^S_{ijt} = c^S_j + \beta^S_1 \Delta(C/Q)_{ijt} + \beta^S_2 \Delta(K/Q)_{ijt} + \beta^S_3 \Delta \ln Q_{ijt} + u^S_{ijt}. \quad (6)$$

In the robustness tests, we also consider augmenting equation (6) in various ways. Since ICT is only one aspect of technical change, we also consider using research and development (R&D) expenditures. This is a more indirect measure of task-based technical change, but it has been used in the prior literature, so it could be an important omitted variable. Additionally, we consider trade variables (such as imports plus exports over value added) to test whether industries that were exposed to more trade upgraded the skills of their workforce at a more rapid rate than those that did not. This is a pragmatic empirical approach, to examining trade effects. Under a strict Heckscher-Ohlin approach, trade is a general equilibrium effect increasing wage inequality throughout the economy, so looking at the variation by industry would be uninformative. However, since trade costs have declined more rapidly in some sectors than others (for example, due to trade liberalization) we would expect the actual flows of trade to proxy this change and there to be a larger effect on workers in these sectors than in others who were less affected (Krugman, 2008, also makes this argument).

Appendix A, found online, considers a theoretical model with parameter restrictions over equation (1) that implies that ICT is a substitute for middle-skilled labor and a complement with highly-skilled labor. Comparative static results from the model suggest that as ICT increases (caused by a fall in the quality-adjusted price of ICT), the wage bill share of skilled workers rises and the share of middle-skilled workers falls. It also shows that all else equal, an exogenous increase in the supply of middle-skilled workers will cause their wage bill share to rise. Thus, although ICT could reduce the demand for the middle-skilled group, their share could still rise because of the long-run increase in supply.

III. Data

A. Data Construction

The main source of data for this paper is the EUKLEMS data set, which contains data on value added, labor, capital, skills, and ICT for various industries in many developed countries (see Timmer et al., 2007). The EUKLEMS data are constructed using data from each country's National Statistical Office (such as the U.S. Census Bureau) and harmonized with each country's national accounts. EUKLEMS contains some data on most OECD countries. But since we require data on skill composition, ICT, and non-ICT capital and value added between 1980 and 2004, our sample of countries is restricted to eleven: Austria, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Spain, the United Kingdom, and the United States.[8]

Another choice we had to make is about the set of industries we analyze. Since our baseline year (1980) was close to the peak of the oil boom, we have dropped energy-related sectors—mining and quarrying, coke manufactures, and the supply of natural gas—from the sample (we report results that are very robust to the inclusion of these sectors). The remaining sample includes twenty seven industries in each country (see appendix table A1). Wage data by skill category are reported only separately by industry in some countries. We therefore aggregate industries to the lowest possible level of aggregation for which all the variables we use could be constructed to have unique values for each industry. The precise level of disaggregation varied by country (see appendix table A2).[9] Our final sample has 208 observations on country-industry cells for 1980 and 2004. We also have data for intervening years, which we use in some of the robustness checks.

For each country-industry-year cell in our data set, we construct a number of variables. Our main outcome is the wage bill share of workers of different educational groups, a standard indicator for skill demand. In nine of the eleven countries, the high-skilled group indicates whether

[6] The exact correspondence between the coefficients on the capital inputs and the Hicks-Allen elasticity of complementarity is more complex (see Brown & Christensen, 1981).

[7] The range of $\Delta \ln(C/Q)$ lies between -1 and 23.5. We report robustness checks using $\frac{\Delta(C/Q)}{C/Q}$ as an approximation for $\Delta \ln(C/Q)$.

[8] In order to increase the number of countries, we would need to considerably shorten the period we analyze. For example, limiting our analysis to 1992 to 2004 (twelve years instead of twenty-five) adds only Belgium. To add the Czech Republic, Slovenia, and Sweden, we would need to restrict the sample to 1995 to 2004. In order to preserve the longer time series, we focused on the eleven core OECD countries.

[9] Results are robust to throwing away information and harmonizing all countries at the same level of industry aggregation.

an employee has attained a college degree.[10] A novel feature of our analysis is that we also consider the wage bill of middle-skilled workers. The precise composition of this group varies across countries, since educational systems differ considerably. But typically this group consists of high school graduates, people with some college education, and people with nonacademic professional degrees.

Our main measure for use of new technology is ICT capital divided by value added. Similarly, we also use the measure of non-ICT capital divided by value added. EUKLEMS builds these variables using the perpetual inventory method from the underlying investment flow data for several types of capital. For the tradable industries (agriculture and manufacturing), we construct measures of trade flows using UN COMTRADE data.[11] Details are contained in the online data appendix.

Finally, we construct measures of skill and task content by occupation. We begin with U.S. Census microdata for 1980 from IPUMS, which identify each person's education (which we aggregate to three skill levels using the EUKLEMS concordance for the United States) and occupation. We then use the "80-90" occupation classification from Autor et al. (2003) to add information on the task measures they construct. These include routine cognitive tasks (measured using set limits, tolerances, or standards); routine manual tasks (measured using finger dexterity); nonroutine manual tasks (measured using eye-hand-foot coordination); and nonroutine cognitive tasks measured using both (a) quantitative reasoning requirements and (b) direction, control, and planning. We standardize each of these five task measures by subtracting the mean task score across occupations, weighted by person weights, and dividing the result by the standard deviation of the measure across occupations. (For further details on the construction of these measures, see the data appendix.)

B. *Descriptive Statistics*

The routineness of occupations by skill level. We begin the description of the data by examining the relationship between education and tasks. Table 1 reports the top ten occupations for each of the three education categories using U.S. data for 1980. This table shows that the occupations with the largest shares of highly educated workers (such as physicians, lawyers, and teachers) and those with the highest shares of low-educated workers (such as cleaners and farmworkers) have low scores on routine cognitive tasks. These groups also have typically low scores on routine manual tasks. By contrast, occupations with high shares of middle-educated workers (mostly clerical occupations and bank tellers) typically score high on both routine cognitive and routine manual tasks. Therefore, if the only contribution of ICT was to automate (and replace) routine tasks, it should benefit both high-skilled and low-skilled workers at the expense of middle-skilled workers.

However, as Autor et al. (2003) argued, information technology should also complement nonroutine tasks, especially cognitive ones. Here the picture is more nuanced: high-skilled occupations typically score high on nonroutine cognitive tasks, though not on nonroutine manual tasks. Middle-skilled occupations tend to score around average in nonroutine tasks, and low-skilled workers score low on nonroutine cognitive tasks but above average on nonroutine manual tasks. Therefore, to the extent that information technology both replaces routine tasks and complements nonroutine tasks, the overall picture suggests that ICT should increase the relative demand for high-skilled workers at the expense of middle-skilled workers, with no clear effect on low-skilled workers.

We further explore the relationship between education groups and tasks in table 2, which reports the average tasks content by skill group, again using 1980 U.S. data. On average, high-skilled occupations rank lowest in terms of routine tasks and nonroutine manual tasks, but highest in terms of nonroutine cognitive tasks, so the Autor et al. (2003) model suggests that they benefit from ICT improvements. Middle-skilled occupations score above average on routine tasks and a little below average on nonroutine tasks, so ICT should probably reduce the relative demand for their services. Finally, the picture for low-skilled workers is once again mixed for both routine and nonroutine tasks, so the theory gives no clear prediction on how ICT improvements should affect the demand for their services.

Having discussed the relationship between skills and tasks, we now move on to describe the changes in skill demand using the EUKLEMS data.

Cross-country trends. Panel A of table 3 shows summary statistics for the levels of the key variables in 1980 across each country, and panel B presents the same for the changes through 2004. The levels have to be interpreted with care as exact comparison of qualifications between countries is difficult, which is why wage bill shares are useful summary measures as each qualification is weighted by its price (the wage).[12] The ranking of countries looks sensible, with the United States having the highest share of those which are highly skilled (29%), followed by Finland (27%). All countries have experienced significant skill upgrading as indicated by the growth in the high-skilled wage bill share in column 1 of panel B; on average, the share increased from 14.3% in 1980 to 24.3% in 2004.

The United Kingdom had the fastest absolute increase in the high-skilled wage bill share (16.5 percentage points) and is also the country with the largest increase in ICT intensity. The United States had the second-largest growth of ICT and the third-largest increase in the high-skilled wage bill

[10] In two countries, the classification of high-skilled workers is different: in Denmark, it includes all people in "long-cycle" higher education, and in Finland it includes people with tertiary education or higher.

[11] Using a crosswalk (available from the authors on request), we calculate the value of total trade, imports, and exports with the rest of the world and separately with OECD and non-OECD countries. We identify all thirty countries that were OECD members in 2007 as part of the OECD.

[12] Estimating in differences also reduces the suspected bias from international differences as the definitions are stable within country over time.

TABLE 1.—TOP OCCUPATIONS BY SHARE OF WORKERS OF DIFFERENT SKILL LEVELS, WITH TASK MEASURES

						Standardized Skill Measures				
						Routine Tasks		Nonroutine Tasks		
						Cognitive	Manual	Cognitive		Manual
occ8090	Occupation Description	Employment in 1980	Fraction High Skilled	Fraction Middle Skilled	Fraction Low Skilled	Set Limits, Tolerances, or Standards	Finger Dexterity	Quantitative Reasoning Requirements	Direction, Control, and Planning	Eye-Hand-Foot Coordination
Top ten occupations ranked by share of high-skilled workers										
84	Physicians	460,260	0.97	0.03	0.00	−0.96	4.18	1.94	1.87	0.50
178	Lawyers	534,780	0.95	0.05	0.00	−0.96	−1.11	1.05	−0.51	−0.80
85	Dentists	135,620	0.94	0.06	0.00	1.47	4.73	1.99	−0.55	0.89
133	Medical science teachers	9,860	0.93	0.06	0.01	−1.05	−0.90	1.73	2.08	−0.80
126	Social science teachers, n.e.c.	2,480	0.93	0.04	0.03	−1.05	−1.12	2.01	2.33	−0.80
146	Social work teachers	1,060	0.92	0.06	0.02	−1.05	−1.12	2.01	2.33	−0.80
123	History teachers	6,380	0.92	0.06	0.02	−1.05	−1.12	1.73	2.17	−0.80
118	Sociology teachers;Psychology teachers	9,200	0.92	0.06	0.02	−1.05	−1.12	2.01	2.33	−0.80
147	Theology teachers	3,940	0.91	0.07	0.03	−1.05	−1.12	1.97	2.27	−0.80
86	Veterinarians	37,440	0.91	0.08	0.01	1.00	4.06	0.96	−0.52	−0.71
Top ten occupations ranked by share of middle-skilled workers										
314	Stenographers	106,360	0.07	0.88	0.05	1.40	1.13	−0.58	−0.64	−0.80
529	Telephone installers and repairers	273,980	0.03	0.87	0.10	1.45	1.38	0.47	−0.60	2.16
383	Bank tellers	639,180	0.07	0.86	0.07	1.48	2.53	0.29	−0.49	−0.80
313	Secretaries	5,020,140	0.08	0.86	0.07	−0.71	2.73	0.17	−0.61	−0.79
385	Data-entry keyers	472,880	0.05	0.85	0.10	1.31	0.23	0.08	0.16	−0.76
206	Radiologic technicians	110,060	0.10	0.85	0.04	1.51	0.98	1.13	−0.59	0.92
527	Telephone line installers and repairers	65,560	0.03	0.85	0.12	1.32	1.06	0.34	−0.37	1.80
315	Typists	969,040	0.05	0.84	0.11	−0.06	1.50	−0.12	−0.63	−0.76
338	Payroll and timekeeping clerks	200,940	0.06	0.83	0.11	1.47	0.79	0.05	−0.52	−0.80
525	Data processing equipment repairers	48,140	0.10	0.83	0.06	1.43	1.19	0.81	−0.34	−0.70
Top ten occupations ranked by share of low-skilled workers										
407	Private household cleaners and servants	569,980	0.02	0.27	0.71	−1.05	−1.12	−0.86	−0.58	0.54
488	Graders and sorters, agricultural products	40,100	0.01	0.30	0.69	−0.04	−0.42	−0.87	−0.49	0.78
404	Cooks, private household	18,460	0.03	0.30	0.67	−1.05	−1.12	−0.80	−0.38	−0.14
747	Pressing machine operators	145,740	0.01	0.33	0.67	−0.91	0.16	−1.47	−0.66	0.42
405	Housekeepers and butlers	101,220	0.02	0.32	0.65	−1.05	−1.12	−0.83	0.04	0.28
738	Winding and twisting machine operators	140,080	0.01	0.35	0.65	0.51	0.69	−1.46	−0.61	−0.11
403	Launderers and Ironers	3,160	0.02	0.34	0.65	−1.05	−1.12	−1.49	−0.66	0.25
479	Farm workers	1,337,020	0.03	0.33	0.64	−0.03	−0.39	−0.87	−0.49	0.78
443	Waiters'/waitresses' assistants	422,800	0.01	0.36	0.62	−1.01	−0.98	−1.34	−0.64	0.73
449	Maids and housemen	969,720	0.01	0.36	0.62	−0.98	−1.05	−1.33	−0.47	0.38

This table reports the top ten occupations for each of the three skill categories, along with mean standardized task measures, using 1980 U.S. Census microdata and the occ8090 classification from Autor et al. (2003). For each task measure, the standardized measure is derived by subtracting from each occupation's task score the weighted mean task score across all occupations, and then dividing the difference by the standard deviation of the task measure across the 453 occupations.

