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Explaining Job Polarization in Europe: The Roles of Technology, Globalization and Institutions

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Abstract
This paper shows the employment structure of 16 European countries has been polarizing in recent years with the employment shares of managers, professionals and low-paid personal services workers increasing at the expense of the employment shares of middling manufacturing and routine office workers. To explain this job polarization, the paper develops and estimates a simple model to capture the effects of technology, globalization, institutions and product demand effects on the demand for different occupations. The results suggest that the routinization hypothesis of Autor, Levy and Murnane (2003) is the single most important factor behind the observed shifts in employment structure. We find some evidence for offshoring to explain job polarization although its impact is much smaller. We also find that shifts in product demand are acting to attenuate the polarizing impact of routinization and that differences or changes in wage-setting institutions play little role in explaining job polarization in Europe.

JEL Classifications: J21, J23, J24
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1. INTRODUCTION

Economists and non-economists alike have long been fascinated by the ever-changing occupational structure of employment. Economists have developed a number of hypotheses about the driving forces behind these changes. The most popular emphasize the importance of technological change, globalization (partly driven by technology, but perhaps partly also an independent force from declining man-made barriers to trade), and labor market institutions (e.g. that alter the relative wages of different types of labor).

In the 1980s and 1990s, the dominant view among labor economists was that technology was more important than trade as a driving force behind changes in the structure of employment (see, for example, Johnson 1997; Desjonqueres, Machin and Van Reenen 1999; Autor and Katz 1999), and that technological change was biased in favor of skilled workers, leading to the hypothesis of skill-biased technological change (SBTC) (see, for example, Krueger 1993; Berman, Bound and Griliches 1994; Berman, Bound and Machin 1998; Machin and Van Reenen 1998; Autor, Katz and Krueger 1998). More recently, views have been shifting somewhat.

First, there is a more nuanced view of the impact of technological change on the demand for different types of labor. Autor, Levy and Murnane (2003) (ALM) argue persuasively that technology can replace human labor in routine tasks – tasks that can be expressed in step-by-step procedures or rules – but (as yet) cannot replace human labor in non-routine tasks. The routinization hypothesis is intuitively plausible and ALM provide evidence that industries in which routine tasks were heavily used have seen the most adoption of computers, and this has reduced the usage of labor input of routine tasks in those industries. The important point is that 'routine' does not map simply into a one-dimensional definition of skill (Goos and Manning 2007). Although low-skill production-line jobs in manufacturing can be characterized as 'routine', so can many more skilled craft jobs and many clerical jobs that never were the lowest paid jobs in the economy. In contrast, many of the worst-paying jobs, for example in housekeeping, hotel and catering and personal care, are non-routine in nature and therefore have been relatively unaffected by technological change. As a result, the distribution of jobs is 'polarizing' with faster employment growth in the highest and lowest-paying jobs and slower growth in the middling jobs. Recent empirical work has shown how this has been happening in the US (Juhn 1994, 1999; Acemoglu 1999; Autor, Katz and Kearney 2006, 2008; Lemieux 2008; Autor and Dorn 2010; Acemoglu and Autor 2011), the UK (Goos and Manning 2007), West-Germany (Spitz-Oener 2006; Dustmann, Ludsteck and Schönberg 2009) and across European countries (Goos, Manning and Salomons 2009; Michaels, Natraj and Van Reenen 2010).

Secondly, views about the likely impact of globalization on employment in OECD economies have also been changing. The concern in the 1980s and 1990s was largely about the displacement of manufacturing as a whole (i.e. as an industry) to lower-wage countries. More recently, the focus of concern has been about the relocation of certain parts of the production process (usually specific occupations, often those involved in the production of services) to developing countries, a process known as offshoring (Feenstra and Hanson 1999; Grossman and Rossi-Hansberg 2008; Rodriguez-Clare and Ramondo 2010; Acemoglu, Gancia and Zilibotti 2010; Acemoglu and Autor 2011).[1] The rapid growth of countries like India and China in recent years has made many feel that globalization is having a more powerful effect on the structure of employment now than in the 1980s.[2] For example, Blinder (2007, 2009) and Blinder and Krueger (2009) estimate that approximately 25% of US jobs might become offshorable within the next 20 years. However, evidence on the importance of offshoring remains mixed. For instance, Liu and Trefler (2008) examine the employment effects of service offshoring by US companies to unaffiliated firms abroad as well as the employment effects of service inshoring (the sale of services to US firms by unaffiliated firms

[1] Throughout this paper, by "offshoring" we mean the use of intermediate inputs imported from abroad, also known as "offshore outsourcing". This is different from "outsourcing" or the use of intermediate inputs imported from abroad or produced domestically. The difference between offshoring and outsourcing is important here since our model and data only capture the offshore component of outsourcing.

[2] For example, the issue of offshoring of US jobs has become a major political issue – see the accounts in Blinder (2006, 2007, 2009) and Mankiw and Swagel (2006).

abroad) and find only small positive effects of service inshoring and even smaller negative effects of service offshoring.

Although there is broad agreement that, in very general terms, technology, globalization and institutions are the most important drivers of the changing occupational structure of employment, quantifying the effects in empirical work is not straightforward because general equilibrium effects are likely to be very important and cannot be ignored. A simple example, inspired by one of the popular works of Krugman (1999) (though none the worse for that) will illustrate. A hamburger requires one bun and one patty. Suppose there is an improvement in the technology of patty-making so that one now only needs half the number of workers to produce one patty. This change obviously only directly affects patty-making so a simple-minded approach would choose an empirical specification in which the technical change variable only appears in the equation for the number of patty-makers. But, if the empirical specification assumes that the technical change does not affect the employment of the bun-makers and the number of buns and patties must remain in the same proportion, the only possible conclusion is that the innovation reduces the employment of patty-makers and employment overall. Non-economists only often see this direct effect and Krugman's point is that this is a serious mistake.

The innovation reduces the cost of producing patties and, hence, the cost of producing hamburgers. This leads to a reduction in the price of hamburgers causing an increase in the demand for them (assuming they are non-Giffen). The employment of the bun-makers then rises and the employment of the patty-makers is higher than one would predict if one assumed the production of hamburgers remained constant but not necessarily so large as to prevent an overall fall in employment. Employment in bun-making is affected by innovation in patty-making and we have a clear idea of the channel – through changes in product demand induced by changes in costs and prices.[3] None of these ideas are new – they date back to at least the work of Baumol (1967).[4]

But this is not the end. Because hamburgers are now cheaper there is an income and substitution effect on the demand for other consumer products too. If preferences are non-homothetic induced changes in the level and distribution of income will also induce changes in the occupational structure of employment. For example, Clark (1957) argued that the income elasticity of demand for services is greater than unity, in which case a rise in real income will tend to shift employment towards service-intense occupations.[5]

The bottom line from this is that if one wants an adequate understanding of the changing occupational structure of employment, it is impossible to ignore general equilibrium effects by which a change affecting the demand for one type of labor is likely to spill-over to every other type of labor. In empirical modeling one could take a non-theoretical approach to quantifying these general equilibrium effects and adopt an empirical specification in which every change potentially affects every occupation. However, there are likely to be serious identification issues with such an approach and it is extremely profligate with degrees of freedom, likely leading to very imprecise estimates. The alternative – and the approach we take in this paper – is to use a theoretical model of the demand for labor to put more structure on the linkages between the demand for different sorts of labor. We do not think much is lost in imposing this structure as we do have a fairly clear idea of the channels that link the demands for different types of labor. In the hamburger example, the demand for bun-

[3] The example assumes two input factors that are perfect complements (buns and patties) and one output good (hamburgers). In general, the effects of innovation on factor demands will depend on the degree of substitutability between factors in production as well as the degree of substitutability between goods in consumption.

[4] It is worth noting that there has been a renewed interest in equilibrium models of unbalanced productivity growth across tasks or sectors. See Ngai and Pissarides (2007), Weiss (2008), Reshef (2009) and Autor and Dorn (2010).

[5] More recent examples of models assuming different income elasticities for different goods or services yielding structural change are Echevarria (1997), Laitner (2000), Caselli and Coleman II (2001), Gollin, Parente and Rogerson (2002).

makers only rises to the extent to which the demand for hamburgers rises and this occurs because the cost of making hamburgers has fallen.

So, the first main contribution of this paper is to use a simple theoretical framework (that has clear antecedents in papers like Katz and Murphy 1992; Card and Lemieux 2001) to develop estimable equations that can be used to identify and quantify all of the channels discussed above. Ours is not the only paper to write down a theoretical model to inform thinking (e.g. Autor and Dorn 2010; Acemoglu and Autor 2011) but there is a tighter link between our theory and empirical specification.

Our second main contribution is that we use data from 16 European countries to demonstrate that job polarization is pervasive. Most other studies use data from only one country, a notable exception being Michaels, Natraj and van Reenen (2010) who investigate the impact of ICT on the changing educational composition of employment. Using data from multiple countries gives us more ability to investigate the potential role of labor market institutions, and more data to investigate the importance of technology and globalization, whose effects one would expect to be pervasive on our sample of countries.

The paper is organized as follows. Section 2 describes the data and shows how the employment structure in 16 European countries is polarizing. Section 3 then presents our simple theoretical framework of the demand for occupations within industries to organize our thoughts about how the hypotheses outlined above affect the demand for labor. The fourth section describes the variables we use to capture these hypotheses. In the fifth section we estimate this model of within-industry changes in occupational labor demand across countries. The sixth section then seeks to move beyond within-industry equations to consider the importance of changes in relative product demand through the introduction and estimation of product demand curves. Finally, the seventh section evaluates to what extent job polarization can be explained by each of these different channels affecting labor demand. Our main conclusion is that the ALM routinization hypothesis has the most explanatory power for understanding job polarization in Europe, but offshoring does play a role. We find some role for the importance of changes in relative output prices following technological progress and globalization whereas income and institutional effects are found to be relatively unimportant in explaining job polarization in Europe.

2 A PICTURE OF CHANGES IN THE EUROPEAN JOB STRUCTURE

2.A Employment data[6]

In this paper we model employment by industry and occupation. Our main data source for employment is the harmonized individual-level European Union Labor Force Survey (ELFS) for the period 1993-2006. The ELFS contains data on employment status, weekly hours worked, 2-digit International Standard Occupational Classification (ISCO) codes and 1-digit industry codes from the Classification of Economic Activities in the European Community (NACE revision 1). Throughout this paper, we use weekly hours worked as a measure for employment, although our results are not affected by using persons employed instead.

Out of the 28 countries available in the ELFS, we exclude 9 new EU member countries[7], 2 candidate member countries[8] and Iceland because of limited data availability. We also discarded Germany from the ELFS because of its too small sample size and limited time span and replaced it with data from the German Federal Employment Agency's IABS dataset[9]. Data for the remaining 15 European countries (Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, the

[6] See Appendix A for details.
[7] Cyprus, the Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Slovenia and Slovakia
[8] Romania and Bulgaria
[9] The IABS dataset is a 2% random sample of German social security records for the period 1993-2002. For each individual it contains data on occupation and industry, as well as several demographic characteristics (among others, region of work, full-time or part-time work). We drop workers who are not legally obliged to make social security contributions (some 9% of all observations) because for them the IABS is not a random sample. Lacking a measure of hours worked, we use time-varying information on average weekly hours worked for full-time and part-time workers in both East- and West-Germany, obtained from the European Foundation for the Improvement of Living and Working Conditions to proxy for total hours worked in IABS occupation-industry-year cells (though our results are robust to restricting the sample to full-time workers). We then manually convert the German occupation and industry codings to match ISCO and NACE in the ELFS.

Netherlands, Norway, Portugal, Spain, Sweden and the United Kingdom) is used in the analysis.

We drop some occupations and industries from the sample – those related to agriculture and fishing because they do not consistently appear in the data and because OECD STAN industry output data is not suited for comparison across countries for these sectors (see Section 5.B for details); and those related to the public sector (public administration and education) both because our model is better-suited as a model of the private sector and because German civil servants are not liable to social security and therefore not included in the IABS, and because OECD STAN net operating surplus data is not reliable for these two sectors. Our results are never driven by the exclusion of these occupations and industries.

2.B Data summary

To provide a snapshot of changes in the European job structure, Table 1 shows the employment shares of occupations and their percentage point changes between 1993 and 2006 after pooling employment for each occupation across our 16 European countries.[10] This table shows that the high-paying managerial (ISCO 12, 13), professional (ISCO 21 to 24) and associate professional (ISCO 31 to 34) occupations experienced the fastest increases in their employment shares. On the other hand, the employment shares of some clerks (ISCO 41, which are office clerks; but not ISCO 42, which are customer service clerks), craft and related trades workers (ISCO 71 to 74) and plant and machine operators and assemblers (ISCO 81 to 83), which pay around the mean occupational wage, have declined. Similar to patterns found for the US and UK, there has been an increase in the employment shares for some low-paid service workers (ISCO 51, of which the main task consists of providing services related to travel, catering and personal care; but not ISCO 52, of which the main task consists of

[10] Since all countries do not have data for the entire time-span of 1993-2006, we calculate average annual changes for each country and use these to impute the employment shares in 1993 and/or 2006 where they are not available.

selling goods in shops or at markets) and low-paid elementary occupations (ISCO 91, which are service elementary workers including cleaners, domestic helpers, doorkeepers, porters, security personnel and garbage collectors; and ISCO 93, which mainly includes low-educated laborers in manufacturing performing simple tasks that require the use of hand-held tools and often some physical effort). This is an indication that the existing evidence to date that there is job polarization in the US, UK or Germany is not an exception but rather the rule. Pooling our 16 European countries together, there is job polarization occurring in which employment rises fastest for the best-paying jobs and falls most for those in the middle of the earnings distribution.

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

Figure 2 further illustrates this process by plotting a fitted kernel regression line of the percentage point change in occupation-industry employment shares pooled across the European countries against 1994 UK mean earnings at the occupation-industry level.[11] We see a U-shaped relationship, indicating relatively faster employment growth in high paying and some low paying jobs. At the European level, job polarization does seem to have occurred over our sample period.

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[11] We use the UK occupation-industry wage (from the UK LFS) since there is no European-wide equivalent available. Results should not be affected given the high correlation of wage ranks across countries and time as we explain in Section 4.C.

There may, of course, be heterogeneity across countries in the extent of polarization. Table 2 groups the occupations listed in Table 1 into three groups – just as we did for Figure 1. We then compute the percentage point change in employment share for each of these groups in each country between 1993 and 2006. Table 2 confirms that employment polarization is pervasive across European countries – the share of high-paying occupations increases relative to the middling occupations in all countries but Portugal, and the share of low-paying occupations increases relative to the middling occupations in all countries.[12,13]

As outlined in the introduction, there are a number of possible hypotheses – technological progress, globalization and induced effects operating through changes in product demand – that can explain these changes and the next section outlines a simple theoretical framework to help us to understand and estimate the relative importance of these factors.

3. A SIMPLE MODEL OF WITHIN-INDUSTRY DEMANDS FOR OCCUPATIONS

Our ultimate aim is to explain the changes in the aggregate occupational structure of employment documented in the previous section. In order to do this we first develop a model of the within-industry occupational structure of employment conditional on industry output and then seek to model (in section 6) the demand for industry output. Our reason for doing this is that looking within industries gives us a cleaner estimate of the effect of technology and globalization on labor demand, while taking account of shifts in industry demand then allows us to evaluate product demand effects.

3.A The production of goods and the demand for tasks

[12] This result is upheld when we add customer service clerks, a middle-paid service occupation, to the four lowest-paid occupations: indeed, in this case, we observe an increase in the share of high- and low-paying occupations relative to the middling occupations in all countries, i.e. including Portugal.

[13] Acemoglu and Autor (2011) argue that the numbers in Table 2 show that job polarization is at least as pronounced in our sample of European countries as in the United States.

Industry-level production function

Assume that output in all industries is produced by combining certain common building blocks that we will call tasks. Some industries are more intensive users of some tasks than others. In particular, assume the following production function for industry *i* using tasks $T_1, T_2, ..., T_J$ as inputs:

$$Y_i(T_{i1}, T_{i2}, ..., T_{iJ}) = \left[\sum_{j=1}^{J} \left(\beta_{ij} T_{ij} \right)^{\eta} \right]^{\frac{1}{\eta}} \text{ with } \eta < 1. \tag{1}$$

The cost-minimizing demand for task *j* conditional on Y_i is:

$$T_{ij}\left(c_1, c_2, ..., c_J \mid Y_i\right) = Y_i \frac{1}{\beta_{ij}} \left(\frac{c_j}{\beta_{ij}} \right)^{-\frac{1}{1-\eta}} \left[\sum_{j=1}^{J} \left(\frac{c_j}{\beta_{ij}} \right)^{-\frac{\eta}{1-\eta}} \right]^{-\frac{1}{\eta}} = Y_i \frac{1}{\beta_{ij}} \left(\frac{c_j}{\beta_{ij}} \right)^{-\frac{1}{1-\eta}} \Gamma_i^{\frac{1}{1-\eta}} \tag{2}$$

where c_j is the real unit cost of using task *j* (derived below) and Γ_i real industry marginal cost that is given by:

$$\Gamma_i = \left[\sum_j \left(\frac{c_j}{\beta_{ij}} \right)^{-\frac{\eta}{1-\eta}} \right]^{-\frac{1-\eta}{\eta}} \tag{3}$$

It should be noted that in the empirical work that follows we also have country and time subscripts but we ignore these for the moment to avoid excessive notation.

Task-level production function

We assume that output of task *j* can be produced using labor of one occupation and some other inputs. For convenience we will subscript the type of labor used in producing task *j* output by *j*, so that tasks and occupations are equated. In particular, assume that in industry *i* tasks are produced using domestic labor of occupation *j*, N_{ij}, and any other input, K_{ij}, according to:

$$T_{ij}(N_{ij}, K_{ij}) = \left[\left(\alpha_{Nj} N_{ij} \right)^{\rho} + \left(\alpha_{Kj} K_{ij} \right)^{\rho} \right]^{\frac{1}{\rho}} \text{ with } \rho < 1 \tag{4}$$

where we are making the assumption that the technology to produce task j is common across industries so the i subscript only appears on the input factors. This is a strong assumption (though it has been used in other models e.g. Grossman and Rossi-Hansberg 2008)[14] which we do seek to test later. In this specification the input K_{ij} should be interpreted very generally to mean all other inputs that are not domestic employment (e.g. it could be capital or offshored overseas employment to capture globalization) – we proceed assuming these other inputs are one-dimensional but that is just for simplicity and explicitly accounting for multiple inputs only adds algebraic complication.

This type of two-stage set-up for modeling the production process is increasingly standard in the literature, although different papers make somewhat different assumptions. Autor and Dorn (2010) have two industries (goods and services), three occupations (routine, abstract and manual) and assume the goods industry production function uses abstract and routine labor and capital and the services sector uses only manual labor. Those assumptions fit within our set-up. In Acemoglu and Autor (2011) the single final good is produced from 'tasks' that can be produced by different types of labor and capital though with different relative efficiencies. Their set-up is close to ours if one interprets what they call 'tasks' as our industries.

The associated demand for labor of type j conditional on task output is given by:

$$N_{ij}(w_j, r_j \mid T_{ij}) = \left(\frac{1}{\alpha_{Nj}}\right) T_{ij} \left(\frac{w_j}{\alpha_{Nj}}\right)^{-\frac{1}{1-\rho}} \left[\left(\frac{w_j}{\alpha_{Nj}}\right)^{-\frac{\rho}{1-\rho}} + \left(\frac{r_j}{\alpha_{Kj}}\right)^{-\frac{\rho}{1-\rho}}\right]^{-\frac{1}{\rho}}$$

$$= \left(\frac{1}{\alpha_{Nj}}\right) T_{ij} \left(\frac{w_j}{\alpha_{Nj} c_j}\right)^{-\frac{1}{1-\rho}} \qquad (5)$$

[14] Though they assume that domestic and foreign labor are perfect substitutes.

where w_j is the real wage in occupation *j* and r_j the real price of the other input used in the production of task *j* and where the cost of producing one unit of task *j* is given by:

$$c_j = \left[\left(\frac{w_j}{\alpha_{Nj}} \right)^{-\frac{\rho}{1-\rho}} + \left(\frac{r_j}{\alpha_{Kj}} \right)^{-\frac{\rho}{1-\rho}} \right]^{-\frac{1-\rho}{\rho}} \approx \left(\frac{w_j}{\alpha_{Nj}} \right)^{\kappa_{N|j}} \left(\frac{r_j}{\alpha_{Kj}} \right)^{\left(1-\kappa_{N|j}\right)} \tag{6}$$

with $\kappa_{N|j}$ the share of domestic labor in the total costs of producing task *j*. The final expression in (6) is an approximation if the task-level production function is not Cobb-Douglas but is useful for producing log-linear estimating equations.

3.B The conditional demand for labor

Combining equations (2) through (6) and taking logs leads to the following expression for the demand for labor conditional on industry output:

$$\log N_{ij}(w_j, r_j \mid Y_i) = \log Y_i + \frac{\log \Gamma_i}{1-\eta} + \frac{\eta}{1-\eta} \log \beta_{ij} - \left[\frac{1-\kappa_{N|j}}{1-\rho} + \frac{\kappa_{N|j}}{1-\eta} \right] \left(\log w_j - \log \alpha_{Nj} \right)$$

$$- \log \alpha_{Nj} + \left[\frac{1}{1-\rho} - \frac{1}{1-\eta} \right] (1-\kappa_{N|j}) \left(\log r_j - \log \alpha_{Kj} \right) \tag{7}$$

We will use this framework to capture different influences on labor demand. Note that changes affecting the task-level production function for a single occupation will also affect the conditional labor demand curve for other occupations through the industry marginal cost term in (7), with the size of the effect depending on the elasticity of substitution between tasks.

In our framework technology can affect the demand for labor by working either at the level of the industry production function (1) – that is, changes in β_{ij} – or the task-level production function (4) allowing for task-biased technological progress – that is, occupation specific trend changes in $\left(\alpha_{Nj}, \alpha_{Kj}\right)$. Offshoring can be thought to affect the demand for occupations through an occupation specific gradual decline in the cost of foreign inputs (i.e. r_j) other than domestic labor – though one could also model it through an effect on technology.

In section 5 we seek to estimate the conditional labor demand curve of (7). In principle, most of the parameters in equation (7) could vary at all levels of our observations (industry-occupation-country-year), rendering our model unidentified. So, it is helpful to outline the identifying assumptions that we are going to make in our baseline specification.

First, we will assume that all technological progress and offshoring can be modeled, without loss of generality, as affecting the task-level production function (4) and not the industry-level production function (1). Because task-level output is a construct and not an observable, what this assumption really means is that there is only an occupation specific and no industry-occupation specific component to technological change or globalization so that if one did incorporate technological change into the industry-level production function (1), one could re-define the task output so that all technological change appeared in the task-level production function (4).

Secondly, we will assume that the impact of technology and offshoring is the same for all countries, an assumption that seems reasonable given that they are at a similar level of economic development and, being members of the EU, face the same trade regime.

We also make a number of simplifications. We assume that the occupational wage, w_j, can vary across country and years but that any industry effect on wages is constant. The reason is that wage measures can be constructed for occupation-country-year cells but not occupation-industry-country-year combinations in our data (see Section 4.C for details). We also assume that $\kappa_{N|j}$ can reasonably be approximated by a constant.

Introducing country (*c*) and year (*t*) subscripts, this gives us an equation of the following form:

$$\log N_{ijct} = \log Y_{ict} + \frac{\log \Gamma_{ict}}{1-\eta} + \frac{\eta}{1-\eta}\log \beta_{ij} - \left[\frac{1-\kappa}{1-\rho} + \frac{\kappa}{1-\eta}\right]\left(\log w_{jct} - \log \alpha_{Njt}\right)$$

$$-\log \alpha_{Njt} + \left[\frac{1}{1-\rho} - \frac{1}{1-\eta}\right](1-\kappa)\left(\log r_{jt} - \log \alpha_{Kjt}\right) \qquad (8)$$

Because we have over-identification, we can and do some investigation of heterogeneity at country and industry level in what follows. But, we are unable to allow saturated variation.

3.C Testing the assumptions of the model

One way of testing for the adequacy of equation (8) as a basic description of the data is to estimate ANOVA models. To see how this can help note that the first two terms in equation (8) are industry-country-time effects, the third term is an industry-occupation effect, the wage is an occupation-country-year effect and the technology and globalization variables are occupation-year effects.