TABLE 2.—MEAN STANDARDIZED SCORES BY SKILL GROUP, 1980 U.S. DATA

			High Skilled	Middle Skilled	Low Skilled
Routine tasks	Cognitive	Set limits, tolerances, or standards	−0.32	0.06	0.07
	Manual	Finger dexterity	−0.21	0.13	−0.14
Nonroutine tasks	Cognitive	Quantitative reasoning requirements	0.79	−0.02	−0.43
		Direction, control, and planning	0.90	−0.11	−0.32
	Manual	Eye-hand-foot coordination	−0.36	−0.04	0.29

This table reports the mean standardized task measures by skill group, using 1980 U.S. Census microdata and the occ8090 classification from Autor et al. (2003). For each task measure, the standardized measure is derived by subtracting from each occupation's task score the weighted mean task score across all occupations, and then dividing the difference by the standard deviation of the task measure across the 453 occupations.

TABLE 3.—SUMMARY STATISTICS BY COUNTRY

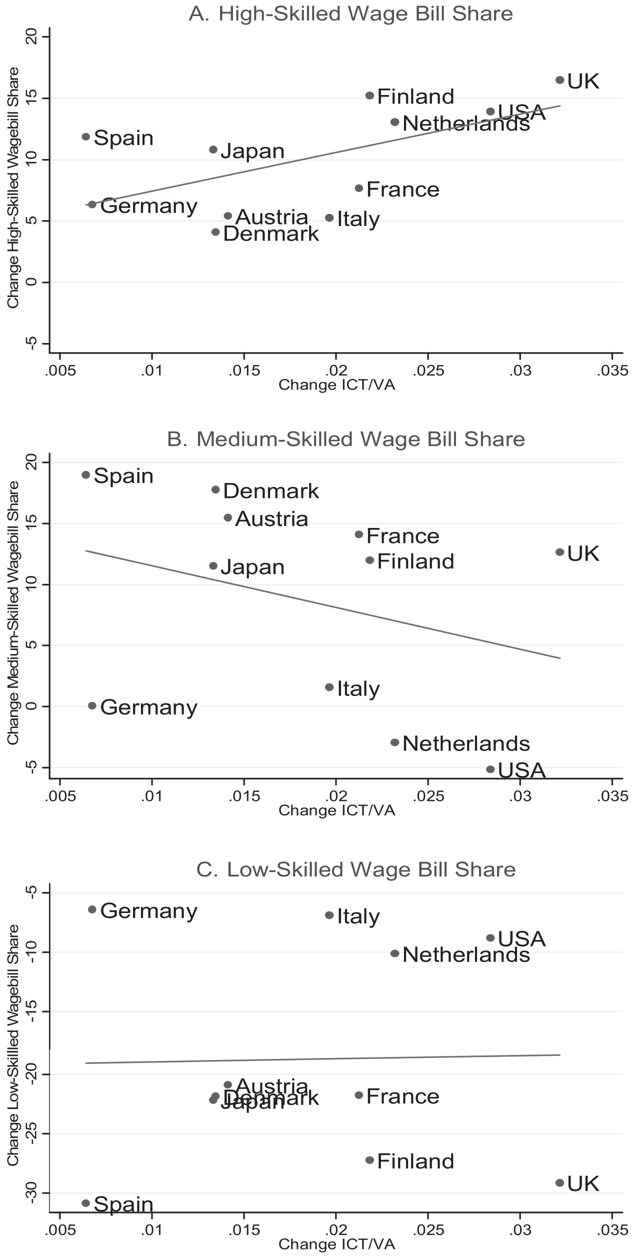
	A. 1980 Levels Averaged by Country						
Country	(1) High-Skilled Wage Bill Share	(2) Medium-Skilled Wage Bill Share	(3) Low-Skilled Wage Bill Share	(4) ln(Value Added)	(5) ((ICT Capital)/ (Value Added))	(6) ((Non-ICT Capital)/ (Value Added))	(7) ((Imports+Exports)/ (Value Added))
Austria	8.8	51.6	39.6	8.0	0.012	0.227	1.43
Demark	5.3	50.5	44.2	7.8	0.029	0.174	2.24
Finland	26.9	28.5	44.6	7.6	0.015	0.195	1.36
France	11.2	49.6	39.2	10.1	0.011	0.158	1.23
Germany	9.4	66.0	24.7	10.3	0.020	0.168	1.31
Italy	5.8	86.9	7.3	9.7	0.021	0.174	0.91
Japan	17.7	49.0	33.1	10.8	0.016	0.230	0.55
Netherlands	21.6	62.1	16.3	8.8	0.012	0.155	3.39
Spain	12.7	9.6	77.7	9.1	0.021	0.265	0.53
United Kingdom	9.2	52.7	38.1	9.8	0.019	0.180	1.54
United States	28.7	56.0	15.3	11.6	0.016	0.224	0.54
Mean	14.3	51.1	34.5	9.4	0.018	0.195	1.367
	B. Changes from 1980 to 2004, Averaged by Country						
Country	Δ(College Wage Bill Share)	Δ(Medium-Skilled Wage Bill Share)	Δ(Low-Skilled Wage Bill Share)	Δln(Value Added)	Δ((ICT Capital)/ (Value Added))	Δ((Non-ICT Capital)/ (Value Added))	Δ((Imports+Exports)/ (Value Added))
Austria	5.4	15.5	−20.9	1.2	0.014	0.010	0.87
Denmark	4.1	17.8	−21.9	1.3	0.013	−0.011	1.26
Finland	15.2	12.0	−27.2	1.2	0.022	−0.001	0.35
France	7.7	14.1	−21.8	1.1	0.021	0.066	0.99
Germany	6.3	0.1	−6.4	1.1	0.007	0.023	1.03
Italy	5.3	1.6	−6.9	1.2	0.020	0.051	0.55
Japan	10.8	11.5	−22.2	1.1	0.013	0.035	0.33
Netherlands	13.1	−2.9	−10.1	1.3	0.023	0.041	3.01
Spain	11.9	19.0	−30.9	1.5	0.006	0.056	1.13
United Kingdom	16.5	12.6	−29.1	1.3	0.032	−0.031	1.26
United States	13.9	−5.1	−8.8	1.4	0.028	0.032	0.62
Mean	10.0	8.7	−18.7	1.2	0.018	0.025	1.037

The table reports means weighted by 1980 share of each country's employment. All variables are measured for the full sample, except for trade variables, measured only for traded goods.

share (13.9 percentage points), but all countries have experienced rapid increases in ICT intensity at the country level, which doubled its 1980 share of value added. Figure 1 shows the correlation between the growth of the wage bill share of each of the three education groups and ICT intensity. There appears to be a positive relationship for the highly educated (figure 1A), a negative relationship for the middle educated (figure 1B), and no relationship for the least educated (figure 1C). Although this is supportive of our model's predictions, there are many other unobservable influences at the country level; our econometric results below will focus on the within-country, across-industry variation.

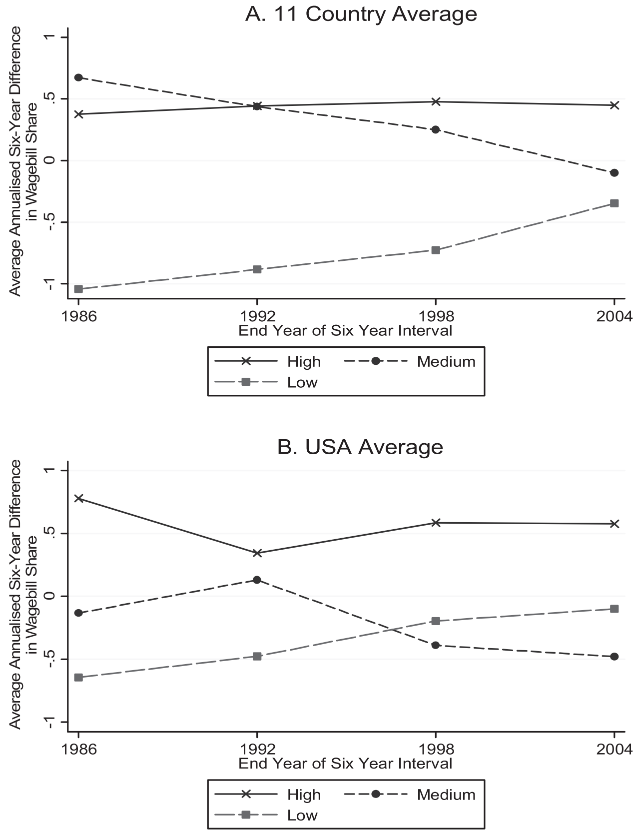
Returning to table 3, note that the change of the middle education share in column 2 is more uneven. Although the mean growth is positive, it is relatively small (8.7 percentage points on a base of 51.1%) compared to the highly educated, with several countries experiencing no growth or a decrease (the United States and the Netherlands). The model in appendix A shows how the wage bill share of the middle skilled could rise as the supply of this type of skill increases, so this supply increase can offset the fall in relative demand caused by technical change. Moreover, as figure 2A shows, although the wage bill share of the middle group rose more rapidly (in percentage point terms) between 1980 and 1986, it subsequently decelerated. Indeed, in the last six-year subperiod, 1998 to 2004, the wage bill share of middle-skilled workers actually fell. At the same time, the wage bill share of low-skilled workers continued to decline throughout the period 1980 to 2004, but at an increasingly slower rate. Figure 2B shows data for the United States, the technology leader that is often a future indicator for other nations. From 1998 to 2004 the wage bill share of the middle educated declined more rapidly than that of low-educated workers. Figure 2B is in line with the finding that while college-educated U.S.

FIGURE 1.—CROSS-COUNTRY VARIATION IN GROWTH OF HIGH-, MEDIUM-, AND LOW-SKILLED WAGE BILL SHARES AND ICT INTENSITY, 1980–2004



The figure plots the growth of high-, medium-, and low-skilled college wage bill shares against the growth of ICT intensity (ICT over value added) for eleven OECD countries (see table 3). Lines show regressions of the growth of each wage bill share against the growth of ICT intensity.

FIGURE 2.—AVERAGE ANNUAL PERCENTAGE POINT CHANGES IN HIGH-, MEDIUM-, AND LOW-SKILLED WAGE BILL SHARES OVER SIX-YEAR INTERVALS, 1980–2004 (ELEVEN-COUNTRY AVERAGE AND UNITED STATES)



Annualized six-year average growth rates of high-, medium-, and low-skilled wage bill shares from 1980 to 2004, weighted by employment share in the starting year of the six-year interval (for example, the 1980–1986 annualized difference is weighted by each industry's share in the 1980 employment of the country).

workers continued to gain relative to high school graduates, high school graduates gained relative to college dropouts in the 1980s but not in the 1990s (see Autor et al., 2008; see also figure 5).

Cross-industry trends. Table 4 breaks down the data by industry. In levels (column 1) the highly educated were disproportionately clustered into services in both the public sector (especially education) and private sector (real estate and business services, for example). The industries that upgraded skills rapidly (column 8) were also mainly services (for example, finance, telecoms, and business services), but also in manufacturing (for example, chemicals and electrical equipment). At the other end of the skill distribution, the textile industry, which initially had the lowest wage bill share of skilled workers, upgraded somewhat more than other low-skill industries (transport and storage, construction, hotels and restaurants, and agriculture). This raises the issue of mean reversion, so we are careful to later show robustness tests to conditioning on the initial levels of the skill shares in our regressions. In fact, the ranking of industries in terms of skill intensity in 1980 and their skill upgrading over the next twenty-five years was quite similar across countries. This is striking, because the countries we analyze had different labor market regulations and different institutional experiences over the period we analyze. This suggests something fundamental is at play that cuts across different sets of institutions.