Column 1 of Table 3 presents ANOVA F-test statistics (with p-values in brackets) for this model.[15] As we would expect from equation (8), F-test statistics are significant for industry-country-year, industry-occupation and occupation-year effects. If there is a country-specific component to task-biased technical change or offshoring, we would expect to see that occupation-country-year effects have significant extra explanatory power – the F-test statistic of 0.93 with a p-value of 1 in column 1 of Table 3 shows they do not. It should be noted that in our model wages are allowed to vary at the country-occupation-year level and the finding that such effects are not very significant suggests that either country-specific changes in relative occupational wages are not very important (i.e. there is little change in wage inequality in most countries in our sample period so that differences in relative wages across countries are approximately

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

constant) or that the occupational wage is not very important. The significance of occupation-year effects suggests pervasive effects across countries and industries, which indicates scope for the importance of factors that vary at this level, such as task-biased technological change and offshoring.

Now consider how we can use this set-up to further test our identifying assumptions. The variation in employment that remains unaccounted for in column 1 of Table 3 is industry-occupation-year, industry-occupation-country or industry-occupation-country-year specific. Column 2 of Table 3 therefore adds an industry-occupation-year effect. This effect does not have significant explanatory power, which is inconsistent with task-biased technological change or offshoring having an industry-occupation specific component.

Finally, the third column of Table 3 adds an industry-occupation-country instead of an industry-occupation-year effect to the ANOVA. The F-test statistic of 15.39 is statistically significant. One possible explanation could be that the technology to combine tasks in production varies across countries (that is, β_{ij} varies with country but not time). Our preferred interpretation for the significance of the industry-occupation-country effect is that our industries and occupations are quite aggregated and that the product mix within aggregate industry groups differs across countries. If, for example, the single industry "manufacturing" that we observe in our data in one country mainly consists of the manufacture of textiles and in another country mainly consists of the manufacture of chemical products, one would expect to see significant industry-occupation-country variation in employment even if countries use the same technologies.[16] To account for this, the regression results presented below will control for industry-occupation-country fixed effects rather than only an industry-occupation fixed effect. Finally note from column 3 of Table 3 that the inclusion of an industry-occupation-country effect increases the F-test statistic for the occupation-country-year interaction, which – although it remains relatively small – becomes statistically

[16] Appendix B shows that much of the significance of the industry-occupation-country interaction is indeed due to differences between countries in the composition of more disaggregated industries within our industry classification.

significant. Also note from column 4 of Table 3 that the inclusion of an industry-occupation-country effect increases the F-test statistic on the industry-occupation-year interaction slightly.[17]

Of course, this ANOVA does not tell us anything about the importance of these different potential factors: to do that we need to have variables to capture the effects of task-biased technological progress and offshoring. How we construct those variables is the subject of the next section.

4. DATA ON TECHNOLOGY, GLOBALIZATION AND WAGES

In this section we describe our main sources of our measures of technological change, offshoring and wages at the level of occupations.

4.A Technology[18]

The technology measures we use do not have country or time variation. The lack of country variation is probably not a problem as we believe technological change to be similar in all the countries in our sample. To capture the idea that technology changes over time, we interact our technology variables with linear time trends.[19] This assumes that, for example, occupations that are intensive in routine tasks have been more affected by technological change that makes replacing human routine labor easier.[20]

[17] It is not computationally possible to add industry-occupation-country together with both occupation-country-year as well as industry-occupation-year effects to the ANOVA using our full sample. However, dividing the sample into two subsamples of countries and decomposing the variation in employment accounting for all possible dimensions simultaneously gives qualitatively identical results.

[18] See Appendix C for details.

[19] Note that we cannot, nor do we need to, identify whether technical change in the task-level production functions is labor- or capital-augmenting: we are only interested in the total effect on the demand for labor.

[20] There is no time variation in ONET, which would be problematic for the analysis below if the task composition within occupations is changing over time. However, using similar DOT measures across US occupations and over time, Goos and Manning (2007) find that most of the overall changes in mean task measures happened between and not within occupations. Also note that ONET does not contain any variation in job task measures within occupations. However, Autor and Handel (2009) use the individual level PDII (Princeton Data Improvement Initiative) data to show that occupation is the dominant predictor for the variation in the task measures that are also used in this paper.

To measure the type of work done in occupations, we use data from the December 2006 version of the Occupational Information Network (ONET) database. ONET is a primary source of occupational information, providing comprehensive data on key attributes and characteristics of workers in US occupations. It is a replacement for the Dictionary of Occupational Titles (DOT) which has been used in earlier research, notably by Autor, Levy and Murnane (2003). ONET data comes from job incumbents, occupational analysts and occupational experts and is collected for 812 occupations which are based on the 2000 Standard Occupational Code (SOC). We manually converted the 2000 Standard Occupational Code (SOC) used in the ONET data to ISCO.

One part of ONET consists of some 100 variables related to worker characteristics, worker requirements and general work activities. We select 96 of these task measures which are closest to the DOT task requirements used by Autor, Levy and Murnane (2003) and Autor and Dorn (2010). Each respondent is asked how important the task is for her job, where importance ranges from 1 (not important at all) to 5 (extremely important). Each of the 96 ONET variables is categorized into one of three groups: *Abstract*, *Routine* or *Service*.[21]

We choose these three measures following Autor and Dorn (2010) to capture technological progress biased towards occupations intense in non-routine tasks – the ALM hypothesis. Routine tasks are those which computers can perform with relative ease, such as jobs that require the input of repetitive physical strength or motion, as well as jobs requiring repetitive and non-complex cognitive skills. The non-routine dimension is split up into Abstract and Service to capture the different skill content of these non-routine tasks: examples of Abstract tasks are "complex problem solving" (e.g. needed by engineers and medical doctors) and Service tasks are "caring for others" (e.g. needed by hairdressers and medical doctors), respectively. Although Abstract tasks are non-routine tasks mainly carried out by highly educated workers,

[21] Appendix C provides robustness checks where the task dimensions are determined by means of principal component analysis rather than by manual assignment.

Service tasks are non-routine tasks that workers with lower levels of education commonly perform.

Examples of ONET variables used as measures of Abstract tasks are “critical thinking”, “judgment and decision making”, “complex problem solving”, “interacting with computers” and “thinking creatively”. Examples of Routine task measures are “arm-hand steadiness”, “manual dexterity”, “finger dexterity”, “operation monitoring”, and “estimating the quantifiable characteristics of products, events, or information”. Examples of Service task measures are “social perceptiveness”, “service orientation”, “assisting and caring for others”, “establishing and maintaining interpersonal relationships”, “selling”, and “performing for or working directly with the public”.

For each of these three task measures, we calculate an average across SOC occupations, which we collapse to the ISCO level weighted by US employment in each SOC cell taken from ONET. Columns 1 through 3 of Table 4 show the values of these three principal components, with mean zero and unit standard deviation, for 2-digit ISCO occupations ranked by their mean 1993 wage across the 16 European countries. Following Autor and Dorn (2010), column 4 of Table 4 summarizes the information in columns 1-3 by constructing a one dimensional Routine Task Index (RTI), defined as routine task importance divided by the sum of abstract and service task importances and standardized to have unit standard deviation and mean zero.

Columns 1 to 3 of Table 4 allow us to categorize occupations into three broad groups. Firstly, some occupations are highly routine and relatively low in abstract and service task importance (craft and related trade workers (ISCO 71-74); plant and machine operators and assemblers (ISCO 81-83)). Secondly, some occupations are low in routine task importance and high in both abstract and service task importance (managers (ISCO 12,13); professionals (ISCO 21-24); furthermore, technicians and associate professionals (ISCO 31-34) generally consist of doing fewer abstract and service and more routine tasks relative to the corresponding professional occupations (ISCO 21-24)). Thirdly, some occupations are low in routine and abstract but high in service task importance (clerks (ISCO 41,42) although customer service clerks (ISCO

42) are much more service orientated compared to office clerks (ISCO 41); low-paid service workers (ISCO 51,52); low-paid elementary occupations (ISCO 91,93) although these occupations are relatively low in service importance compared to low-paid service workers).

Finally, to capture the idea of skill-biased technical change or SBTC, the sixth column of Table 4 also presents the mean educational attainment by occupation. This variable derives from a three-level education variable (categorized with the International Standard Classification of Education, ISCED) available in the ELFS, which we average by occupation across countries.[22]

4.B Offshoring[23]

There are a number of existing approaches to measuring the impact of offshoring on the labor market. Typically, use is made of measures of foreign direct investment by OECD countries or measures of imports in total GDP; the share of intermediate goods imports in total imports; or the share of imports from non-OECD countries in total imports. This type of data is available at the country-industry-time level but never at the occupation level.

One exception is a recent study by Blinder and Krueger (2009) who use Princeton Data Improvement Initiative data to construct various measures of offshorability. The authors conclude that their preferred measure is constructed by professional coders based on a worker's occupational classification. In contrast, our measure is derived from data on actual offshoring, but it is reassuring to see that it corresponds closely to the preferred measure by Blinder and Krueger (2009).

We obtain a measure of offshorability from the European Restructuring Monitor (ERM) of the European Monitoring Centre on Change (EMCC), which is a part of

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[22] Occupational education levels are very highly correlated among countries, the average correlation coefficient being 0.93 with a standard deviation of 0.03 (the average Spearman rank correlation coefficient is 0.86).

[23] See Appendix D for details.

Eurofound. ERM is available online[24] and provides summaries of news reports (so-called fact sheets) since 2002 about companies located in Europe that announce offshoring plans. These fact sheets contain information on the company that is offshoring part(s) of its production process, such as the country and the industry in which it operates, how many workers are employed nationwide or in that particular location, how many jobs are being offshored and to which country, and, most importantly for our purposes, what kinds of jobs (i.e. which occupations) are being offshored.

We process 415 fact sheets (covering May 31st, 2002 up to June 30th, 2008), or cases of offshoring, to construct an index of how offshorable the different occupations are. We sum the number of cases for each ISCO occupation[25], and generate a rank by rescaling the number of cases across occupations to a distribution with mean zero and unit standard deviation. The fifth column of Table 4 shows this occupation-level measure of offshorability. It can be seen from Table 4 that some occupations that are high in routine task importance and low in abstract and service task importance are offshored most often (metal, machinery and related trade workers (ISCO 72); plant and machine operators and assemblers (ISCO 81,82)). However, Table 4 also shows that other occupations in the same major groups are much less offshorable (construction workers (ISCO 71); precision, handicraft, craft printing and related trade workers (ISCO 73,74); drivers (ISCO 83)). Similarly, some occupations low in routine but high in abstract or service task importance (physical, mathematical and engineering (associate) professionals (ISCO 21,31); other associate professionals which includes call-centre workers (ISCO 34); office clerks (ISCO 41); low-educated elementary workers mainly in manufacturing (ISCO 93)) are still much more offshorable than others (managers (ISCO 12,13), life science and health (associate) professionals (ISCO 22,32); customer service clerks (ISCO 42); low-paid service (elementary) workers (ISCO 51,52,91)). This all seems sensible.

[24] http://www.eurofound.europa.eu/emcc/index.htm

[25] Note that one fact sheet often contains more than one ISCO occupation that is being offshored.

4.C Wages[26]

Since the ELFS does not contain any earnings information, we obtain time-varying country-specific occupational wages from the European Community Household Panel (ECHP) and European Union Statistics on Income and Living Conditions (EU-SILC). The ECHP contains gross monthly wages for the period 1994-2001, whereas the EU-SILC reports gross monthly wages for the period 2004-2006. For the UK, we use the gross weekly wage from the Labor Force Survey (UK LFS) because it contains many more observations and is available for 1993-2006. All wages have been converted into 2000 Euros using harmonized price indices and real exchange rates.

To match our employment dataset, we construct an occupational wage measure weighted by hours worked. Because sample sizes in the ECHP and EU-SILC are relatively small and certainly too small to obtain reliable industry-occupation means in each country and year, we smooth wages by pooling together all years for each occupation and estimating a model in which the dummy on occupation varies smoothly with a quadratic time trend. We also use this procedure to impute wages for years that are missing.

Given the less than perfect nature of the wage data, it is reassuring that the wage rank of occupations is intuitive, and highly and significantly correlated within countries over time. Table 5 provides the wage rank of occupations in 1993 and 2006, averaged across the 16 countries and rescaled to mean zero and unit standard deviation. The ranking is as expected, with managers and professionals being the most highly paid, service workers and workers in elementary occupations the lowest paid, and manufacturing and office workers somewhere in between. This ranking is very stable within countries over time, with Spearman rank correlation coefficients of around 0.90, and all significant at the 1% level.

[26] The methodology we use to construct occupational wages is described in Appendix E.

5. ESTIMATION RESULTS FOR CONDITIONAL LABOR DEMAND

The starting point for our empirical investigation is equation (8), the demand for labor conditional on industry output. This conditional labor demand curve is well-suited to estimating the effect of technology and offshoring on production functions i.e. the impact of these variables ignoring product demand effects. In the hamburger example from the introduction, the estimation of a conditional labor demand curve would tell us that, for given output of hamburgers, there has been no change in the employment of bun-makers but a fall in the employment of patty-makers, a true indication of where technology has been changing.[27]

To estimate that equation we replace the first two terms by industry-country-year dummies and we capture the third term – the β_{ij} – by including industry-occupation-country dummies.[28] We also include occupation-country-year varying wages. We then interact the occupation specific measures of technology and offshoring discussed in the previous section with a time trend to capture secular changes. Note that because we standardize each task measure and our measure of offshorability to have mean zero and unit standard deviation across occupations, point estimates are comparable between them. To account for serial correlation across years, we cluster standard errors by industry-occupation-country.

The first estimation results are presented in Table 6A. Columns 1 to 3 report point estimates for each task measure separately whereas column 4 adds them simultaneously to the regression. The point estimates suggest that employment increases by 1.33% and 1.28% faster annually for occupations one standard deviation more intense in abstract and service tasks, respectively, whereas employment in occupations one standard deviation more intense in routine tasks increases 1.33% slower annually. Although the point estimates in column 4 are generally smaller in

[27] Note that the assumption of perfect complementarity in the hamburger example is not innocuous in that the elasticity of substitution between tasks in goods production is assumed to approach zero in (8).

[28] Note that we add industry-occupation-country rather than the industry-occupation dummies. The reason for this is the significance of industry-occupation-country specific employment variation in our data discussed in Section 3.C. However, adding industry-occupation dummies instead does not affect our results.

absolute value, they have the expected sign and remain highly statistically significant for abstract and routine tasks. Using the one-dimensional RTI index, column 5 suggests that employment in occupations that are one standard deviation more routine has grown 1.52% slower each year.

Columns 6 to 11 add the offshorability measure. The estimated coefficients on the task measures are very similar to those reported in columns 1 to 5 whereas the impact of offshorability is smaller in absolute value and significantly decreases in magnitude when task measures – especially service task importance or the one-dimensional measure- are controlled for. In sum, Table 6A suggests that task-biased technological progress is an important driver of changes in within-industry demand for occupations. There is also evidence in support of the hypothesis that employment in some occupations has recently been offshored, although the estimated employment impact is smaller and not robust to the controls for technology.

We have until now ignored the other hypothesis for the impact of technological change on employment: skill-biased technological change. Within the context of our model, SBTC would imply that tasks vary by the amount of schooling required to perform them, and that technology is a better substitute for tasks the lower their educational requirement. Productivity would then be predicted to increase over time for tasks that can only be performed by highly educated workers. Table 6B therefore addresses the SBTC hypothesis by including the occupational education level interacted with a linear time trend as a regressor.

Column 1 of Table 6B shows that the education level is indeed a significant predictor for employment: on average, occupations that have an education level one standard deviation above the mean experience 1.34% higher employment growth per annum. However, if SBTC were to be the correct model, the task-dimension of employment should disappear once the education level is controlled for, bringing the point estimates on abstract, routine, and service task importance (close) to zero. Column 2 shows that this is clearly not the case. The final column of Table 6B replaces the task measures by the RTI index. Although higher-educated occupations on average increase their employment faster than lower-educated occupations, the task dimension of employment continues to be a significant predictor of employment changes.

5.A Country and industry heterogeneity

Until now, we have assumed that technology and offshoring have the same impact in all 16 countries and that the effect is the same for all industries. If all countries and industries in our sample can be assumed to be equally affected by similar changes in the within-industry demand for occupations, an additional test would be to see whether point estimates do not differ significantly between countries or industries. Table 7 therefore shows F-test statistics (with p-values in brackets) for the interactions with country or industry dummies of the technology and offshorability specific time trends estimated in columns 10 and 11 of Table 6A.

Column 1 of Table 7 shows that as far as technological progress is concerned, country heterogeneity only exists for growth in abstract intense occupations – this also explains the significance of the country dummy interactions in column 2 where the task measures have been replaced by the RTI index. The F-test statistic for the impact of offshoring, however, is statistically significant in both columns 1 and 2. This suggests that the impact of offshoring is generally less pervasive compared to technological progress.[29] Columns 3 and 4 of Table 7 interact the technology and offshoring specific time trends with industry instead of country dummies. The reported p-values of the F-test statistics show that none of the industry specific time trends are different at less than the 5% significance level. In sum, Table 7 shows that the impact of task-biased technological progress on the within-industry demand for occupations is pervasive across countries and industries and that there is perhaps some modest country heterogeneity in the impact of offshoring.

[29] Appendix F reports the point estimates for all the interactions in Table 7. We were unable to find any interesting patterns to the nature of this heterogeneity.

5.B Estimates including industry output and industry marginal costs

The estimates we have reported so far treat industry output and industry marginal costs in equation (8) as country-year-industry dummies. That is sufficient if one is just interested in estimating the impact of technology and offshoring within industries. But, to take our estimates further as we do in the next section, we need to be able to model these terms more explicitly. To that end this section reports estimates that replace those dummy variables with industry output and industry marginal costs.

Measures of industry output and industry marginal costs are taken from the OECD STAN Database for Industrial Analysis.[30] Each of our 16 countries except Ireland is included in STAN. This data covers the period 1993-2006 for all 15 of these countries. STAN uses an industry list for all countries based on the International Standard Industrial Classification of all Economic Activities, Revision 3 (ISIC Rev.3) which covers all activities (including services) and is compatible with NACE revision 1 used in the ELFS.[31]

The measure of output used in the analysis below is value added, available in STAN as the difference between production (defined as the value of goods and/or services produced in a year, whether sold or stocked) and intermediate inputs. Value added comprises labor costs, capital costs and net operating surplus. To obtain variation in output, value added has been deflated using industry-country-year specific price indices available from STAN. Finally, we approximate real industry marginal costs by the difference between production and net operating surplus, divided by production. This gives an estimate of the real average cost of using labor, capital and intermediate

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[30] See Appendix G for details.

[31] Due to limited data on net operating surplus for the NACE industry “Private households with employed persons”, we have one less industry when using STAN data in our regressions. The exceptions are France, Portugal, Spain and the UK, where this industry is instead included in “Other community, social and personal service activities” in STAN. Although the industry “Private households with employed persons” mainly employs low-paid service elementary workers and its employment share has increased from 0.82% in 1993 to 0.90% in 2006, it is too small to be important.

inputs per Euro of output. This measure can be seen as a proxy for the variation in real industry average costs, which in our model is identical to real industry marginal cost.

Table 8 uses the specifications in columns 10 and 11 of Table 6A but replaces the country-year-industry dummies by country-year specific measures of industry output and of industry marginal costs. To account for measurement error in industry output over time, columns 1 and 2 of Table 8 show 2SLS estimates using the logarithm of industry gross capital stock (also taken from the OECD STAN Database) as an instrument for log industry output.[32] The point estimates on the technology measures are similar in magnitude and significance to those reported in Table 6A whereas the point estimates on offshorability are somewhat larger in absolute value and significant at the 5% level. In line with the predictions of our model, the coefficient on log industry marginal costs is positive and significant. The coefficient on log industry output is 1 with a standard error of 0.08 confirming the assumption of constant returns to scale in (8).[33] To check for the robustness of these results in the larger sample of 15 countries, columns 3 and 4 estimate (8) using OLS while imposing constant returns to scale by constraining the coefficient on log industry output to be unity. This does not qualitatively affect the other point estimates. In sum, the results in Table 8 show that equation (8) is a reasonable approximation of the employment variation observed in our data.

5.C Endogenous wages

Our estimates so far condition on wages. This is appropriate if one is interested – as we have been – in estimating labor demand curves, though one should perhaps instrument wages, a topic we discuss further below. However, if labor supply to particular occupations is not perfectly elastic one would expect that technology and

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[32] This restricts the number of observations because gross capital stock data is not available for a number of countries (Austria, Greece, Luxembourg, the Netherlands and Portugal).

[33] The OLS estimate is 0.44 with a standard error of 0.04.

globalization also affect relative occupational wages and thereby relative occupational employment.

It is not entirely clear what is the appropriate view to take about the elasticity in the supply of labor to different occupations. Studies that segment the labor market by education typically assume that the supply of different skills is inelastic in the short-run because individuals primarily fix their education level at the beginning of their working life. But, occupational mobility is higher than educational mobility (though much more so for those occupations without much specific human capital) so we would not expect the elasticity in the supply of labor to many occupations to be totally inelastic even in the short-run. In the long-run, studies like Goldin and Katz (2008) suggest that the supply of labor of different education levels is very elastic and the same is probably true of supply to different occupations.

Given these conceptual issues, it makes sense to look at evidence on whether technology and offshoring seem to affect wages. Autor, Katz and Kearney (2008), Lemieux (2008) and Autor and Dorn (2010) find a positive correlation between employment polarization and wage growth across US occupations. In line with this finding, Firpo, Fortin and Lemieux (2009) and Acemoglu and Autor (2011) argue that routinization has had non-trivial effects on US wage inequality.

However, the evidence is much less clear for European countries. Dustmann, Ludsteck and Schönberg (2009) find that occupational employment and wage growth during the 1990s in Germany are only weakly positively correlated across all occupations and even negatively correlated across occupations paying below the median. Goos and Manning (2007) report a similar finding for the UK for the period 1975-99.

We investigate the potential endogeneity of wages in our data in a number of ways. First, we estimate the specification in columns 3 and 4 of Table 8 while instrumenting the wage using demographic changes in labor supply as an exclusion restriction (Dustmann, Ludsteck and Schönberg (2009) suggest such supply changes might explain the wage changes they observe in Germany). Specifically, we use as an instrument counterfactual occupational employment only accounting for economy-wide changes in employment by gender-migration while keeping the occupational composition within each gender-migration combination constant over time.[34] The results are reported in the first two columns of Table 9. The first-stage coefficients on counterfactual labor supply are negative and significant. The estimates of the impact of technology and offshorability are also as expected. Note that the coefficient on wages is now much larger, perhaps an indication that our wage measure is imperfect so the OLS estimates suffer from attenuation bias.

Secondly, we can simply estimate models excluding the wage and possibly including counterfactual labor supply which can be thought of – perhaps somewhat loosely – as a reduced form specification. This does not significantly change the estimated impact of technological change and offshoring either. For example, the last two columns of Table 9 exclude wages as well as industry marginal costs and industry output – as these are influenced by wages – showing it does not qualitatively affect the point estimates on technology and offshoring.

In sum, the evidence suggests that relative occupational wage movements in Europe are not strongly correlated with our technology and offshoring variables. This result differs from evidence for the US but is not necessarily inconsistent with it since many European countries have institutions (e.g. minimum wages and collective bargaining) that mute or stop a wage response, especially across middling and lower-paying occupations. Although it is an interesting question why technological progress and globalization do not seem to explain changes in relative occupational wages in Europe very well, it does serve our purpose here since all the impact of task-biased technological progress and offshoring can be seen from changes in relative labor demand.[35]

[34] This restricts the number of observations because migration data is not available for Germany and Italy. Note that Ireland is also excluded, due to the lack of OECD STAN data.

[35] This is consistent with Acemoglu and Autor (2011) who argue that employment polarization is at least as pronounced in our sample of European countries as in the United States. Also see footnote 13.

6. PRODUCT DEMAND EFFECTS

All our estimates so far have been of the demand for labor of different occupations conditional on industry output. While that is an interesting exercise well-suited to isolating the effects of technology and globalization on production functions, it does have limitations when it comes to our ultimate aim – explaining the phenomenon of job polarization in the economy as a whole – because, as explained in the introduction, it cannot take account of the general equilibrium effects that we know must be very important.

In this section we discuss these product demand effects in more detail. One mechanism is that changes in production functions will shift the pattern of industry output through the effect they have on relative industry marginal costs and therefore relative output prices. In the hamburger example, the improvement in patty-making reduced the price of hamburgers inducing a rise in the demand for bun-makers. More generally, routinization will result in larger falls in prices in industries that historically used a lot of routine labor, and this will tend to benefit all labor that is used in these industries.