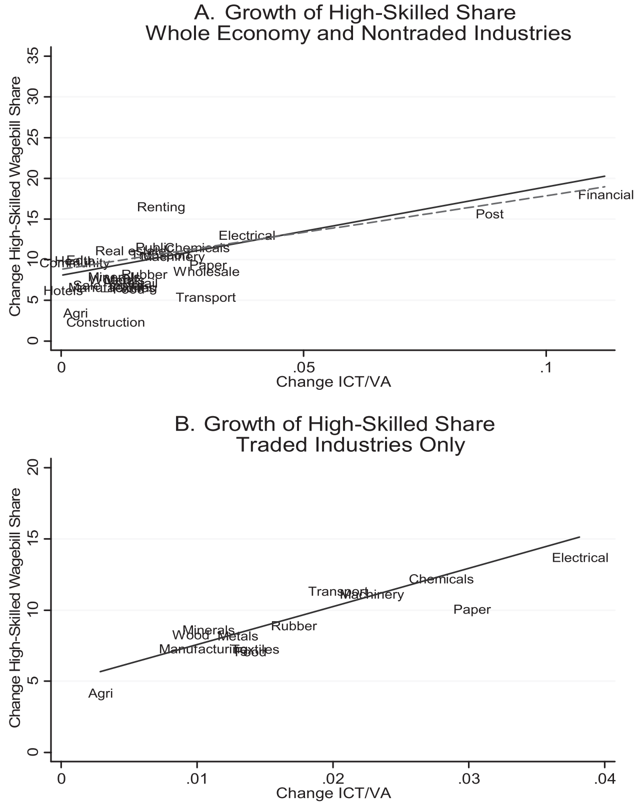
ICT grew dramatically from 1980 to 2004, accounting for more than 42% of the average increase in capital services (see columns 12 and 13). The increased ICT diffusion was also quite uneven: financial intermediation and telecoms experienced rapid increases in ICT intensity, while in other industries, such as agriculture, there was almost no increase.

TABLE 4.—SUMMARY STATISTICS BY INDUSTRY

	1980 Levels Averaged by Industry							Changes 1980–2004 Averaged by Industry							Mean weight	
Code Description	High-Skilled Wage Bill Share (1)	Medium-Skilled Wage Bill Share (2)	Low-Skilled Wage Bill Share (3)	ln(Value Added) (4)	((ICT Capital) /(Value Added)) (5)	((Non ICT Capital) /(Value Added)) (6)	((Imports+Exports) /(Value Added)) (7)	Δ (High-Skilled Wage Bill Share (8)	Δ (Medium-Skilled Wage Bill Share (9)	Δ (Low-Skilled Wage Bill Share (10)	Δ ln(Value Added) (11)	Δ ((ICT Capital) /(Value Added)) (12)	Δ ((Non ICT Capital) /(Value Added)) (13)	Δ((Imports+Exports) /(Value Added)) (14)	Full Sample (15)	Tread Goods Only (16)
Agriculture, hunting, forestry and fishing	5.9	39.7	54.4	9.49	0.002	0.246	0.73	5.1	21.8	−26.9	0.56	0.003	0.009	0.25	0.10	0.28
Food products, beverages and tobacco	6.4	47.7	45.9	9.12	0.012	0.341	1.09	8.0	15.8	−23.9	1.00	0.014	0.010	0.29	0.03	0.09
Textiles, textile products, leather and footwear	5.0	45.8	49.2	8.60	0.006	0.168	2.13	8.2	17.3	−25.4	0.16	0.014	0.027	3.79	0.03	0.09
Wood and products of wood and cork	7.8	46.8	45.4	7.53	0.010	0.232	2.30	9.2	16.4	−25.5	0.93	0.010	0.020	0.02	0.01	0.03
Pulp, paper, paper products, printing and publishing	10.8	51.4	37.8	8.75	0.021	0.242	0.84	11.0	10.9	−21.8	1.17	0.030	0.047	0.02	0.02	0.07
Chemicals and chemical products	13.3	49.2	37.4	8.67	0.016	0.370	2.51	13.1	9.2	−22.2	1.22	0.028	0.070	1.18	0.01	0.04
Rubber and plastics products	9.0	49.1	41.9	7.81	0.010	0.255	0.42	9.8	14.0	−23.8	1.28	0.017	0.022	0.04	0.01	0.02
Other non-metallic mineral products	8.6	47.4	44.0	8.14	0.014	0.270	0.57	9.5	15.3	−24.9	0.90	0.011	0.052	0.13	0.01	0.03
Basic metals and fabricated metal products	8.7	50.1	41.2	9.22	0.010	0.267	1.01	9.1	14.3	−23.4	0.97	0.013	0.009	0.18	0.03	0.10
Machinery, not elsewhere classified	9.8	55.7	34.5	8.92	0.017	0.209	1.59	12.0	8.5	−20.5	1.05	0.023	−0.003	0.98	0.03	0.08
Electrical and optical equipment	12.6	54.7	32.7	8.88	0.024	0.176	3.78	14.6	6.2	−20.8	1.23	0.038	0.052	5.42	0.03	0.08
Transport equipment	10.5	54.9	34.5	8.58	0.010	0.167	1.35	12.3	8.3	−20.6	1.11	0.020	0.080	0.94	0.02	0.06
Manufacturing not elsewhere classified; recycling	7.0	47.7	45.3	8.02	0.013	0.213	3.21	8.2	15.6	−23.8	1.05	0.010	0.004	0.41	0.01	0.04
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	6.5	59.6	33.9	8.49	0.016	0.195		8.5	9.7	−18.1	1.3	0.0	0.0		0.02	
Wholesale trade and commission trade, except of motor vehicles and motorcycles	10.2	57.1	32.6	9.70	0.032	0.247		10.2	7.7	−17.8	1.42	0.030	0.055		0.05	
Retail trade, except of motor vehicles and motorcycles; repair of household goods	8.3	58.1	33.6	9.55	0.011	0.084		8.7	9.1	−17.8	1.29	0.016	0.079		0.09	
Transport and storage	6.1	53.7	40.2	9.56	0.020	0.200		7.0	13.5	−20.5	1.36	0.030	0.072		0.04	
Post and telecommunications	8.1	60.5	31.4	8.65	0.143	0.238		17.2	1.9	−19.2	1.60	0.088	0.119		0.02	
Real estate activities	26.8	52.4	20.8	9.85	0.014	0.891		12.7	−1.1	−11.6	1.81	0.014	−0.008		0.01	
Renting of machinery and equipment and other business activities	29.3	51.2	19.5	9.53	0.051	0.180		18.1	−7.1	−11.0	2.16	0.020	−0.027		0.05	
Construction	7.3	52.1	40.6	9.98	0.005	0.180		4.0	16.2	−20.2	1.19	0.009	0.013		0.08	
Hotels and restaurants	6.2	54.4	39.4	8.78	0.013	0.136		7.8	12.5	−20.3	1.59	0.000	0.041		0.04	
Financial intermediation	18.3	65.0	16.6	9.49	0.051	0.297		19.6	−8.2	−11.3	1.57	0.112	0.009		0.03	
Public admin and defence; compulsory social security	20.8	58.4	20.7	9.96	0.017	0.171		13.1	0.7	−13.7	1.30	0.019	−0.022		0.07	
Education	51.7	38.2	10.1	9.58	0.013	0.078		11.6	−5.4	−6.1	1.47	0.004	−0.010		0.06	
Health and social work	27.0	53.1	19.8	9.58	0.011	0.119		11.5	0.8	−12.2	1.70	0.003	−0.008		0.07	
Other community, social and personal services	18.4	50.1	31.5	9.07	0.038	0.215		11.2	7.1	−18.3	1.65	0.003	0.029		0.04	

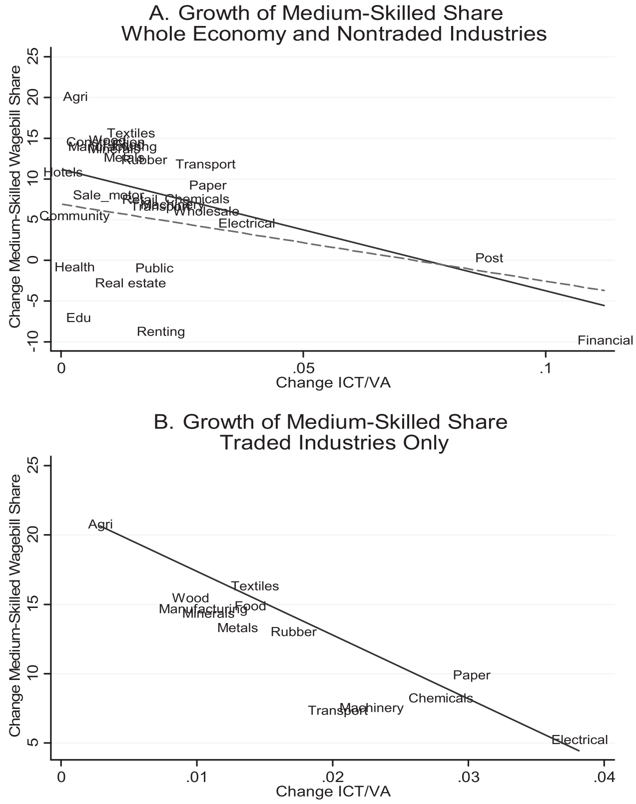
Notes: Industry values are simple unweighted averages across all countries. Regressions in subsequent tables use the maximum level of disaggregation available in each country (method described in Web Appendix). Mean weight is the industry's share of employment in each country's total employment.

FIGURE 3.—CROSS-INDUSTRY VARIATION IN GROWTH OF HIGH-SKILLED WAGE BILL SHARE AND ICT INTENSITY, 1980–2004 (ELEVEN COUNTRY MEANS)



Panel A plots the growth from 1980 to 2004 of high-skilled wage bill shares against the growth of ICT intensity (ICT over value added), by industry, averaged across countries. Lines show fitted values from regressions weighted by the cross-country average of each industry's share in 1980 employment (solid line for entire economy, dashed line for nontraded industries only). Panel B restricts the sample to traded industries.

FIGURE 4.—CROSS-INDUSTRY VARIATION IN GROWTH OF MEDIUM-SKILLED WAGE BILL SHARE AND ICT INTENSITY, 1980–2004 (ELEVEN COUNTRY MEANS)



Panel A plots the growth from 1980 to 2004 of medium-skilled wage bill shares against the growth of ICT intensity (ICT over value added), by industry, averaged across countries. Lines show fitted values from regressions weighted by the cross-country average of each industry's share in 1980 employment (solid line for entire economy, dashed line for nontraded industries only). Panel B restricts the sample to traded industries.

Figures 3, 4, and 5 plot changes by industry in the wage bill shares of high-, medium-, and low-skilled workers, respectively, against changes in ICT intensity. Panel A of each figure includes all industries with fitted regression lines (solid line for all industry and dashed line for nontraded sectors only). Panel B restricts attention to the traded sectors. Figure 3A shows that the industries with the fastest ICT upgrading had the largest increase in the high-skilled wage bill share. One might be worried that two service sectors, post and telecommunications and financial intermediation, are driving this result, which is one reason Figure 3B drops all the nontraded sectors. In fact, the relationship between high-skilled wage bill growth and ICT growth is actually stronger in these well-measured sectors.

Figure 4 repeats this analysis for the middle-educated groups. We observe the exact opposite relationship to figure 3: the industries with the faster ICT growth had the largest fall in the middle-skilled share whether we look at the whole economy (panel A) or just the traded sectors (panel B). Finally, figure 5 shows that there is essentially no relationship (panel A) or a mildly positive one (panel B) between the change of the share of the least educated and ICT growth.

These figures are highly suggestive of empirical support for the hypothesis that ICT polarizes the skill structure: increasing demand at the top, reducing demand in the middle, and having little effect at the bottom. To examine this link more rigorously, we now turn to the econometric analysis.