Another possibility discussed in the introduction is that relative product demand shifts because preferences are non-homothetic. Models assuming different income elasticities for different goods or services yield structural change even if productivity growth is balanced across tasks or sectors (Echevarria 1997; Laitner 2000; Caselli and Coleman II 2001; Gollin, Parente and Rogerson 2002).[36] Non-homothetic preferences also imply that changes in the distribution of income will lead to changes in relative product demand. A related but distinct hypothesis, proposed by Manning (2004) and Mazzolari and Ragusa (2008), is that rising wage inequality will cause high-wage

[36] Concerns about the importance of non-homothetic preferences have also recently been raised in the trade literature: Markusen (2010) argues that taking non-homothetic preferences into account causes the theoretical predictions from a standard Heckscher-Ohlin model to better account for certain well-known phenomena such as growing wage gaps, home bias and missing trade. The empirical evidence on this importance is somewhat mixed: Trefler (1995) finds that allowing for non-homothetic preferences has limited value added, whereas Hunter (1991) finds it can explain a non-negligible part of missing trade.

workers to demand more low-skill service work so as to free up more of their time for market work. However, Autor and Dorn (2010) failed to find much evidence in support of this hypothesis.

As a first indication that these industry shifts can be quantitatively important, Table 10 shows the result of decomposing aggregate occupational employment share changes into within- and between-industry components. As the model we estimated above suggests, one sees large negative within-industry components for some occupations such as office clerks (ISCO 41), building workers, craft and related trades workers (ISCO 71-74), stationary plant and related operators (ISCO 81) and machine operators and assemblers (ISCO 82) and large positive effects for others, e.g. managers (ISCO 12,13) and some (associate) professional occupations (ISCO 21,31,34). However, Table 10 also shows that the between-industry component may be important – in particular, it suggests an increase in the demand for industry output intense in life science and health (associate) professionals (ISCO 22,32), other (associate) professionals (ISCO 24,34) and some low-paid service (elementary) workers (ISCO 51,91) at the expense of demand for manufactured goods which use operators, assemblers and other production occupations (ISCO 72,74,81,82) intensively.[37]

6.A Product demand curves

To analyze these effects, we need to go further and not condition on industry output. To do this, we need an industry demand curve: we will start by deriving this from a demand curve at the individual level. Assume that individual *k* has income Z_k and that the demand for the output of industry *i* by individual *k* is given by:

$$Y_{ik} = Z_k^{\theta_i} P_i^{-\frac{1}{1-\gamma}} \tag{9}$$

[37] These results are qualitatively identical to those reported in Acemoglu and Autor (2011) for the US after 1979.

where θ_i is the income elasticity of demand for good *i* which will be equal to one if preferences are homothetic but not otherwise, P_i the price of good *i* relative to the aggregate price index and $1/(1-\gamma)$ the elasticity of substitution between goods in consumption with $\gamma<1$. Where $\theta_i \neq 1$ for all industries one should acknowledge that this iso-elastic formulation of the demand curve does not satisfy the budget constraint in which case (9) is best thought of as a local approximation to the demand curve that will not be too bad if, as we find below, departures from homotheticity are fairly small.

If there are *L* individuals in the economy and we assume that income has a log-normal distribution with variance σ^2, we can add up the demand curve (9) over all individuals in the economy to arrive at the following aggregate demand equation:

$$\log Y_i = \theta_i \log Y + \left(1-\theta_i\right)\log L + \frac{1}{2}\theta_i\left(\theta_i - 1\right)\sigma^2 - \frac{1}{1-\gamma}\log P_i \qquad (10)$$

where Y_i is aggregate demand for good *i* and Y is real aggregate income. This equation shows that there are a number of ways to test for non-homotheticity (i.e. $\theta_i \neq 1$) in the data. Firstly, non-homotheticity implies that the elasticity of industry demand with respect to aggregate income will not be unity. Secondly, it implies that, for a given aggregate income, population affects relative product demand. The intuition for this is simple: if we compare two economies with the same aggregate GDP but with different populations, the economy with the lower population will have a higher total demand for luxury goods as GDP per capita is higher there. Thirdly, if preferences are non-homothetic, we would expect income inequality to affect the patterns of demand: for a given GDP more income inequality will be associated with higher demand for luxury goods. We test these three predictions of non-homotheticity below.

If we further assume that individual firms in each industry face iso-elastic demand curves (which we would expect to be more elastic than the industry demand curves and might be infinitely elastic if industries are perfectly competitive), firms maximize profits by setting prices as a constant mark-up over marginal costs, or

$\log P_i = \log \Gamma_i - \log \gamma$ with γ^{-1} the price mark-up. Adding time (*t*) and country (*c*) subscripts, this gives the following equation for the demand for good *i*:

$$\log Y_{ict} = \theta_i \log(Y_{ct} / L_{ct}) + \log L_{ct} + \frac{1}{2}\theta_i(\theta_i - 1)\sigma_{ct}{}^2 + \frac{\log \gamma}{1-\gamma} - \frac{1}{1-\gamma}\log \Gamma_{ict} \tag{11}$$

Given that equation (11) enters equation (8) additively, we can estimate it separately to derive the impact of changes in relative product demand on employment.

6.B Estimating product demand curves

Results from estimating equation (11) are in Table 11. The first column shows estimates if we assume homothetic preferences. As predicted by our model, the point estimate on industry marginal cost is negative and significant, the point estimate on log income per capita is 1, and the point estimate on log population is 1.01 and not significantly different from unity.

The next two columns of Table 11 test for non-homotheticity using the framework described above. Column 2 interacts log income per capita with a vector of industry dummies. Service industries are ranked from high-paid to low-paid by their mean UK wage in 1994 and their point estimates are deviations from the income elasticity for manufacturing. The estimated income elasticity of demand is significantly bigger only for three high-paid service industries: financial intermediation; real estate, renting and business activity; and transport, storage and communication. Also note that the point estimates for the three lowest-paid service industries (health and social work, other community, social and personal service activities and hotels and restaurants, which are all are intense in personal protective and service occupations (ISCO 51) and service elementary occupations (ISCO 91)) are not statistically significant from zero. Finally, the magnitude of these departures from homotheticity is broadly consistent with estimates found in the literature: Hunter (1991) finds income elasticities for different types of goods that range between 0.45 for food and 1.91 for medical products.

In sum, the second column of Table 11 is not clearly supportive of the idea that the relative growth in low-paid service (elementary) occupations that we observe in Table 1 is best explained by an increase in real income and non-homothetic preferences.

Finally, column 3 of Table 11 repeats the analysis in column 2 while adding to the regression specification a measure of income inequality – rescaled to have mean 0 and standard deviation 1 across our sample of countries – and its interaction with industry dummies to further capture the possibility that the demand for low-paid services partially reflects the marketization of household production by high-wage workers who are finding that market work is more rewarding.[38] Just as in column 2, the left-hand panel of column 3 reports the income elasticity by industry. The higher income elasticities for the three high-paid service industries remain, while there is again no general support of the idea that real income growth drives up demand for workers in low-paid service jobs.

The right-hand panel of column 3 shows the interaction effects of overall log income inequality with a vector of industry dummies. These point estimates could capture the idea that in countries with more wage inequality, high-income workers want to buy more market-provided low-paid services. The point estimate is positive and significant for financial intermediation as well as for one low-paid industry, hotels and restaurants. This indicates some scope for the income inequality channel for explaining job polarization, but it should be noted that Table 11 is estimated using cross-country variation in wage inequality whereas only variation in wage inequality over time can explain job polarization. Since the standard deviation in wage inequality over our 14 year time period is around 15% of the standard deviation of the cross-country variation in wage inequality, one standard deviation increase in inequality between 1993 and 2006 is associated with a 3% faster increase in the demand for

[38] The inequality measure used is the log(p90/p10) derived from the ECHP and EU-SILC data discussed in section 4.C. For each country, the log(p90/p10) has been averaged over observations available for the period 1993-2006 and rescaled to mean 0 and standard deviation 1. Our results are robust to using other measures of inequality (log(p90/p50) or log(p50/p10)) whether or not averaged over time – although the latter reduce the sample size due to incomplete time series for several countries.

financial intermediation and hotels and restaurants. This effect is small compared to the estimated impacts of technological progress and globalization.

The evidence provided in this section does not suggest systematic non-homotheticity in preferences at our level of aggregation which suggests that product demand effects cannot explain a significant part of job polarization. To further examine the relative importance of technological progress, offshoring and product demand changes in explaining job polarization, the next section brings these channels together.

7. EXPLAINING JOB POLARIZATION

In this section we examine to what extent our task-based framework can explain job polarization documented in Tables 1 and 2, attempting to break down the total effect into the different channels. To do this we compare actually observed changes in the job structure with a variety of counterfactuals constructed from our model in which we turn off and on different channels of influence.

In all these simulations we assume, in the interests of keeping results to a digestible length, that relative wages are constant (in line with our earlier findings that, in our European countries, there seems to be little wage response), that there is no country heterogeneity in the impact of technology and off-shoring at the task level and that preferences are homothetic[39].

7.A The effects of technological progress and globalization on occupational employment

Our aim is to work out the predictions of our framework for the *shares* of employment in different occupations. To do this we work out the predictions for the

[39] This last assumption is very convenient as it means that we do not have to keep track of the way in which technology and globalization are changing the distribution of income as any such changes will have no effect on the mix of product demand.

level of employment by industry, occupation, country and year, N_{ijct}, and then aggregate. So, for example, the total employment by occupation country and year can be derived as:

$$N_{jct} = \sum_i N_{ijct} \tag{12}$$

Using (8) and retaining only the terms that will influence the shares of total employment (e.g. excluding time effects that affect all countries, industries and occupations equally) we can derive the following expression for the change in $\log N_{ijct}$:

$$\frac{\partial \log N_{jct}}{\partial t} = \frac{\partial \log G_{jt}}{\partial t} + \sum_i s_{i|jct} \left[\frac{1}{1-\eta} \frac{\partial \log \Gamma_{ict}}{\partial t} + \frac{\partial \log Y_{ict}}{\partial t} \right] \tag{13}$$

where $s_{i|jct}$ is the (observable) share for industry *i* of total employment in country *c*, year *t* and occupation *j*.

In (13) G_{jt} represents the impact of technology and offshoring on the demand for occupation *j* conditional on output and industry marginal costs as reported in Tables 6 and 7 of section 5. The first terms in square brackets in equation (13) reflect changes in the demand for occupation *j* because of changes in industry marginal costs. This term corresponds to the importance of the conditional demand estimates for industry marginal costs in Tables 8 and 9 of section 5. Finally, the last term in square brackets in equation (13) captures the importance of changes in industry output, examined in section 6 above. It is this decomposition that we will use to examine to which extent the different channels in our model can explain job polarization.

Let us therefore first consider the first term on the right-hand side of (13) in more detail. Here we make the assumption that the occupation specific trend changes in $(\alpha_{Nj}, \alpha_{Kj})$ can be captured by keeping α_{Nj} constant while allowing α_{Kj} to vary over time. This means technology and offshoring are assumed to affect the task-level production function only by augmenting the productivity of factors apart from domestic labor (e.g. capital for technology, foreign labor for offshoring). Said differently, this simplification rules out that technological progress (in part) implies human workers becoming “innately” increasingly productive in performing non-routine tasks relative to routine tasks.[40] Given our conclusion that wages have not been affected by technology and offshoring, we get from (8) that:

$$\frac{\partial \log G_{jt}}{\partial t} = \left[\frac{1}{1-\rho} - \frac{1}{1-\eta}\right](1-\kappa)(\frac{\partial \log r_{jt}}{\partial t} - \frac{\partial \log \alpha_{Kjt}}{\partial t}) \tag{14}$$

where the right-hand side of (14) is given by the point estimate on RTI of -1.19/100 in the second column of Table 9 multiplied by the occupation specific RTI measure. When we also want to account for the impact of offshoring, this term is given by the sum of the point estimate on RTI multiplied by the RTI measure and the point estimate on offshoring of -0.32/100 multiplied by our measure of offshorability. Finally note that (14) predicts employment polarization through the direct impact on occupation j of task-biased technological progress and offshoring while holding marginal costs and industry output fixed.

Now let us consider the 'marginal cost' term in square brackets on the right-hand side of equation (13) in more detail. Firstly, the very first term on the right-hand side, $1/(1-\eta)$, is the point estimate on log industry marginal costs of 1.07 in the second column of Table 9. Secondly, we approximate industry marginal cost changes following task-biased technological progress and offshoring by using the following log linear equation:

$$\frac{\partial \log \Gamma_{ict}}{\partial t} \approx \sum_j \kappa_{j|i}\left[(1-\kappa)(\frac{\partial \log r_{jt}}{\partial t} - \frac{\partial \log \alpha_{Kjt}}{\partial t})\right] \tag{15}$$

with $\kappa_{j|i}$ the cost share of task j in industry marginal costs. The terms on the right-hand side of (15) can be calculated as follows:

[40] In other words, we restrict our attention to the hypothesis that all tasks performed are subject to machine displacement or to displacement by foreign labor. This is in line with the general characterization in Autor, Levy and Murnane (2003), Autor and Dorn (2010) and Acemoglu and Autor (2011). Note, however, that this simplifying assumption is not innocuous. For equation (8) to predict employment polarization following technological progress or offshoring, it requires that the elasticity of substitution between labor and other inputs in the production of tasks is larger than the elasticity of substitution between tasks in the production of goods. The estimates in columns 1 and 2 of Table 9 confirm this: the absolute value of the estimated wage elasticity exceeds the point estimate on industry marginal costs.

- The term $\kappa_{j|i}$ is the cost share of task *j* in industry marginal costs, which we approximate by the average employment share of occupation *j* in industry *i* across countries.

- The last term in square brackets is obtained by dividing the right-hand side of equation (14) by $1/(1-\rho)-1/(1-\eta)$. This is be done as follows. Given an estimate for $1/(1-\eta)$, to know $1/(1-\rho)-1/(1-\eta)$ we further need an estimate of $1/(1-\rho)$. Assuming a value of 0.6 for κ, the share of domestic labor in task production, we can get this from the point estimate on the log wage of -3.67 in the second column of Table 9, which in absolute value is an estimate of $(1-\kappa)/(1-\rho)+\kappa/(1-\eta)$. The implied value of $1/(1-\rho)$ is 7.57.[41]

The final term in square brackets in equation (13) is industry output. We impute changes in industry output differentiating equation (11) using the point estimates on industry marginal costs reported in column 1 of Table 11 together with the predicted changes in industry marginal costs which we derive from (15).

7.B Some counterfactuals

Table 12 presents our counterfactuals. To keep the results digestible we report two statistics. Panel A looks at the average percentage point difference in employment share changes between the group of lowest-paying relative to the group of middling occupations defined as Table 2.[42] Panel B looks at the average percentage point difference in employment share changes between the group of highest-paid occupations relative to the group of middling occupations also defined as in Table 2.

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[41] Note that this exercise gives an estimate of the elasticity of substitution between tasks of 1.07 and between factors of task production of 7.57. These are derived from the estimated coefficients on wages and industry marginal costs. However, our wage and marginal cost data are less than ideal and as a consequence our estimates of these elasticities of substitution not very accurate. We will return to this issue in section 7B.

[42] Note that the actual differences of 9.11 and 14.72 reported in Table 12 are not exactly the same as the differences of 9.35 (=1.58+7.77) and 13.96 (=6.19+7.77) between the EU averages reported in Table 2 since Ireland has been excluded from Table 12 because of missing OECD STAN data.

In each panel, let us first consider the first row. The numbers in the first two columns are, respectively, our point estimate for the elasticity of substitution between factors in task production of 7.57 and between tasks in goods production of 1.07. Column I then uses these point estimates – among others – in equations (14) and (15) to predict occupational employment changes: these equations are substituted into equation (13) while holding industry output constant (i.e. $\partial \log Y_{ict} / \partial t = 0$). Note that this counterfactual unambiguously predicts polarization through the effect of technological progress and offshoring (column i), or of only technological progress (column ii).

In addition to column I, column II further accounts for relative price changes induced by technological progress and globalization by substituting predicted changes in industry output from (11) into (13). In doing this, we make use of our point estimate for the price elasticity of product demand of 0.75. The remaining numbers in the first row of each panel repeat this exercise but replace the estimated price elasticity of product demand of 0.75 with realistic but more extreme values of 0.25 and 1.25 respectively.[43]

Finally note that the contribution of the product demand effects is expected to attenuate the extent of polarization. This is because the model predicts a decrease in the relative price of goods intensive in the use of routine task or offshorable inputs. This reduction in relative prices causes a rise in relative product demand thus partially off-setting the fall in the demand for the occupations. In the hamburger example, the fall in the price of burgers leads to a rise in the demand for burgers and this acts to partially off-set the fall in the demand for patty-makers because of the improvement in technology.

Several things can be learnt from the first row of panel A. First of all, the first number in column I shows that – conditional on industry output – technological progress and offshoring can explain a 6.34 percentage point increase in the

[43] Also note these numbers cover the 95% confidence interval of the estimate since the standard error presented in Table 10 is 0.23.

employment share of low-paying occupations relative to middling occupations. Note that this is 70% of the actual difference of 9.11 percentage points. Of these 6.34 percentage points, 78% (=4.92/6.34) can be accounted for by routinization. Secondly, column II allows for industry output to vary following changes in relative output prices due to technological progress and offshoring. Compared to the counterfactuals in column I, the counterfactuals in column II predict less polarization: 50% (=4.52/9.11) rather than 70% (=6.34/9.11) of the actual difference. Also note that the predicted attenuation is robust to choosing more extreme values for the price elasticity of product demand: assuming an elasticity of 0.25 increases the predicted polarization to 51% (=4.67/9.11) whereas assuming an elasticity of 1.25 predicts 48% (=4.37/9.11) of the actual difference. In all cases, comparing columns i and ii again shows that over three quarters of job polarization is explained by the impact of routinization.

In sum, our model can explain a significant part of the observed increase in employment shares of low-paid to middling occupations. The job polarization predicted by our model is driven by the substitution of capital for routine jobs as well as the substitution towards routine tasks and away from other tasks in routine-task intensive industries. However, the impact of task-replacing capital on the different occupations is attenuated by induced changes in relative output prices and this attenuation seems relatively insensitive to the range of product demand elasticities that are realistic for the level of aggregation that we have.

We now turn to the explanatory power of our model with respect to the increase of high-paying occupations relative to middling occupations reported in the first row of panel B. From column I it follows that the combined impacts of technological progress and offshoring can predict a relative employment share increase for high-paying occupations of 10.44 percentage points (or 71% of the actual 14.72 percentage points), of which 84% (=8.75/10.44) is accounted for by the impact of routinization. Less polarization is predicted when industry output is endogenized as in column II, reducing the predictive power from 71% (=10.44/14.72) to 51% (=7.56/14.72). The predictions of our unconditional model do not seem very sensitive to alternative values for the price elasticity of product demand.

An interesting question is how robust our model is to assuming different values for the elasticity of substitution between occupations and other task inputs (of which the point estimate is 7.57) and between tasks in goods production (of which the point estimate is 1.07). The problem in doing this, however, is that there exist no other studies with estimates of these elasticities. At best, we can look at different but distinctly related estimates for guidance. For example, Katz and Murphy (1992) find an elasticity of substitution between high school and college equivalent men and women of 1.4. In line with this, Card and Lemieux (2001) find an estimate between 1.1 and 1.6 for men and women of these different schooling types and an estimate between 2 and 2.5 for men only. Card and Lemieux (2001) also report an elasticity of substitution between five-year age groups between 4 and 6. In this light, our estimates do not seem unrealistic. After all, we argue that our task-based model is better suited to capture the impact of routinization and offshoring – hence the relatively high elasticity of substitution between occupations and other task inputs of 7.57 and the relatively low estimate of 1.07 for the elasticity of substitution between tasks in goods production. In any case, the remaining rows in Table 12 assume lower values for the elasticity of substitution between occupations and other task inputs and higher values for the elasticity of substitution between tasks in goods production since this is expected to decrease the predictive power of our model.

The third row in each panel of Table 12 assumes an elasticity of substitution between occupations and other task inputs of 4 rather than 7.57. This decreases the predictive power of our conditional model from 70% (=6.34/9.11) to 34% (=3.13/9.11) and of our unconditional model from 50% (=4.52/9.11) to 23% (=2.10/9.11) in panel A and from 71% (=10.44/14.72) to 34% (=4.99/14.72) and from 51% (=7.56/14.72) to 24% (=3.49/14.72) in panel B. The final row in each panel of Table 12 assumes an elasticity of substitution between tasks in goods production of 4 rather than 1.07, thereby decreasing the predictive power of our conditional model to 54% (=4.90/9.11) and of our unconditional model to 38% (=3.44/9.11) in panel A and of our conditional model to 49% (=7.16/14.72) and of our unconditional model to 35% (=5.12/14.72) in panel B. In sum, even choosing more extreme values for the substitution elasticities in order to decrease the predictive power of our model, we can still explain about a quarter of job polarization in Europe.

In conclusion, our model is capable of explaining a sizeable fraction of the observed polarization. We have also shown how the 'general equilibrium' effects, the shifts in product demand caused by relative price changes are non-trivial and must be explicitly taken account of.

8. CONCLUSIONS

The employment structure in Western European countries has been polarizing over the period 1993-2006 with rising employment shares for high-paid professionals and managers as well as low-paid personal services workers and falling employment shares of manufacturing and routine office workers.

In this paper we have developed a simple theoretical framework capable of capturing the general equilibrium effects that link the demands for different types of workers. We use this framework to estimate the importance of technological change, globalization, institutions and product demand effects on the demand for different occupations. Some factors (institutional differences between countries possibly affecting relative wages, non-homothetic preferences) are found to be relatively unimportant in explaining polarization. We find that the single most important factor behind the observed changes seems to be the routinization hypothesis of Autor, Levy and Murnane though we find some evidence of decreased demand for jobs that are offshorable. However, we have also shown that induced changes in relative output prices lead to non-negligible effects on occupational employment and that these effects tend to attenuate job polarization but not eliminate it. Hence, job polarization is having a powerful impact on the structure of employment of all European countries.

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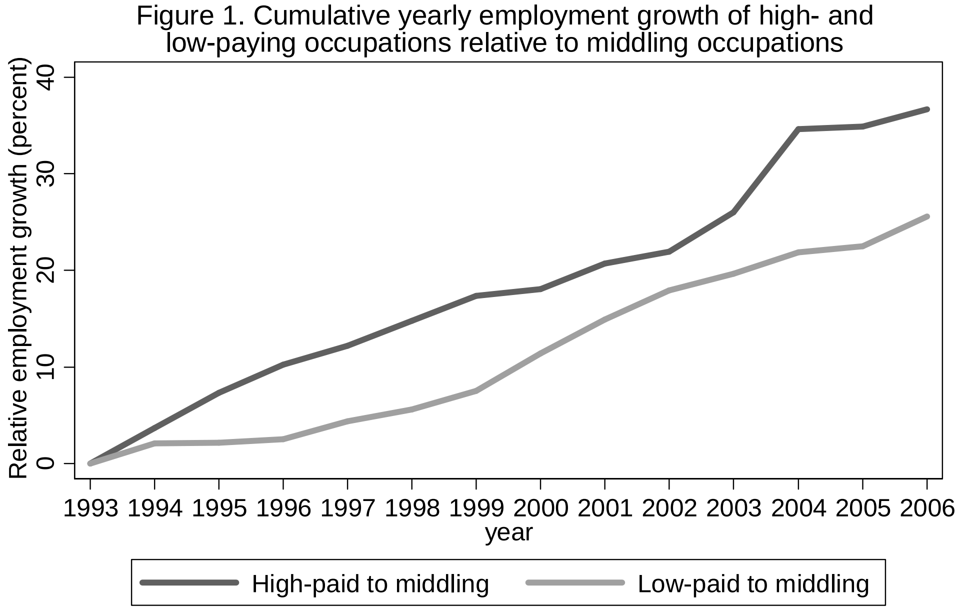
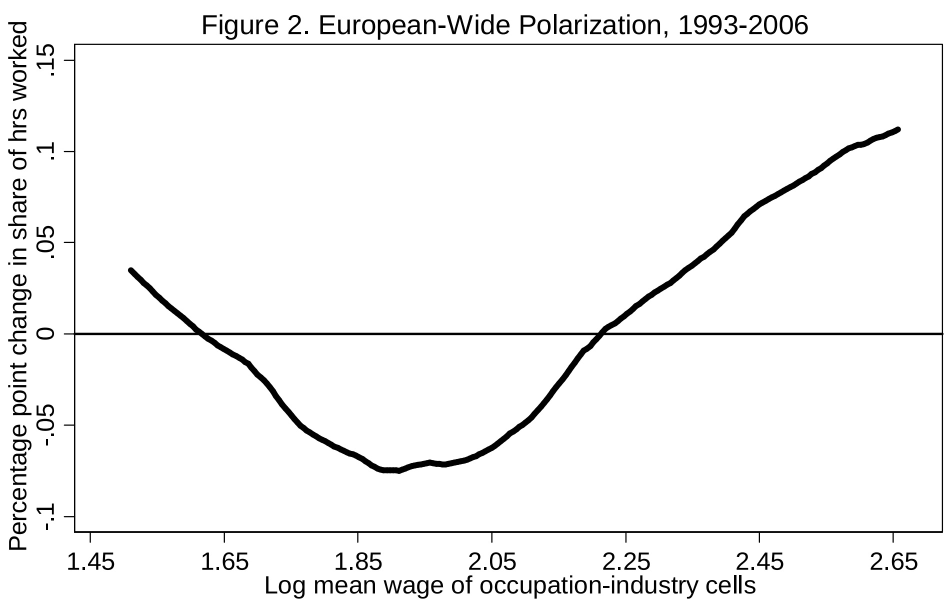


Note: Employment growth averaged across countries, no imputation for countries with shorter data spans.