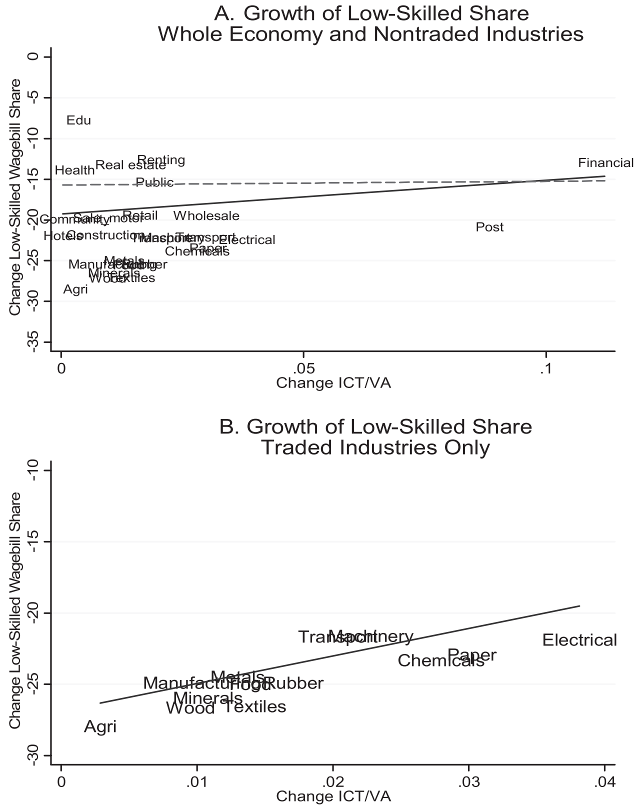
IV. Econometric Results

A. Basic Results

Our first set of results for the skill share regressions is reported in table 5. The dependent variables are changes from 1980 to 2004 in the wage bill share of the highly skilled in panel A, the middle skilled in panel B, and the low skilled in panel C. The first four columns look across the entire economy, and the last four columns condition on the subsample of tradable sectors where we have information on imports and exports.

Column 1 of panel A reports the coefficient on the constant, which indicates that on average, there was a 10 percentage point increase in the college wage bill share. This is a very large increase, considering that the average skill share in 1980 (across our sample of countries) was only 14%. Column 2 includes the growth in ICT capital intensity. The technology variable has a large, positive, and significant coefficient and reduces the regression constant to 8.7.

FIGURE 5.—CROSS-INDUSTRY VARIATION IN GROWTH OF LOW-SKILLED WAGE BILL SHARE AND ICT INTENSITY, 1980–2004 (ELEVEN COUNTRY MEANS)



Panel A plots the growth from 1980 to 2004 of low-skilled wage bill shares against the growth of ICT intensity (ICT over value added), by industry, averaged across countries. Lines show fitted values from regressions weighted by the cross-country average of each industry's share in 1980 employment (solid line for entire economy, dashed line for non-traded industries only). Panel B restricts the sample to traded industries.

Column 3 includes the growth of non-ICT capital intensity and value added. The coefficient on non-ICT capital is negative and insignificant, suggesting that there is no sign of (non-ICT) capital-skill complementarity. Some studies have found capital-skill complementarity (Griliches, 1969), but few of these have disaggregated capital into its ICT and non-ICT components, so the evidence for capital-skill complementarity may be due to aggregating over high-tech capital that is complementary with skills and lower-tech capital that is not. The coefficient on value-added growth is positive and significant, suggesting that skill upgrading has been occurring more rapidly in the fastest-growing sectors (as in Berman, Somanathan, & Tan, 2005). Column 4 includes country fixed effects. This is a demanding specification because the specification is already in differences, so it essentially allows for country-specific trends. The coefficient on ICT falls (from 65 to 47) but remains significant at conventional levels.[13]

We reestimate these specifications for the tradable industries in the next four columns. Column 5 of table 5 shows that the overall increase in the college wage bill share from 1980 to 2004 was 9 percentage points—similar to that in the whole sample. Columns 6 to 8 add in our measure of ICT and other controls. The coefficient on ICT in the tradable sector is positive, highly significant, and larger than in the overall sample (for example, 129 in column 8).

Panel B of table 5 reports estimates for the same specifications as panel A, but this time the dependent variable is the share of middle-educated workers. The association between the change in middle-skilled workers and ICT is strongly negative. In column 4, for example, a 1 percentage point increase in ICT intensity is associated with a 0.8 percentage point fall in the proportion of middle-skilled workers. The absolute magnitude of the coefficients for the sample that includes all industries is quite similar to those for college-educated workers. Panel C shows that technology measures appear to be insignificant for the least educated workers, illustrating the point that the main role of ICT appears to be in changing demand between the high-skilled and middle-skilled groups.[14] Since the adding-up requirement means that the coefficients for the least-skilled group can be deduced from the other two skill groups, we save space by omitting panel C in the rest of the tables.

Overall, table 5 shows a pattern of results consistent with ICT-based polarization. Industries where ICT grew most strongly were those with the largest shifts toward the most skilled and the largest shifts away from the middle skilled, with the least skilled largely unaffected.

B. *Robustness and Extensions*

Initial conditions. Table 6 examines some robustness checks using the results in our preferred specification of column 4 of table 5 (reproduced in the first column). Since there may be mean reversion, we include the level of initial share of skills in 1980 in column 2. This does not qualitatively alter the results, although the coefficient on ICT for the middle skilled does fall somewhat.[15]

Timing of changes in skills and ICT. One limitation of the specifications that we have discussed so far is that the changes on the right-hand side and left-hand side are both concurrent. To mitigate potential concerns about reverse causation, we reestimate the baseline specification of column 1 in table

[13] Including the mineral extraction sectors caused the ICT coefficient to fall from 47 to 45. We also tried including a set of industry dummies in column 4. All the variables became insignificant in this specification. This suggests that it is the same industries that are upgrading across countries.

[14] The difference in the importance of ICT for the middle and lowest skill groups implies that high school graduates are not perfect substitutes for college graduates as Card (2009) argues in the U.S. context. The majority of our data are from outside the United States, however, where there are relatively fewer high school graduates.

[15] As we explain above, our specifications assume that markets are national in scope, so that country fixed effects capture changes in relative wages. To further test this assumption, we reestimated columns 1 and 2 in table 6 with additional controls for the change in the difference in industry-specific relative ln(wages) between the high skilled and middle skilled and between the high skilled and low skilled. The resulting coefficients (standard errors) on our measure of ICT are 41.43 (15.24) and 35.98 (14.82) for highly skilled workers, and −54.38 (20.96) and −33.35 (13.87) for middle-skilled workers.

TABLE 5.—CHANGES IN WAGE BILL SHARES, 1980–2004

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Dependent Variable: High-Skilled Wage Bill Share								
Δ((ICT Capital)/(Value Added))		72.29	64.56	46.92		163.94	139.6	128.71
		(18.28)	(17.31)	(14.94)		(45.48)	(42.74)	(32.19)
Δ ln(Value Added)			5.42	4.76			3.26	3.41
			(1.24)	(0.95)			(2.25)	(1.07)
Δ((Non-ICT-Capital)/(Value Added))			−7.64	−6.45			0.31	−0.47
			(4.92)	(3.51)			(5.59)	(2.45)
Intercept	10.02	8.69	2.22		9.12	6.42	4.04	
	(0.57)	(0.63)	(1.68)		(0.86)	(1.02)	(2.19)	
Country fixed effects				X				X
Sample: All industries	X	X	X	X				
Sample: Traded industries					X	X	X	X
Observations	208	208	208	208	84	84	84	84
R^2		0.09	0.20	0.45		0.20	0.23	0.81
B. Dependent Variable: Medium-Skilled Wage Bill Share								
Δ((ICT-Capital)/(Value Added))		−100.78	−77.76	−64.52		−163.98	−41.59	−288.01
		(30.21)	(25.44)	(20.24)		(115.78)	(84.73)	(83.94)
Δ ln(Value Added)			−13.8	−15.33			−15.64	−7.96
			(2.69)	(2.23)			(4.27)	(3.14)
Δ((Non-ICT-Capital)/(Value Added))			9.76	18.01			−10.79	1.57
			(11.88)	(10.25)			(14.08)	(10.98)
Intercept	8.73	10.59	27.24		15.5	18.20	29.75	
	(1.29)	(1.49)	(3.73)		(1.90)	(2.95)	(4.67)	
Country fixed effects				X				X
Sample: All industries	X	X	X	X				
Sample: Traded industries					X	X	X	X
Observations	208	208	208	208	84	84	84	84
R^2		0.05	0.23	0.58		0.05	0.25	0.74
C. Dependent Variable: Low-Skilled Wage Bill Share								
Δ((ICT-Capital)/(Value Added))		28.55	13.21	17.71		0.50	−97.91	159.65
		(27.34)	(25.66)	(16.41)		(113.51)	(100.71)	(79.30)
Δ ln(Value Added)			8.43	10.62			12.45	4.61
			(2.40)	(1.95)			(4.24)	(3.30)
Δ((Non-ICT-Capital)/(Value Added))			−2.21	−11.68			10.32	−1.28
			(9.63)	(9.07)			(11.91)	(11.73)
Intercept	−18.74	−19.26	−29.5		−24.61	−24.62	−33.84	
	(1.12)	(1.31)	(3.27)		(1.68)	(2.56)	(3.95)	
Country fixed effects				X				X
Sample: All industries	X	X	X	X				
Sample: Traded industries					X	X	X	X
Observations	208	208	208	208	84	84	84	84
R^2		0.01	0.10	0.65		0.00	0.16	0.70

Coefficients estimated by OLS with robust standard errors in parentheses. Regressions in columns 1–4 weighted by each industry's 1980 share of each country's employment, and regressions in columns 5–8 weighted by each industry's 1980 share of each country's employment in traded industries. Columns 1–4 are estimated on all industries and columns 5–8 are on the tradable sectors.

6, where the right-hand-side variables are measured for the first half of the period we consider (1980–1992) and the left-hand-side variable is measured for the second half of the period (1992–2004). The estimated coefficients (and standard errors) on changes in our measure of ICT are 52.62 (23.53) for highly skilled workers and −52.52 (28.97) for middle-skilled workers. These results are almost unchanged—51.31 (22.65) and −58.22 (22.99) respectively)—when we instead use the equivalent of the specification in column 2 of table 6.

Heterogeneity in the coefficients across countries. Wage inequality rose less in Continental Europe than elsewhere, so it is interesting to explore whether technological change induced polarization even there. Columns 3 and 4 of table 6 restrict the sample to the eight Continental European countries (Austria, Denmark, Finland, France, Germany, Italy, Netherlands, and Spain), and the results are similar to those in the full sample of countries. In column 5, we show that the correlation between ICT and polarization is larger for the United States than for the full sample, though column 6 shows that the estimates become imprecise when we control for baseline levels of skill composition. The sample size for most individual countries is rather small, but if we reestimate the specification of table 5, column 2 separately country by country, we obtain negative coefficients on ICT for all eleven countries for medium-skill shares and positive coefficients for ten countries for the high-skill shares (Japan is the single exception).[16] The results are also robust to dropping any single country.[17]

[16] The mean of the eleven country-specific coefficients on ICT is very similar to the pooled results (−112 for the middle-skilled share and 71 for the high-skilled share).

[17] For example, we had concerns about the quality of the education data in Italy, so we dropped it from the sample. In the specification of column 4 of table 5, the coefficient (standard error) on ICT capital was 55.2(1.04) for the high education group and −68.54(22.82) for the middle educated.