Note: Employment pooled across countries. 1993-2006 long difference: employment shares for 1993 and/or 2006 imputed on the basis of average annual growth rates for countries with shorter data spans.

Table 1. Levels and changes in the shares of hours worked 1993–2006 for occupations ranked by their mean 1993 European wage

Occupations ranked by 1993 mean European wage	ISCO code	Average employment share in 1993	Percentage point change over 1993–2006
Corporate managers	12	4.47%	1.23
Physical, mathematical and engineering professionals	21	2.94%	1.02
Life science and health professionals	22	1.96%	−0.12
Other professionals	24	2.80%	0.65
Managers of small enterprises	13	3.53%	1.25
Physical, mathematical and engineering associate professionals	31	3.96%	0.87
Other associate professionals	34	6.85%	2.15
Life science and health associate professionals	32	3.05%	0.69
Drivers and mobile plant operators	83	5.37%	−0.19
Stationary plant and related operators	81	1.71%	−0.38
Metal, machinery and related trade work	72	8.15%	−2.29
Precision, handicraft, craft printing and related trade workers	73	1.29%	−0.40
Office clerks	41	11.96%	−1.94
Customer service clerks	42	1.97%	0.18
Extraction and building trades workers	71	7.98%	−0.51
Machine operators and assemblers	82	6.55%	−1.96
Other craft and related trade workers	74	3.13%	−1.35
Personal and protective service workers	51	7.10%	1.11
Laborers in mining, construction, manufacturing and transport	93	4.03%	0.45
Models, salespersons and demonstrators	52	6.56%	−1.38
Sales and service elementary occupations	91	4.65%	0.89

Notes: All countries, long difference 1993–2006. Employment pooled across countries. Employment shares in 1993 and/or 2006 imputed on the basis of average annual growth rates for countries with shorter data spans. Occupations are ordered by their mean wage rank in 1993 across the 16 European countries.

Table 2. Initial shares of hours worked and percentage changes over 1993-2006 for high-, middling and low-paying occupations

	4 lowest paying occupations		9 middling occupations		8 highest paying occupations	
	Employment share in 1993	Percentage point change 1993-2006	Employment share in 1993	Percentage point change 1993-2006	Employment share in 1993	Percentage point change 1993-2006
Austria	23%	-0.59	53%	-14.58	25%	15.17
Belgium	17%	1.48	49%	-9.50	34%	8.03
Denmark	24%	-0.96	40%	-7.16	36%	8.13
Finland	18%	6.66	39%	-6.54	43%	-0.12
France	22%	-0.74	48%	-12.07	30%	12.81
Germany	22%	3.04	56%	-8.72	22%	5.67
Greece	22%	1.75	48%	-6.08	31%	4.34
Ireland	19%	6.19	46%	-5.47	35%	-0.72
Italy	27%	-8.20	51%	-9.08	22%	17.28
Luxembourg	22%	-1.66	50%	-8.45	28%	10.10
Netherlands	17%	2.27	38%	-4.68	45%	2.41
Norway	23%	4.96	39%	-6.52	38%	1.57
Portugal	26%	2.39	47%	-1.13	27%	-1.26
Spain	28%	0.96	49%	-7.04	23%	6.07
Sweden	22%	1.91	42%	-6.96	37%	5.04
UK	17%	5.77	44%	-10.32	39%	4.55
EU average	*22%*	*1.58*	*46%*	*-7.77*	*32%*	*6.19*

Notes: Long difference 1993-2006. Occupational employment pooled within each country. In each country occupations are ranked according to the mean 1993 European occupational wage rank.

Table 3. Analysis of variance models

Dependent variable: log(hours worked/1000)

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

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

Table 4. Task measures, offshorability, and mean education levels for occupations ordered by their mean 1993 European wage

Occupations ranked by 1993 mean European wage	ISCO code	Abstract task importance (1)	Routine task importance (2)	Service task importance (3)	Routine Task Intensity (4)	Offshora-bility (5)	Mean education level (6)
Corporate managers	12	1.80	−1.18	1.15	−1.29	−0.59	2.05
Physical, mathematical and engineering professionals	21	1.50	−0.86	−0.35	−0.80	−0.37	2.83
Life science and health professionals	22	1.47	−0.16	1.73	−0.81	−0.64	2.92
Other professionals	24	1.29	−1.63	1.14	−1.49	−0.51	2.69
Managers of small enterprises	13	1.80	−1.18	1.15	−1.29	−0.59	2.05
Physical, mathematical and engineering associate professionals	31	0.89	0.20	−0.44	−0.02	−0.27	2.22
Other associate professionals	34	0.75	−1.37	0.93	−1.25	−0.12	2.14
Life science and health associate professionals	32	0.36	0.21	0.86	−0.26	−0.64	2.40
Drivers and mobile plant operators	83	−0.59	1.33	0.01	0.90	−0.63	1.46
Stationary plant and related operators	81	−0.49	1.33	−1.21	1.38	1.63	1.56
Metal, machinery and related trade work	72	0.43	1.16	−0.29	0.65	0.29	1.68
Precision, handicraft, craft printing and related trade workers	73	−1.30	0.81	−1.79	1.51	−0.62	1.69
Office clerks	41	−0.42	−1.29	0.04	−0.89	1.21	1.91
Customer service clerks	42	−0.36	−0.82	0.74	−0.75	−0.27	1.89
Extraction and building trades workers	71	−0.23	0.98	−0.64	0.82	−0.59	1.55
Machine operators and assemblers	82	−0.46	1.31	−1.33	1.41	3.18	1.48
Other craft and related trade workers	74	−1.36	0.67	−1.30	1.18	−0.27	1.57
Personal and protective service workers	51	−0.37	−0.16	0.82	−0.35	−0.64	1.67
Laborers in mining, construction, manufacturing and transport	93	−1.00	0.52	−0.53	0.64	0.87	1.41
Models, salespersons and demonstrators	52	−0.53	−0.94	1.00	−0.86	−0.64	1.66
Sales and service elementary occupations	91	−1.38	−0.11	−0.55	0.28	−0.37	1.40

Notes: *Columns 1-4*: Rescaled to mean 0 and standard deviation 1, a higher value means a task is more important. Values for ISCO 12 and 13 are identical because ONET SOC codes do not allow distinction. Routine task intensity is defined as Routine task importance divided by the sum of Abstract and Service task importances, subsequently standardized. *Column 5*: Rescaled to mean 0 and standard deviation 1, a higher value means more offshorable. Values for ISCO 12 and 13 have been made the same by taking the mean weighted by hours worked. *Column 6*: Weighted by hours worked. 1=up to and including lower secondary education, 2=upper secondary and post-secondary (non-tertiary) education, 3=tertiary or post-graduate education. Unweighted mean across all countries, for the first year in which education data was available (typically 1999). Values for ISCO 12 and 13 have been made the same by taking the mean weighted by hours worked.

Table 5. Real monthly wages of occupations across 16 European countries in 1993 and 2006, sorted by 1993 wage rank

Occupations ranked by the 1993 mean European wage	ISCO	Real monthly wage in 2000 Euros 1993	Real monthly wage in 2000 Euros 2006	Standardized wage rank 1993	Standardized wage rank 2006
Corporate managers	12	3,472	3,724	1.70	1.60
Physical, mathematical and engineering professionals	21	3,038	3,170	1.43	1.47
Life science and health professionals	22	2,720	3,164	1.22	1.39
Other professionals	24	2,712	2,910	1.17	1.26
Managers of small enterprises	13	2,653	2,685	1.15	0.93
Physical, mathematical and engineering associate professionals	31	2,150	2,324	0.74	0.80
Other associate professionals	34	2,115	2,227	0.74	0.69
Life science and health associate professionals	32	1,915	2,018	0.39	0.28
Drivers and mobile plant operators	83	1,789	1,916	0.05	−0.04
Stationary plant and related operators	81	1,793	1,954	0.01	−0.03
Metal, machinery and related trade work	72	1,748	1,927	−0.01	0.02
Precision, handicraft, craft printing and related trade workers	73	1,733	1,968	−0.09	−0.02
Office clerks	41	1,679	1,865	−0.36	−0.15
Customer service clerks	42	1,613	1,732	−0.50	−0.50
Extraction and building trades workers	71	1,624	1,750	−0.58	−0.61
Machine operators and assemblers	82	1,565	1,728	−0.73	−0.61
Other craft and related trade workers	74	1,504	1,598	−0.89	−0.99
Personal and protective service workers	51	1,424	1,538	−1.13	−1.05
Laborers in mining, construction, manufacturing and transport	93	1,402	1,518	−1.22	−1.22
Models, salespersons and demonstrators	52	1,237	1,344	−1.43	−1.50
Sales and service elementary occupations	91	1,112	1,242	−1.68	−1.70

Notes: Mean occupational wages weighted by weekly hours worked in each country in 1993 and 2006, unweighted average across countries. Average unweighted wage rank across countries has been rescaled to mean zero and unit standard deviation. The correlation between the standardized wage rank in 1993 and in 2006 is 0.994.

Table 6A. Conditional effect of task importance and offshorability

Dependent variable: Log(hours worked/1000)

Linear time-trend interacted with:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ABSTRACT task importance	1.33* (0.12)	–	–	0.80* (0.15)	–	–	1.22* (0.12)	–	–	0.81* (0.15)	–
ROUTINE task importance	–	−1.33* (0.12)	–	−0.74* (0.15)	–	–	–	−1.22* (0.12)	–	−0.75* (0.15)	–
SERVICE task importance	–	–	1.28* (0.13)	0.31 (0.18)	–	–	–	–	1.19* (0.14)	0.18 (0.19)	–
RTI	–	–	–	–	−1.52* (0.12)	–	–	–	–	–	−1.44* (0.13)
Offshorability	–	–	–	–	–	−0.75* (0.12)	−0.45* (0.13)	−0.40* (0.12)	−0.20 (0.13)	−0.25 (0.13)	−0.21 (0.13)
Log wage	−0.19 (0.12)	−0.08 (0.12)	−0.14 (0.12)	−0.13 (0.12)	−0.08 (0.12)	−0.14 (0.12)	−0.18 (0.12)	−0.08 (0.12)	−0.13 (0.12)	−0.13 (0.12)	−0.09 (0.12)

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

Table 6B. Conditional effect of task importance, education and offshorability
Dependent variable: Log(hours worked/1000)

Linear time-trend interacted with:	(1)	(2)	(3)
ABSTRACT task importance	–	0.62*	–
		(0.23)	
ROUTINE task importance	–	−0.68*	–
		(0.18)	
SERVICE task importance	–	0.22	–
		(0.20)	
RTI	–	–	−1.07*
			(0.17)
Offshorability	–	−0.22	0.17
		(0.24)	(0.13)
Education level	1.34*	0.25	0.56*
	(0.12)	(0.24)	(0.17)
Log wage	−0.14	−0.12	−0.10
	(0.12)	(0.12)	(0.12)

Notes: All countries; 34,816 observations for each regression; all regressions have an R^2 of 0.96. All regressions contain dummies for industry-country-year and industry-occupation-country. Like the task measures and offshorability, the education level has been rescaled to mean 0 and standard deviation 1. Point estimates on the task measures, offshorability and the education level have been multiplied by 100. Standard errors clustered by occupation-country-industry. *Significant at the 5% level or better.