TABLE 6.—CHANGES IN WAGE BILL SHARES, 1980–2004—ROBUSTNESS CHECKS

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) 2SLS	(8) 2SLS	(9) 2SLS	(10) 2SLS
A. Dependent Variable: High-Skilled Wage Bill Share										
Δ((ICT Capital)/(Value Added))	46.92	42.09	50.98	48.79	132.84	66.1	121.63	103.16	137.99	65.31
	(14.94)	(14.66)	(16.64)	(16.20)	(52.59)	(58.15)	(53.43)	(48.82)	(119.44)	(104.61)
Δ ln(Value Added)	4.76	2.93	5.79	4.4	0.26	−1.97	4.24	4.85	4.12	5.09
	(0.95)	(1.39)	(1.31)	(1.93)	(2.94)	(3.79)	(1.07)	(1.10)	(1.30)	(1.20)
Δ((Non ICT Capital)/(Value Added))	−6.45	−5.06	−9.25	−8.19	15.41	2.56	−8.47	−9.85	−8.91	−8.54
	(3.51)	(3.99)	(4.56)	(5.13)	(12.99)	(12.95)	(4.02)	(4.33)	(5.01)	(5.17)
1980 High-skilled wage bill share		0.06		0.04		0.34				
		(0.06)		(0.07)		(0.19)				
1980 Medium-skilled wage bill share		0.12		0.08		0.6				
		(0.05)		(0.07)		(0.27)				
Country fixed effects	X	X	X	X			X	X	X	X
Sample	All	All	Continental Europe	Continental Europe	United States	United States	All	All except United States	All	All except United States
Observations	208	208	143	143	27	27	208	181	208	181
R^2	0.45	0.467	0.442	0.453	0.209	0.429	0.363	0.409	0.322	0.457
F-statistic for excluded instrument in the first stage							10.5	9.3	6.5	8.0
B. Dependent Variable: Medium-Skilled Wage Bill Share										
Δ((ICT Capital)/(Value Added))	−64.52	−41.72	−62.13	−51.41	−160.15	−80.06	−73.81	−46.74	−42.8	22.21
	(20.24)	(13.35)	(18.79)	(14.28)	(44.52)	(60.98)	(56.75)	(49.05)	(235.73)	(224.75)
Δ ln(Value Added)	−15.33	−2.73	−16.33	−4.36	−7.57	0.45	−15.26	−16.24	−15.48	−16.67
	(2.23)	(1.99)	(3.13)	(2.83)	(3.33)	(3.64)	(2.30)	(2.47)	(2.27)	(2.34)
Δ((Non-ICT Capital)/(Value Added))	18.01	3.89	21.33	7.82	−16.58	−7.9	18.26	20.02	17.42	17.62
	(10.25)	(6.61)	(13.38)	(9.27)	(17.77)	(13.85)	(10.59)	(11.41)	(11.34)	(12.81)
1980 High-skilled wage bill share		−0.55		−0.48		−0.72				
		(0.08)		(0.08)		(0.19)				
1980 Medium-skilled wage bill share		−0.64		−0.57		−0.95				
		(0.07)		(0.09)		(0.28)				
Country fixed effects	X	X	X	X			X	X	X	X
Sample	All	All	Continental Europe	Continental Europe	United States	United States	All	All except United States	All	All except United States
Observations	208	208	143	143	27	27	208	181	208	181
R^2	0.58	0.791	0.593	0.769	0.356	0.676	0.58	0.55	0.578	0.52
F-statistic for excluded instrument in the first stage							10.5	9.3	6.5	8.0

Coefficients estimated by OLS with robust standard errors in parentheses. Regressions weighted by the industry's 1980 share of each country's employment. In columns 7 and 8 we instrument the 25-year difference in ICT Capital/Value Added by the 1980 levels of ICT Capital/Value Added in the United States. In columns 9 and 10 we instrument the 25-year difference in ICT Capital/Value Added by the 1980 levels of routine task input using the 1991 Directory of Occupational Titles (constructed as in Autor et al., 2003).

Instrumental variables. One concern is that measurement error in the right-hand-side variables, especially our measure of ICT, causes attenuation bias.[18] To mitigate this concern, we use the industry-level measures of ICT in the United States in 1980 as an instrument for ICT upgrading over the whole sample. The intuition behind this instrument is that the dramatic global fall in quality-adjusted ICT prices since 1980 (Jorgenson, Ho, & Stiroh, 2008) disproportionately affects industries that (for exogenous technological reasons) have a greater potential for using ICT inputs. An indicator of this potential is the initial ICT intensity in the technological leader, the United States. As column 7 of table 6 shows, this instrument has a first-stage F-statistic of 10.5, and the sign of the first-stage regressions (not reported) is as we would expect: that industries that were more ICT intensive in 1980 upgraded their use of ICT more than others. In the 2SLS estimates of column 7, the coefficient on ICT is roughly twice as large as the OLS coefficients for the college-educated group (and significant at the 5% level) and a little bigger for the middle-skilled group. Column 8 estimates the same specification but this time excluding the United States, and the results are very similar. While we acknowledge that estimates using this instrument do not necessarily uncover the causal effect of ICT, it is reassuring that these 2SLS estimates are somewhat larger than the OLS estimates, as we would expect given the likely measurement error.

As a further check, we use the proportion of routine tasks in the industry (in the United States in the base year) as an instrument for future ICT growth as these industries were most likely to be affected by falling ICT prices (see Autor & Dorn, 2009). The results of using this instrument are shown in columns 9 and 10. Although the first stages are weaker with this instrument[19] and the 2SLS estimates are not very precise,

[18] Estimates of the ICT coefficient for the two twelve-year subperiods of our data are typically about half of the absolute magnitude of those for the full period. In general, our estimates for shorter time periods are smaller and less precise, consistent with the importance of measurement error in the ICT data. For example, in the specification of column 4 of panel A in table 5, the coefficient (standard error) on ICT was 18.30 (10.30) in a pooled twelve-year regression. We could not reject the hypothesis that the ICT coefficient was stable over time (p-value = 0.35).

[19] The signs of the instruments in the first stage are correct. The F-test is 6.5 in column 9 compared to 10.5 in column 7.

TABLE 7.—DECOMPOSING CHANGES IN RELATIVE WAGE BILLS INTO WAGES AND HOURS

	Ln(Relative Wage Bill)				Ln(Relative Wages)				Ln(Relative Hours Worked)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable	(High Skilled/ Medium Skilled)		(Medium Skilled/ Low Skilled)		(High Skilled/ Medium Skilled)		(Medium Skilled/ Low Skilled)		(High Skilled/ Medium Skilled)		(Medium Skilled/ Low Skilled)	
Δ((ICT Capital)/(Value Added))	4.72	4.00	−2.47	−2.04	1.28	0.93	−0.62	−0.77	3.44	3.07	−1.85	−1.28
	(1.36)	(1.26)	(1.07)	(0.99)	(0.48)	(0.43)	(0.60)	(0.68)	(1.33)	(1.26)	(1.14)	(1.12)
Δ ln(Value Added)		0.18		−0.28		0.10		0.04		0.08		−0.32
		(0.10)		(0.08)		(0.06)		(0.07)		(0.09)		(0.10)
Δ((Non-ICT Capital)/(Value Added))		0.98		0.14		0.41		0.18		0.57		−0.03
		(0.51)		(0.38)		(0.21)		(0.17)		(0.51)		(0.34)
Country fixed effects	X	X	X	X	X	X	X	X	X	X	X	X
Sample: All industries	X	X	X	X	X	X	X	X	X	X	X	X
Observations	208	208	208	208	208	208	208	208	208	208	208	208
R^2	0.324	0.376	0.724	0.752	0.283	0.335	0.431	0.436	0.319	0.334	0.517	0.56

Dependent variable in columns 1–4 is the 1980–2004 change in the Ln(relative wage bill); for example, in column 1, this is ln(wage bill of high-skilled workers) − ln(wage bill of medium-skilled workers). The dependent variable in columns 5–8 is the change in Ln(relative hourly wage); for example in column 5 it is the ln(hourly wage of highly skilled) − ln(hourly wage of medium skilled). In columns 9–12, the dependent variable is the change in Ln(relative hours worked); for example, in column 9, this is ln(annual hours of highly skilled) − ln(annual hours of medium skilled). Coefficients estimated by OLS with robust standard errors in parentheses. Regressions weighted by the industry's 1980 share of each country's employment.

these columns again suggest that we are not overestimating the importance of ICT by just using OLS.

Disaggregating the wage bill into wages and hours. The wage bill share of each skill group reflects its hourly wage and hours worked and those of the other skill groups. We estimated specifications that are identical to those in table 5, except that they disaggregate the dependent variable into the growth of relative skill prices (wages) and quantities (hours). In the first two columns of table 7, we reproduce the baseline specifications using the log relative wage bill (which can be exactly decomposed) as the dependent variable.[20] Columns 1 to 4 confirm what we have already seen using a slightly different functional form: ICT growth is associated with a significant increase in the demand for highly skilled workers relative to middle-skilled workers (first two columns) and with a significant (but smaller) increase for low-skilled workers relative to middle-skilled workers (third and fourth columns).

For the high- versus middle-skill group, ICT growth is significantly associated with increases in relative wages and relative hours (columns 5, 6, 9, and 10). In comparing the middle versus low groups, we see that the coefficients are also all correctly signed, but not significant at conventional levels. Overall this suggests that our results are robust to functional form and the shifting pattern of demand operates through both wages and hours worked.[21]

C. *Trade, R&D, and Skill Upgrading*

Having found that technology upgrading is associated with substitution of college-educated workers for middle-educated workers, we now examine whether changes in trade exhibit similar patterns. The first three columns of table 8 suggest that more trade openness (measured as the ratio of imports plus exports to value added) is associated with increases in the wage bill share of college-educated workers and declines in the share for middle-skilled workers. However, when we control for initial R&D intensity, the association between trade and skill upgrading becomes smaller and insignificant. Column 4 repeats the specification of column 3 for the subsample where we have R&D data and shows that the trade coefficient is robust. Column 5 includes R&D intensity in a simple specification and shows that the coefficient on trade falls (say, from 0.50 to 0.24 in panel A) and is insignificant, whereas the coefficient on R&D is positive and significant. In column 6, we include the changes in the ICT and non-ICT, and the coefficient on trade is now very small. Column 7 drops the insignificant trade variable and shows that ICT and R&D are individually (and jointly) significant.

We also used the Feenstra and Hanson (1996) method of constructing an offshoring variable and included it instead of (and alongside) trade in final goods. The offshoring variable has a bit more explanatory power than final goods trade.[22] Column 8 includes offshoring ("Imported Intermediate Inputs" into the full sample as it can be defined for all industries. The results suggest a significant positive correlation between offshoring for high-skilled workers and a negative but insignificant correlation between ICT and demand for middle-skilled workers. Column 9 produces a similar result on the sample of tradable sectors, and column 10 includes ICT and R&D. As with the trade measure in final goods, the offshoring coefficient is insignificant in the final column for both education groups. The ICT effects are robust to the inclusion of the offshoring measures.

[20] Another functional form check was using the growth rate of ICT intensity. For the specification in column 3 of panel A in table 5, we replaced $\Delta(C/Q)$ with $\frac{\Delta(C/Q)}{C/Q}$. The coefficient (standard error) on ICT growth was 2.586 (1.020). The marginal effect of a 1 standard deviation increase (0.581) is 1.50 (= 0.581 × 2.586), almost identical to 1.55 (= 0.024 × 64.6) in table 5.

[21] In examining these results across countries, we found some evidence that the adjustment in wages was stronger in the United States and the adjustment in hours was stronger in Continental Europe. This is consistent with the idea of great wage flexibility in the United States than in Europe.

[22] For example, in the same specification of column 6 of table 8, we replaced the final goods trade variable with the offshoring measure. In the high-skilled equation, the coefficient (standard error) was 4.27 (2.82), and in the middle-skilled equation, the coefficient (standard error) was −11.6 (9.87).

TABLE 8.—TRADE AND TECHNOLOGY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Dependent Variable: High-Skilled Wage Bill Share										
Δ((Imports + Exports)/(Value Added))	0.59	0.71	0.59	0.50	0.24	0.11				
	(0.37)	(0.25)	(0.15)	(0.19)	(0.30)	(0.25)				
Δ(Imported Intermediate Inputs)								16.40	8.78	4.27
								(7.00)	(3.47)	(2.82)
Δ((ICT Capital)/(Value Added))			107.61	94.25		73.59	75.49	47.21	96.63	72.37
			(31.70)	(34.07)		(31.41)	(31.10)	(15.20)	(33.05)	(30.80)
Δ ln(Value Added)			4.09	3.84	4.03	2.57	2.36	5.61	4.16	2.98
			(1.09)	(1.26)	(1.38)	(1.52)	(1.35)	(1.05)	(1.30)	(1.52)
Δ((Non-ICT Capital)/(Value Added))			−0.63	0.16		0.97	1.03	−6.23	0.06	0.85
			(2.41)	(3.41)		(3.12)	(3.03)	(3.51)	(3.46)	(3.18)
1980 (Research and Development Expenditure/Value Added)					34.18	28.04	30.08			25.76
					(18.23)	(17.59)	(14.91)			(16.00)
Intercept	8.60									
	(0.98)									
Country fixed effects		X	X	X	X	X	X	X	X	X
Sample: Traded goods (all countries)	X	X	X							
Sample: Traded goods (except Austria and Spain)				X	X	X	X		X	X
Sample: All goods (all countries)								X		
Observations	84	84	84	65	65	65	65	208	65	65
R^2	0.019	0.666	0.821	0.80	0.80	0.82	0.82	0.458	0.80	0.82
B. Dependent Variable: Medium-Skilled Wage Bill Share										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ((Imports + Exports)/(Value Added))	−1.18	−1.26	−0.95	−0.95	−0.77	−0.49				
	(0.91)	(0.75)	(0.57)	(0.52)	(0.63)	(0.52)				
Δ(Imported Intermediate Inputs)								−14.49	−11.58	−5.02
								(13.56)	(9.87)	(7.94)
Δ((ICT Capital)/(Value Added))			−253.80	−294.15		−269.46	−277.86	−64.78	−309.49	−274.20
			(83.12)	(69.28)		(69.36)	(69.49)	(20.44)	(69.40)	(69.54)
Δ ln(Value Added)			−9.07	−7.07	−9.34	−5.55	−4.61	−16.08	−7.06	−5.34
			(3.42)	(2.92)	(3.18)	(3.18)	(2.65)	(2.56)	(3.12)	(3.31)
Δ((Non-ICT Capital)/(Value Added))			1.84	24.10		23.14	22.86	17.81	24.22	23.07
			(10.75)	(10.03)		(10.59)	(10.62)	(10.16)	(10.25)	(10.72)
1980 (Research and Development Expenditure/ Value Added)					−60.72	−33.51	−42.55			−37.47
					(25.89)	(19.25)	(17.22)			(18.20)
Intercept	16.52									
	(2.21)									
Country fixed effects		X	X	X	X	X	X	X	X	X
Sample: Traded goods (all countries)	X	X	X							
Sample: Traded goods (except Austria and Spain)				X	X	X	X		X	X
Sample: All goods (all countries)								X		
Observations	84	84	84	65	65	65	65	208	65	65
R^2	0.019	0.554	0.749	0.81	0.73	0.82	0.815	0.582	0.81	0.82

Coefficients estimated by OLS with robust standard errors in parentheses. Regressions weighted by the industry's 1980 share of each country's employment, for traded goods (columns 1–7) and for all goods (column 8). The OECD ANBERD data set does not have R&D data for Austria and Spain, which are dropped from the sample (columns 4–7). In column 8, we construct the imported intermediate inputs measure by using the 1987 Input/Output Tables for the United States, and taking the product of the relative use by each industry of all commodities and the ratio of Total Imports to Apparent Consumption (Output + Imports − Exports) of each industry.

These findings are broadly consistent with most of the literature that finds that technology variables have more explanatory power than trade in these kinds of skill demand equations.[23] Of course, trade could be influencing skill demand through affecting the incentives to innovate and adopt new technologies, which is why trade ceases to be important after we condition on technology (Bloom, Draca, & Van Reenen, 2011, argue in favor of this trade-induced technical change hypothesis).[24] Furthermore, there could be many general equilibrium effects of trade that we have not accounted for (these are controlled for by the country time effects).

D. *Magnitudes*

We perform some back-of-the-envelope calculations (see table A4) to gauge the magnitude of the effect of technology on the demand for highly-skilled workers. Column 1 estimates that ICT accounts for 13.2% of the increase in the college share in the whole sample without controls and

[23] These are simple industry-level correlations and not general equilibrium calculations, so we may be missing out the role of trade through other routes.

[24] We further test whether the association between trade and skill upgrading remains similar when we examine different components of trade separately. Table A3 suggests that when we examine imports and exports separately, the picture is quite similar. Greater trade is associated with an increase in the college wage bill share until we control for initial R&D intensity, in which case the coefficient on trade falls and becomes insignificant. Results are similar when we separately analyze imports to (or exports from) OECD countries. For non-OECD countries, the results are again the same, except for exports to non-OECD countries, which remains positively associated with changes in the college wage bill share even after we add all the controls, including R&D. However, it should be noted that the change in exports to developing countries is on average very small.

column 2 reduces this to 8.5% with controls. Many authors (for example, Jorgenson, et al., 2008) have argued that value-added growth has been strongly affected by ICT growth, especially in the later period, so column 2 probably underestimates the effect of ICT. Column 3 reports equivalent calculations for the tradable sectors. Here, ICT accounts for 16.5% of the change and R&D a further 16.1%, suggesting that observable technology measures account for almost a third of the increase in demand for highly skilled workers. If we include controls in column 4, this falls to 23.1%. Finally, columns 5 and 6 report results for the IV specification for the whole sample, showing an ICT contribution of ICT of between 22.1% and 27.7%.[25]

We also note that ICT upgrading alone should have led to decreased demand for middle-skilled workers. While we do not see such a decrease overall, figure 2 shows a slowdown in the growth of demand for the middle skilled over time and a reversal (in other words negative growth) for middle-skilled workers from 1998 to 2004.

We have no general equilibrium model, so these are only back-of-the-envelope calculations to give an idea of magnitudes. Furthermore, measurement error probably means that we are underestimating the importance of the variables. Nevertheless, it seems that our measures of technology are important in explaining a significant proportion of the increase in demand for college-educated workers at the expense of the middle skilled.

V. Conclusion

Recent investigations into the changing demand for skills in OECD countries have found some evidence for polarization in the labor market in the sense that workers in the middle of the wage and skills distribution appear to have fared more poorly than those at the bottom and the top. One explanation that has been advanced for this is that ICT has complemented nonroutine cognitive tasks but substituted for routine tasks while not affecting nonroutine manual tasks (like cleaning, gardening, and child care). This implies that many middle-skilled groups like bank clerks and paralegals performing routine tasks have suffered a fall in demand. To test this, we have estimated industry-level skill share equations distinguishing three education groups and related this to ICT (and R&D) investments in eleven countries over 25 years using newly available data. Our findings are supportive of the ICT-based polarization hypothesis: industries that experienced the fastest growth in ICT also experienced the fastest growth in the demand for the most educated workers and the fastest falls in demand for workers with intermediate levels of education. The magnitudes are nontrivial: technical change can account for up to a quarter of the growth of the college wage bill share in the economy as a whole (and more in the tradable sectors).

Although our method is simple and transparent, there are many extensions that need to be made. First, alternative instrumental variables for ICT would help identify the causal impact of ICT. Second, although we find no direct role for trade variables, there may be other ways in which globalization influences the labor market, for example, by causing firms to "defensively innovate" (Acemoglu, 2003). Third, there are alternative explanations for the improved performance of the least-skilled group through, for example, greater demand from richer-skilled workers for the services they provide as market production substitutes for household production (such as child care, restaurants wait staff, domestic work).[26] These explanations may complement the mechanism that we address here. Finally, we have not used richer occupational data that would focus on the skill content of tasks due to the need to have international comparability across countries. The work of Autor and Dorn (2009) is an important contribution here.

[25] The IV specifications for tradables show an even larger magnitude. For example, in a specification with full controls, R&D and ICT combined account for over half of all the change in the college wage bill share. The first stage for the IV is weak, however; with an F-statistic of 6, these cannot be relied on.

[26] See Ngai and Pissarides (2007) and Mazzolari and Ragusa (2008).

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TABLE APPENDIX

TABLE A1.—LIST OF ALL EUKLEMS INDUSTRIES

Manufacturing		Services	
Code	Code Description	Code	Code Description
AtB	Agriculture, hunting, forestry and fishing	50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
C	Mining and quarrying	51	Wholesale trade and commission trade, except of motor vehicles and motorcycles
15t16	Food products, beverages and tobacco	52	Retail trade, except of motor vehicles and motorcycles; repair of household goods
17t19	Textiles, textile products, leather and footwear	60t63	Transport and storage
20	Wood and products of wood and cork	64	Post and telecommunications
21t22	Pulp, paper, paper products, printing and publishing	70	Real estate activities
23	Coke, refined petroleum products and nuclear fuel	71t74	Renting of machinery and equipment and other business activities
24	Chemicals and chemical products	E	Electricity, gas and water supply
25	Rubber and plastics products	F	Construction
26	Other non-metallic mineral products	H	Hotels and restaurants
27t28	Basic metals and fabricated metal products	J	Financial intermediation
29	Machinery, not elsewhere classified	L	Public administration, defence, and compulsory social security
30t33	Electrical and optical equipment	M	Education
34t35	Transport equipment	N	Health and social work
36t37	Manufacturing not elsewhere classified; recycling	O	Other community, social and personal services

TABLE A2.—LIST OF INDUSTRIES POOLED BY COUNTRY

	NACE Codes
Austria	15t16 plus 17t19 plus 36t37; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29 plus 30t33 plus 34t35; 50 plus 51 plus 52 plus H; 60t63; 64; 70 plus 71t74; AtB; F; J; L; M; N; O
Denmark	15t16; 17t19; 36t37; 20; 21t22; 24; 25; 26; 27t28; 29; 30t33; 34t35; 50; 51; 52; H; 60t63; 64; 70; 71t74; AtB; F; J; L; M; N; O
Finland	15t16 plus 17t19 plus 36t37; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29 plus 30t33 plus 34t35; 50 plus 51 plus 52 plus H; 60t63; 64; 70 plus 71t74; AtB; F; J; L; M; N; O
France	15t16 plus 17t19 plus 36t37; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29 plus 30t33 plus 34t35; 50 plus 51 plus 52 plus H; 60t63; 64; 70 plus 71t74; AtB; F; J; L; M; N; O
Germany	15t16 plus 17t19; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28 plus 29; 30t33 plus 34t35; 36t37; 50 plus 51 plus 52 plus H; 60t63 plus 64; 70 plus 71t74; AtB; F; J; L; M; N; O
Italy	15t16; 17t19; 20; 21t22;24; 25; 26; 27t28; 29; 30t33; 34t35; 36t37; 50; 51; 52; H; 60t63; 64; 70; 71t74; AtB; F; J; L; M; N; O
Japan	AtB; 20; 60t63; 64; H; 17t19; 26; 27t28; 50; 25 plus 36t37; 34t35; 15t16; O; 29; 52; 30t33; F; 21t22; 24; 71t74; 51; J; 70; L plus M plus N
Netherlands	AtB; F; 50 plus 51 plus 52 plus H; 64; 15t16 plus 17t19; 60t63; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28 plus 36t37; J; 29 plus 30t33 plus 34t35; L; N; 70 plus 71t74; M; O
Spain	15t16; 17t19; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29; 30t33; 34t35; 36t37; 50 plus 51 plus 52; 60t63; 64; 70 plus 71t74; AtB; F; H; J; L; M; N; O
United Kingdom	64; F; 50 plus 51 plus 52 plus H; 15t16 plus 17t19 plus 36t37; AtB; 60t63; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29 plus 30t33 plus 34t35; O; L; J; N; 70 plus 71t74; M
United States	15t16; 17t19; 36t37; 20; 21t22; 24; 25; 26; 27t28; 29; 30t33; 34t35; 50; 51; 52; H; 60t63; 64; 70; 71t74; AtB; F; J; L; M; N; O

TABLE A3.—TRADE, ICT, AND RESEARCH AND DEVELOPMENT

	Dependent Variable: High-Skilled Wage Bill Share																	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Δ ((Imports + Exports)/(Value Added))	0.59	0.11																
	(0.15)	(0.25)																
Δ ((Imports)/(Value Added))			1.07	0.21														
			(0.30)	(0.45)														
Δ((Exports)/(Value Added))					1.16	0.21												
					(0.30)	(0.54)												
Δ ((Imports OECD + Exports OECD)/(Value Added))							0.68	−0.05										
							(0.18)	(0.37)										
Δ ((Imports OECD)/(Value Added))									1.44	−0.43								
									(0.52)	(0.91)								
Δ((Exports OECD)/(Value Added))											1.10	0.03						
											(0.30)	(0.61)						
Δ ((Imports + Exports non-OECD)/(Value Added))													2.21	1.38				
													(0.58)	(0.74)				
Δ((Imports non-OECD)/(Value Added))															2.09	1.13		
															(0.63)	(0.84)		
Δ((Exports non-OECD)/(Value Added))																	10.97	9.30
																	(3.38)	(3.41)
Δ((ICT Capital)/(Value Added))	107.61	73.59	107.29	73.22	110.10	74.17	109.89	76.18	110.56	78.66	112.20	75.32	110.15	69.78	113.49	71.75	116.71	67.65
	(31.70)	(31.41)	(31.52)	(31.32)	(32.04)	(31.41)	(31.93)	(31.56)	(31.53)	(31.36)	(32.52)	(31.53)	(31.15)	(30.48)	(32.09)	(30.78)	(29.66)	(29.74)
Δ ln(Value Added)	4.09	2.57	4.30	2.62	3.80	2.50	3.94	2.29	4.08	2.01	3.74	2.38	4.28	3.07	4.16	2.86	3.76	3.04
	(1.09)	(1.52)	(1.13)	(1.52)	(1.06)	(1.49)	(1.09)	(1.50)	(1.11)	(1.41)	(1.07)	(1.48)	(1.12)	(1.47)	(1.16)	(1.50)	(0.97)	(1.18)
Δ((Non-ICT Capital)/(Value Added))	−0.63	0.97	−0.50	0.99	−0.76	0.95	−0.47	1.04	−0.01	0.91	−0.82	1.01	−1.09	0.62	−1.19	0.48	0.24	2.77
	(2.41)	(3.12)	(2.38)	(3.11)	(2.45)	(3.13)	(2.39)	(3.05)	(2.33)	(2.98)	(2.46)	(3.13)	(2.50)	(3.22)	(2.51)	(3.24)	(2.42)	(2.97)
1980 (Research and Development Expenditure/Value Added)		28.04		28.05		28.27		30.88		32.93		29.83		25.37		26.73		25.85
		(17.59)		(16.88)		(18.06)		(18.25)		(17.32)		(18.33)		(15.55)		(15.90)		(13.84)
Country fixed effects	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Observations	84	65	84	65	84	65	84	65	84	65	84	65	84	65	84	65	84	65
R^2	0.821	0.82	0.821	0.82	0.82	0.82	0.819	0.82	0.819	0.82	0.817	0.82	0.822	0.826	0.817	0.823	0.826	0.834

Coefficients estimated by OLS with robust standard errors in parentheses. Regressions weighted by the industry's 1980 share of each country's employment, for traded goods. The OECD ANBERD data set does not have R&D data for Austria and Spain, which are dropped from the sample (columns 2,4,6,8,10,12,14,16, and 18).

TABLE A4.—CONTRIBUTION OF CHANGES IN ICT AND R&D TO CHANGES IN THE HIGH-SKILLED WAGE BILL SHARE

	(1)	(2)	(3)	(4)	(5)	(6)
Sectors	All	All	Traded	Traded	All	All
Method	No Controls, OLS	Full Controls, OLS	No Controls, OLS	Full Controls, OLS	No Controls, IV	Full Controls, IV
Δ (High-Skilled Wage Bill share)	10.02	10.02	9.37	9.37	10.02	10.02
Δ ((ICT Capital)/(Value Added))	0.018	0.018	0.017	0.017	0.018	0.018
Coefficient on ICT	72.3	46.9	83.1	75.5	152.3	121.6
Mean × Coefficient of ICT	1.32	0.86	1.45	1.31	2.78	2.22
Mean contribution % of ICT	13.16	8.54	15.43	14.03	27.72	22.14
Table and columns used	Table 5, column 2	Table 5, column 4		Table 8, column 7		Table 6, column 6
Research and Development/Value Added			0.028	0.028		
Coefficient on R&D			52.79	30.08		
Mean × Coefficient on R&D			1.49	0.84		
Mean contribution of R&D			15.90	8.99		

This table contains a set back-of-the-envelope calculation of the contribution of technology to accounting for the changes in the high-skilled wage bill share.

This article has been cited by:

1. Maarten Goos, Alan Manning, Anna Salomons. 2014. Explaining Job Polarization: Routine-Biased Technological Change and Offshoring †. *American Economic Review* **104**, 2509-2526. [CrossRef]
2. Neil Foster-McGregor, Robert Stehrer, Gaaitzen J. Vries. 2013. Offshoring and the skill structure of labour demand. *Review of World Economics* **149**:4, 631-662. [CrossRef]
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Appendix for "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over 25 years"

Guy Michaels[1], Ashwini Natraj[2] and John Van Reenen[3]

A. Theory Appendix: A simple model of the effect of ICT on demand for three skill groups.

We present a simple model that illustrates how we could derive the relationships we observe in the data. The exogenous variable is an increase in ICT capital generated by a large fall in ICT prices. The prediction is that we can observe an increase in the share of the high-skilled and a decline in the share of the middle-skilled. Note that an increase in the supply of the middle-skilled will also generate an increase in their wage bill share.

The model below considers an aggregate (sectoral) production function using three labor inputs: low-skilled (L), middle-skilled (M), and high-skilled (H) workers and ICT capital (C). The model also assumes a constant elasticity of substitution $\sigma = \frac{1}{1-\rho} > 1$ between the three types of (ICT-augmented) labor inputs, so $\rho \in (0,1)$. We assume that output, Q, is produced using the following production function:

$$Q = \left[\alpha_L L^\rho + (\alpha_M M + \beta C)^\rho + (\alpha_H H^\mu + \gamma C^\mu)^{\rho/\mu}\right]^{\frac{1}{\rho}},$$

where α_j denotes the effectiveness of each type of labor, $j \in \{L, M, H\}$. β measures the effectiveness of ICT in substituting middle-skilled labor and γ measures ICT effectiveness in complementing high-skilled labor. The model assumes that ICT capital (C) is a substitute for middle-skilled workers, and a complement to high-skilled labor, where $\eta = \frac{1}{1-\mu} \in (0,1)$, so $\mu < 0$. Note that the model only

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[2]Centre for Economic Performance and London School of Economics
[3]Centre for Economic Performance, LSE, NBER and CEPR

treats the relationship between C and H in exactly the opposite way from the relationship between C and M if $\eta \longrightarrow 0$ (or equivalently $\mu \longrightarrow -\infty$).

Assuming perfect competition, the wage of the three types of labor and the cost of ICT are:

$$\begin{aligned}
w_H &= \left[\alpha_L L^\rho + (\alpha_M M + \beta C)^\rho + (\alpha_H H^\mu + \gamma C^\mu)^{\rho/\mu}\right]^{\frac{1}{\rho}-1} (\alpha_H H^\mu + \gamma C^\mu)^{(\rho/\mu)-1} \alpha_H H^{\mu-1} \\
w_M &= \left[\alpha_L L^\rho + (\alpha_M M + \beta C)^\rho + (\alpha_H H^\mu + \gamma C^\mu)^{\rho/\mu}\right]^{\frac{1}{\rho}-1} (\alpha_M M + \beta C)^{\rho-1} \alpha_M \\
w_L &= \left[\alpha_L L^\rho + (\alpha_M M + \beta C)^\rho + (\alpha_H H^\mu + \gamma C^\mu)^{\rho/\mu}\right]^{\frac{1}{\rho}-1} \alpha_L L^{\rho-1} \\
p &= \left[\alpha_L L^\rho + (\alpha_M M + \beta C)^\rho + (\alpha_H H^\mu + \gamma C^\mu)^{\rho/\mu}\right]^{\frac{1}{\rho}-1} \\
&\quad * \left[(\alpha_M M + \beta C)^{\rho-1} \beta + (\alpha_H H^\mu + \gamma C^\mu)^{(\rho/\mu)-1} \gamma C^{\mu-1}\right] \\
&= \frac{\beta}{\alpha_M} w_M + \frac{\gamma C^{\mu-1}}{\alpha_H H^{\mu-1}} w_H
\end{aligned}$$

In this model an increase in ICT raises the wage of high-skilled and low-skilled workers, but has an ambiguous effect on the wage of middle-skilled workers:

$$\frac{\partial w_H}{\partial C} > 0, \frac{\partial w_L}{\partial C} > 0.$$

The wage bill shares of the three types of labor are:

$$\begin{aligned}
\theta_H &= \frac{w_H H}{w_L L + w_M M + w_H H} = \\
&= \frac{\left(\alpha_H H^\mu + \gamma C^\mu\right)^{(\rho/\mu)-1} \alpha_H H^\mu}{\alpha_L L^\rho + \alpha_M \left(\alpha_M M^{\frac{-\rho}{1-\rho}} + \beta C M^{\frac{-1}{1-\rho}}\right)^{\rho-1} + \left(\alpha_H H^\mu + \gamma C^\mu\right)^{(\rho/\mu)-1} \alpha_H H^\mu} \\
\theta_M &= \frac{w_M M}{w_L L + w_M M + w_H H} = \\
&= \frac{\alpha_M \left(\alpha_M M^{\frac{-\rho}{1-\rho}} + \beta C M^{\frac{-1}{1-\rho}}\right)^{\rho-1}}{\alpha_L L^\rho + \alpha_M \left(\alpha_M M^{\frac{-\rho}{1-\rho}} + \beta C M^{\frac{-1}{1-\rho}}\right)^{\rho-1} + \left(\alpha_H H^\mu + \gamma C^\mu\right)^{(\rho/\mu)-1} \alpha_H H^\mu} \\
\theta_L &= \frac{w_L L}{w_L L + w_M M + w_H H} = \\
&= \frac{\alpha_L L^\rho}{\alpha_L L^\rho + \alpha_M \left(\alpha_M M^{\frac{-\rho}{1-\rho}} + \beta C M^{\frac{-1}{1-\rho}}\right)^{\rho-1} + \left(\alpha_H H^\mu + \gamma C^\mu\right)^{(\rho/\mu)-1} \alpha_H H^\mu}
\end{aligned}$$

One can verify that in this specification:

$$\frac{\partial \theta_H}{\partial C} > 0, \frac{\partial \theta_M}{\partial C} < 0,$$

so increased supply of ICT raises the college wage bill share and reduces the middle-skilled wage bill share. The ratio of the wage bill of high (middle) skilled workers to low-skilled workers increases (decreases) with ICT:

$$\begin{aligned}
\frac{\partial}{\partial C}\left(\frac{w_H H}{w_L L}\right) &= \frac{\partial}{\partial C}\left[\frac{\left(\alpha_H H^\mu + \gamma C^\mu\right)^{(\rho/\mu)-1} \alpha_H H^\mu}{\alpha_L L^\rho}\right] > 0 \\
\frac{\partial}{\partial C}\left(\frac{w_M M}{w_L L}\right) &= \frac{\partial}{\partial C}\left[\frac{\alpha_M \left(\alpha_M M^{\frac{-\rho}{1-\rho}} + \beta C M^{\frac{-1}{1-\rho}}\right)^{\rho-1}}{\alpha_L L^\rho}\right] < 0
\end{aligned}$$

Note that an increase in the supply of middle-skilled workers raises their wage bill relative to low-skilled workers:

$$\frac{\partial}{\partial M}\left(\frac{w_M M}{w_L L}\right) = \frac{\partial}{\partial M}\left[\frac{\alpha_M \left(\alpha_M M^{\frac{-\rho}{1-\rho}} + \beta C M^{\frac{-1}{1-\rho}}\right)^{\rho-1}}{\alpha_L L^\rho}\right] > 0$$

B. Data Appendix

B.1. Construction of main dataset

Our main dataset is EUKLEMS (http://www.euklems.net/), which is an industry-level panel dataset created by economic researchers funded by the European Commission. It covers the European Union, the US, Japan, and other countries, and contains a wealth of information on productivity-related variables. These were constructed through joint work with census bureau in each country and are designed to be internationally comparable. Details of the methodology are in Timmer et al. (2007, 2010) and O'Mahony and Timmer (2009).

In the construction of our sample we faced a number of technical issues. First, although college wage bill shares are reported for 30 industries in each country, these reported wage bill shares are not unique within each country. For example, in a certain country the reported college wage bill share for industry A and industry B may be (college wage bill in A + college wage bill in B)/(total wage bill in A + total wage bill in B). The identity and number of industries pooled together vary across countries. In order to use as much of variation as possible, we aggregate industries within each country up to the lowest level of aggregation that ensures that the college wage bill share is unique across the aggregated observations. This is also sufficient to ensure that other variables we use, such as our ICT and value added measures, have unique values across observations.

Second, as a measure of ICT intensity we use ICT capital compensation divided by value added directly from EUKLEMs. ICT capital is built using the Perpetual Inventory method based on real ICT investment flows (using a quality-adjusted price deflator). ICT capital compensation is the stock of ICT capital multiplied by its user cost. Non-ICT capital compensation is built in the same way[4].

Third, matching trade variables into our main dataset required data required currency conversions, since EUKLEMS reports data in historical local currency and COMTRADE reports data in historical dollars. To overcome this difference, we convert nominal values to current US Dollars using exchange rates from the

[4] Because EUKLEMS calculates capital compensation as a residual in a few cases observations can have negative capital compensation. Of the 208 country-industry cells we use, negative capital compensation occurs in 12 cases in 1980 and in 3 cases in 2004. These are typically agriculture (which is heavily subsidized and becomes smaller over time) and industries where public services play an important role (e.g. education and health). To overcome this problem, we bottom-coded negative values of ICT and non-ICT capital compensation to zero. Our results are robust to dropping these observations from the sample.

IMF IFS website. To convert national currency to the Euro (for Eurozone countries), we use exchange rates from the website:

http://ec.europa.eu/economy_finance/euro/transition/conversion_rates.htm

We use trade figures from the UN's COMTRADE dataset. Data is downloaded in the four digit Standard International Trade Classification format (revision 2), and converted to the European NACE Rev 1 classification used in the EUKLEMS dataset (concordance available on request). Our trade regressions contain the updated data from 21st March 2008.

To decompose trade into OECD versus non-OECD, we use the 2007 definition of OECD countries (Austria, Australia, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland, Turkey, the UK and the USA). This means that Czechoslovakia and Belgium-Luxembourg were treated as OECD countries in 1980.

Finally, we account for the fact that the (aggregated) industries we use differ substantially in their employment shares within each country's population. We therefore use the employment shares of each industry in 1980 (our base year) in total employment as analytical weights in the regressions using both tradable and non-tradable industries. For trade regressions, which use only the traded industries, each industry's weight is its employment share in the traded industries for that country, so that the sum of weights for each country is still equal to one.

B.2. Construction of task measures by skill

To construct measures of task content by occupation and education group, which we use in Tables 1 and 2, we begin with US Census micro data for 1980 from IPUMS, which identify each person's occupation (using the three-digit 1980 occupation definitions from IPUMS) and education (measured in years of schooling completed). We assign each person to one of three educational categories - high, medium, or low - using the EUKLEMS classification for the US. In other words, high-skill workers are those who have at least 16 years of education, middle-skilled workers are those with 13-15 years of education, and low-skilled workers are those with 12 years of education. We then assign to each person the "80-90" occupation code using the concordance from Autor, Levy, and Murnane (2003), and we match to each occupation the task measures, which Autor, Levy, and Murnane (2003) derive from the 1991 Dictionary of Occupational Titles. These include routine cognitive tasks (measured using Set limits, Tolerances, or Standards); routine manual tasks (measured using Finger Dexterity); non-routine cognitive tasks measured using both (i) Quantitative reasoning requirements and (ii) Direction, Control, and Planning and non-routine manual tasks (measured using Eye-Hand-Foot coordination).

We then collapse the data to the occupation-skill level, using 1980 person weights from IPUMS. Finally, we standardize each of these five task measures by subtracting the mean task score across occupations, weighted by person weights, and dividing the resulting difference by the standard deviation of the task measure across occupations. The results in Tables 1 and 2 discussed below use these standardized task measures.

We calculate the intensity of occupation O in terms of skill level $S \in \{H, M, L\}$ as

$$Share_S^O = \frac{E_{OS}}{E_O},$$

where E_{oS} is the number of people in occupation O with skill level S, and E_O is the total number of people with occupation O. We then rank the occupations in terms of their intensity of each of the three skill groups, and Table 1 presents the ten top occupations in each skill category, and the score of each of these occupations on each task k.

Finally, we calculate the average score on each task k for each skill level S as

$$I_S^k = \sum_O \frac{E_{OS}}{E_S} I_o^k,$$

where I_O^k is occupation O's score on task k, E_{oS} is the number of people in occupation O with skill level S, and E_S is the total number of people with skill level S. These scores are reported in Table 2.

Appendix Table A1: List of all EUKLEMS Industries:

Manufacturing		Services	
Code	**Code Description**	**Code**	**Code Description**
AtB	Agriculture, hunting, forestry and fishing	50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
C	Mining and quarrying	51	Wholesale trade and commission trade, except of motor vehicles and motorcycles
15t16	Food products, beverages and tobacco	52	Retail trade, except of motor vehicles and motorcycles; repair of household goods
17t19	Textiles, textile products, leather and footwear	60t63	Transport and storage
20	Wood and products of wood and cork	64	Post and telecommunications
21t22	Pulp, paper, paper products, printing and publishing	70	Real estate activities
23	Coke, refined petroleum products and nuclear fuel	71t74	Renting of machinery and equipment and other business activities
24	Chemicals and chemical products	E	Electricity, gas and water supply
25	Rubber and plastics products	F	Construction
26	Other non-metallic mineral products	H	Hotels and restaurants
27t28	Basic metals and fabricated metal products	J	Financial intermediation
29	Machinery, not elsewhere classified	L	Public administration, defence, and compulsory social security
30t33	Electrical and optical equipment	M	Education
34t35	Transport equipment	N	Health and social work
36t37	Manufacturing not elsewhere classified; recycling	O	Other community, social and personal services

Appendix Table A2: List of Industries Pooled by Country

	NACE codes
Austria	15t16 plus 17t19 plus 36t37; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29 plus 30t33 plus 34t35; 50 plus 51 plus 52 plus H; 60t63; 64; 70 plus 71t74; AtB; F; J; L; M; N; O
Denmark	15t16; 17t19; 36t37; 20; 21t22; 24; 25; 26; 27t28; 29; 30t33; 34t35; 50; 51; 52; H; 60t63; 64; 70; 71t74; AtB; F; J; L; M; N; O
Finland	15t16 plus 17t19 plus 36t37; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29 plus 30t33 plus 34t35; 50 plus 51 plus 52 plus H; 60t63; 64; 70 plus 71t74; AtB; F; J; L; M; N; O
France	15t16 plus 17t19 plus 36t37; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29 plus 30t33 plus 34t35; 50 plus 51 plus 52 plus H; 60t63; 64; 70 plus 71t74; AtB; F; J; L; M; N; O
Germany	15t16 plus 17t19; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28 plus 29; 30t33 plus 34t35; 36t37; 50 plus 51 plus 52 plus H; 60t63 plus 64; 70 plus 71t74; AtB; F; J; L; M; N; O
Italy	15t16; 17t19; 20; 21t22;24; 25; 26; 27t28; 29; 30t33; 34t35; 36t37; 50; 51; 52; H; 60t63; 64; 70; 71t74; AtB; F; J; L; M; N; O
Japan	AtB; 20; 60t63; 64; H; 17t19; 26; 27t28; 50; 25 plus 36t37; 34t35; 15t16; O; 29; 52; 30t33; F; 21t22; 24; 71t74; 51; J; 70; L plus M plus N
Netherlands	AtB; F; 50 plus 51 plus 52 plus H; 64; 15t16 plus 17t19; 60t63; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28 plus 36t37; J; 29 plus 30t33 plus 34t35; L; N; 70 plus 71t74; M; O
Spain	15t16; 17t19; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29; 30t33; 34t35; 36t37; 50 plus 51 plus 52; 60t63; 64; 70 plus 71t74; AtB; F; H; J; L; M; N; O
UK	64; F; 50 plus 51 plus 52 plus H; 15t16 plus 17t19 plus 36t37; AtB; 60t63; 20 plus 21t22 plus 24 plus 25 plus 26 plus 27t28; 29 plus 30t33 plus 34t35; O; L; J; N; 70 plus 71t74; M
USA	15t16; 17t19; 36t37; 20; 21t22; 24; 25; 26; 27t28; 29; 30t33; 34t35; 50; 51; 52; H; 60t63; 64; 70; 71t74; AtB; F; J; L; M; N; O

Appendix Table A3: Trade, ICT, and Research and Development

Dependent variable: High-Skilled Wage Bill Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Δ ((Imports+ Exports) / (Value Added))	0.59	0.11																
	(0.15)	(0.25)																
Δ ((Imports) / (Value Added))			1.07	0.21														
			(0.30)	(0.45)														
Δ ((Exports) / (Value Added))					1.16	0.21												
					(0.30)	(0.54)												
Δ ((Imports OECD+ Exports OECD) / (Value Added))							0.68	-0.05										
							(0.18)	(0.37)										
Δ ((Imports OECD) / (Value Added))									1.44	-0.43								
									(0.52)	(0.91)								
Δ ((Exports OECD) / (Value Added))											1.10	0.03						
											(0.30)	(0.61)						
Δ ((Imports+Exports nonOECD) / (Value Added))													2.21	1.38				
													(0.58)	(0.74)				
Δ ((Imports nonOECD) / (Value Added))															2.09	1.13		
															(0.63)	(0.84)		
Δ ((Exports nonOECD) / (Value Added))																	10.97	9.30
																	(3.38)	(3.41)
Δ ((ICT capital) / (Value Added))	107.61	73.59	107.29	73.22	110.10	74.17	109.89	76.18	110.56	78.66	112.20	75.32	110.15	69.78	113.49	71.75	116.71	67.65
	(31.70)	(31.41)	(31.52)	(31.32)	(32.04)	(31.41)	(31.93)	(31.56)	(31.53)	(31.36)	(32.52)	(31.53)	(31.15)	(30.48)	(32.09)	(30.78)	(29.66)	(29.74)
Δ ln(Value Added)	4.09	2.57	4.30	2.62	3.80	2.50	3.94	2.29	4.08	2.01	3.74	2.38	4.28	3.07	4.16	2.86	3.76	3.04
	(1.09)	(1.52)	(1.13)	(1.52)	(1.06)	(1.49)	(1.09)	(1.50)	(1.11)	(1.41)	(1.07)	(1.48)	(1.12)	(1.47)	(1.16)	(1.50)	(0.97)	(1.18)
Δ ((Non ICT capital) / (Value Added))	-0.63	0.97	-0.50	0.99	-0.76	0.95	-0.47	1.04	-0.01	0.91	-0.82	1.01	-1.09	0.62	-1.19	0.48	0.24	2.77
	(2.41)	(3.12)	(2.38)	(3.11)	(2.45)	(3.13)	(2.39)	(3.05)	(2.33)	(2.98)	(2.46)	(3.13)	(2.50)	(3.22)	(2.51)	(3.24)	(2.42)	(2.97)
1980 (Research and Development Expenditure/ Value Added)		28.04		28.05		28.27		30.88		32.93		29.83		25.37		26.73		25.85
		(17.59)		(16.88)		(18.06)		(18.25)		(17.32)		(18.33)		(15.55)		(15.90)		(13.84)
Country fixed effects	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Obs.	84	65	84	65	84	65	84	65	84	65	84	65	84	65	84	65	84	65
R-squared	0.821	0.82	0.821	0.82	0.82	0.82	0.819	0.82	0.819	0.82	0.817	0.82	0.822	0.826	0.817	0.823	0.826	0.834

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. Regressions weighted by the industry's 1980 share of each country's employment, for traded goods. The OECD ANBERD dataset does not have R&D data for Austria and Spain, which are dropped from the sample (columns 2,4,6,8,10,12,14,16 and 18).

Appendix Table A4: Contribution of Changes in ICT and R&D to Changes in the High-Skilled Wage Bill Share

	(1)	(2)	(3)	(4)	(5)	(6)
Sectors	**All**	**All**	**Traded**	**Traded**	**All**	**All**
Method	No Controls, OLS	Full Controls, OLS	No Controls, OLS	Full Controls, OLS	No controls, IV	Full controls, IV
Δ (High-skilled wage-bill share)	10.02	10.02	9.37	9.37	10.02	10.02
Δ ((ICT capital) / (Value Added))	0.018	0.018	0.017	0.017	0.018	0.018
Coefficient on ICT	72.3	46.9	83.1	75.5	152.3	121.6
Mean*Coefficient of ICT	1.32	0.86	1.45	1.31	2.78	2.22
Mean contribution % of ICT	13.16	8.54	15.43	14.03	27.72	22.14
Table and columns used	Table 5 column (2)	Table 5 column (4)		Table 8 column (7)		Table 6 column (6)
Research and Development/Value Added			0.028	0.028		
Coefficient on R&D			52.79	30.08		
Mean*Coefficient on R&D			1.49	0.84		
Mean contribution of R&D			15.90	8.99		

Notes: This table contains a "back of the envelope" calculation of the contribution of technology to accounting for the changes in the high-skilled wage bill share.