Table 7. Country and industry heterogeneity in the conditional impacts of technological change and offshoring

Dependent variable: Log(hours worked/1000)

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

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

Table 8. Conditional labor demand

Dependent variable: Log(hours worked/1000)

Estimator:	2SLS		CONSTRAINED OLS	
Linear time-trend interacted with:	(1)	(2)	(3)	(4)
ABSTRACT task importance	1.07* (0.19)	–	0.86* (0.16)	–
ROUTINE task importance	−0.50* (0.20)	–	−0.58* (0.17)	–
SERVICE task importance	0.07 (0.25)	–	0.29 (0.22)	–
RTI	–	−1.21* (0.17)	–	−1.38* (0.14)
Offshorability	−0.50* (0.16)	−0.45* (0.15)	−0.23 (0.14)	−0.23 (0.14)
Log industry marginal costs	0.99* (0.21)	0.99* (0.22)	0.83* (0.14)	0.83* (0.14)
Log industry output	1.00* (0.08)	1.00* (0.08)	1 –	1 –
Log wage	−0.58* (0.15)	−0.56* (0.15)	−0.81* (0.10)	−0.78* (0.10)
R^2	0.96	0.96	–	–
	First stage (dependent variable: log output)			
Log gross industry capital stock	0.67* (0.02)	0.66* (0.02)		
R^2	0.99	0.99		

Notes: Belgium, Denmark, Finland, France, Germany, Italy, Norway and Spain in columns 1-2 (17,242 observations); all countries except Ireland in columns 3-4 (32,044 observations). Each regression includes dummies for industry-occupation-country. Point estimates on the task measures and offshorability have been multiplied by 100. Standard errors clustered by country-industry-occupation. *Significant at the 5% level or better.

Table 9. Conditional labor demand: instrumented wages and reduced form

Dependent variable: Log(hours worked/1000)

	CONSTRAINED 2SLS		REDUCED FORM	
Linear time-trend interacted with:	(1)	(2)	(3)	(4)
ABSTRACT task importance	1.10* (0.10)	–	0.81* (0.17)	–
ROUTINE task importance	−0.26* (0.11)	–	−0.69* (0.17)	–
SERVICE task importance	0.32* (0.13)	–	0.19 (0.21)	–
RTI	–	−1.19* (0.09)	–	−1.38* (0.14)
Offshorability	−0.28* (0.09)	−0.32* (0.09)	−0.25 (0.15)	−0.22 (0.14)
Log wage	−3.79* (0.14)	−3.67* (0.14)	–	–
Log industry marginal costs	1.07* (0.09)	1.07* (0.09)	–	–
Log industry output	1 –	1 –	–	–
R^2	–	–	0.96	0.96
	First stage (dependent variable: log wage)			
Log supply shift	−0.38* (0.02)	−0.40* (0.02)		
R^2	0.98	0.98		

Notes: All countries except Germany, Ireland and Italy in columns 1 and 2 (28,817 observations); all countries in columns 3 and 4 (34,816 observations). All regressions contain dummies for industry-occupation-country cells. Supply shift includes gender and immigrant status; distribution of demographics across occupations averaged across countries. Point estimates on the task measures and offshorability have been multiplied by 100. Standard errors clustered by country-industry-occupation in columns 3 and 4. *Significant at the 5% level or better.

Table 10. Shiftshare analysis of changes in share of hours worked between and within industries for occupations ranked by the mean 1993 European wage

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

Notes: All countries, long difference 1993-2006. Employment pooled across countries. All changes are in percentage points.

Table 11. Product demand
Dependent variable: Log(industry output)

	(1)	(2)	(3)	
Log industry marginal costs	−0.76* (0.29)	−0.79* (0.24)	−0.75* (0.23)	
Log income/capita	1.00* (0.09)	–	–	
Log population	1.01* (0.02)	1.01* (0.02)	1.00* (0.02)	
		Measure:	Measure:	
			(a)	(b)
		Log income /capita	Log income /capita	Log income inequality
Measure interacted with manufacturing	–	0.70* (0.21)	0.68* (0.22)	−0.01 (0.05)
Deviation from interaction with manufacturing:				
Electricity, gas and water supply	–	−0.14 (0.23)	−0.16 (0.24)	−0.05 (0.05)
Financial intermediation	–	1.28* (0.65)	1.35* (0.52)	0.23* (0.11)
Real estate, renting and business activity	–	0.62* (0.26)	0.62* (0.28)	0.03 (0.06)
Transport, storage and communication	–	0.64* (0.21)	0.63* (0.22)	−0.04 (0.05)
Construction	–	0.22 (0.26)	0.24 (0.24)	0.08 (0.07)
Wholesale and retail	–	0.12 (0.23)	0.13 (0.23)	0.03 (0.05)
Health and social work	–	0.55 (0.45)	0.51 (0.42)	−0.13 (0.09)
Other community, social and personal service activities	–	0.14 (0.25)	0.15 (0.28)	0.04 (0.06)
Hotels and restaurants	–	−0.42 (0.38)	−0.36 (0.33)	0.21* (0.09)
R^2	0.96	0.97	0.97	

Notes: All countries except Ireland; 2,100 observations per regression. Industry "Private household with employed persons" included in "Other community, social.." for France, Portugal, Spain and the UK. Each regression includes dummies for industry cells. Industries ranked by their mean gross real hourly UK wage in 1994; the rank of manufacturing is 6. Log income inequality is log(p90/p10) averaged over 1993-2006 and rescaled to mean 0 and standard deviation 1. Standard errors clustered by country-industry. *Significant at the 5% level or better.

Table 12. Actual and counterfactual differences for changes in employment shares between low-paying and middling and between high-paying and middling occupations

		I. CONDITIONAL		II. UNCONDITIONAL					
				$1/(1-\gamma)=0.75$		$1/(1-\gamma)=0.25$		$1/(1-\gamma)=1.25$	
$1/(1-\rho)$	$1/(1-\eta)$	i. ALM + OFF	ii. ALM	i. ALM + OFF	ii. ALM	i. ALM + OFF	ii. ALM	i. ALM + OFF	ii. ALM
		A. Percentage point difference in employment share changes between low-paying and middling occupations (actual=9.11):							
7.57	1.07	6.34	4.92	4.52	3.48	4.67	3.61	4.37	3.36
6.00	1.07	4.93	3.84	3.46	2.67	3.61	2.80	3.30	2.54
4.00	1.07	3.13	2.45	2.10	1.63	2.26	1.76	1.95	1.49
7.57	2.00	5.88	4.60	4.18	3.24	4.33	3.37	4.02	3.11
7.57	4.00	4.90	3.90	3.44	2.72	3.59	2.85	3.29	2.59
		B. Percentage point difference in employment share changes between high-paying and middling occupations (actual=14.72):							
7.57	1.07	10.44	8.75	7.56	6.32	7.70	6.45	7.41	6.19
6.00	1.07	8.05	6.76	5.77	4.83	5.92	4.96	5.62	4.69
4.00	1.07	4.99	4.20	3.49	2.92	3.64	3.06	3.33	2.78
7.57	2.00	9.39	7.90	6.78	5.68	6.93	5.81	6.63	5.55
7.57	4.00	7.16	6.06	5.12	4.32	5.27	4.45	4.96	4.18

Notes: Long difference 1993-2006, unweighted averages across 15 countries: no counterfactuals could be constructed for Ireland because of missing OECD STAN data. Occupational employment pooled within the occupation groups as in Table 2. Counterfactual percentage point changes in employment shares calculated from counterfactual percentage changes in occupational employment.

EXPLAINING JOB POLARIZATION IN EUROPE:

THE ROLES OF TECHNOLOGY, GLOBALIZATION AND INSTITUTIONS

MAARTEN GOOS ALAN MANNING ANNA SALOMONS

APPENDICES

Appendix A: ELFS and IABS

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

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

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

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

These occupations and industries were dropped because German data is not random for workers who are not legally obliged to make social security contributions and because the OECD STAN data, especially the net operating surplus data, covering several public industries is unreliable (particularly, NACE L and M, and by association, ISCO 23 and 33). Others were eliminated because the data appears unreliable: employment in these occupations or industries occurs only in a small number of country-year cells, suggesting classification problems (ISCO 11, 92, and ISCO 61 by association through ISCO 92; NACE A, B, C, Q). However, our results[44] are qualitatively identical when we do not drop these occupations and industries.

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

[44] Those that can be reproduced with the full set of occupations and industries, i.e. summary statistics and conditional labor demand where industry output and marginal costs are proxied by industry-country-year dummies.

and year. Table A4 shows the number of observations (individual and by country-year-occupation-industry cells) we have left.

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

Lastly, Table A6 gives an idea of the absolute and relative employment sizes of the 16 European countries in our restricted[45] sample.

[45] I.e. where the aforementioned occupations and industries have been dropped.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Table A6. Employment compared across 16 European countries

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

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

Appendix B: Explaining the industry-occupation-country specific variation in the data

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

In this Appendix we find that the significance of the industry-occupation-country effect mainly captures the fact that the product mix within aggregate industry groups differs between countries. To this end we use data from the ELFS that are not in the anonymized version and where the industry dimension is 2-digit rather than 1-digit. However, these data cannot be published and we report some statistics here.

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

$$\hat{E}_{i1jc} = \sum_{i2 \in i1} E_{i2c} * \overline{E}_{j|i2}$$

where *i1* is the 1-digit industry level; *i2* is the 2-digit industry level, *j* is occupation, and *c* is country. That is, we predict employment at the 1-digit industry-occupation-country level by restricting the distribution of occupations in 2-digit industries to be identical across countries while allowing for the different employment weights 2-digit industries have within 1-digit industries across countries. We then plot the (1-digit) industry-occupation-country specific variation in the logarithm of this predicted employment series against the (1-digit) industry-occupation-country specific variation in the actual log employment data[46]– it can be seen that all data points lie very close to a 45 degree line: the coefficient in a bivariate regression is 0.9920 with a standard error of 0.0035 and an R^2 of 0.96.

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

Appendix C: ONET

C.1 Construction of the ONET dataset

The ONET database, version 11, contains 161 occupation-specific variables (ordered within a so-called content model), many of which can be seen as representing certain tasks. We use 96 variables from 5 different sections: from Worker Characteristics, we use Abilities (section 1A), from Worker Requirements, we use Basic Skills and Cross-Functional Skills (sections 2A and 2B), and from Occupational Requirements, we use Generalized Work Activities and Work Context (sections 4A and 4B). Several other sections exist, but they were either not good measures of tasks (sections covering education levels and study specialization such as in section 2D-Education and section 3-Experience Requirements; working conditions and job satisfaction such as in section 4B-Organizational Context); not yet available (ONET is still regularly being updated: e.g. sections 1B-Interests and 1C-Work Styles are not yet available); or did not allow for comparison across occupations (e.g. section 4D-Detailed Work Activities).

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

C.2 Special issues for the ONET data set

1. Differences between ONET occupational codes and SOC 2000

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

2. Mapping of ONET occupational codes to ISCO

For lack of an official crosswalk between SOC 2000 and ISCO, we have mapped ONET occupational codes to ISCO occupations by hand. Since the ONET occupational code is much more disaggregate, this was relatively straightforward in most cases. However, the ONET occupational code does not contain any clear equivalent of the ISCO occupation "managers of small enterprises" (ISCO 13); and does not contain data for the equivalent of "legislators and senior officials" (ISCO 11). Since we drop ISCO 11 (see Appendix A), only ISCO 13 remains: we have recoded it as "corporate managers" (ISCO 12), and hence assumed that the importance scores for task measures of corporate managers also apply to managers of small enterprises.

C.3 Robustness checks of task measures using principal components

In this appendix, we construct alternative task measures which, rather than based on manual assignment into categories, are principal components. We perform two analyses here: one where we use the same sub-sample of ONET measures used in the construction of Abstract, Routine, and Service task measures; and one where we use the full sample of ONET measures with the “importance” scale. To test the predictive power of these “mechanically” generated task measures, we report estimates of the conditional labor demand equation (Table 8 in the main text). The results show that the two principal components generated broadly correspond to the Routine task dimension, and the Abstract and Service task dimension, respectively. We therefore also find negative employment effects associated with one and positive employment effects associated with the other principal component.

Table C2 reports standardized principal components for occupations ranked by the mean European wage. The principal components reported in panel A are constructed from the same 96 ONET task measures as the Abstract, Routine, Service task measures used in the main text whereas those in panel B are constructed from all 161 ONET task measures that have the importance scale. Within each panel, the first two columns show principal components that were calculated across SOC 2000 occupations, and then averaged to ISCO occupations using US employment in SOC 2000 occupations. The last two columns in each panel show principal components that have been calculated while simultaneously weighting by US employment in SOC 2000 occupations. We refer to this first type as “unweighted” principal components, and the second as “weighted” ones, since only the latter has been weighted at the level of SOC 2000 occupations, but it is worth stressing that both are weighted at the level of ISCO occupations (albeit in slightly different ways, as describe above).

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

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

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

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

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

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

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

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

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

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

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

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

Table C4. Conditional labor demand

Dependent variable: Log(hours worked/1000)

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

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

Appendix D: European Restructuring Monitor (ERM)

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

We then count the number of cases by ISCO occupation as a measure for that occupation's offshorability: this is reported in Table D1. This table shows that apart from the manufacturing occupations (a combined 532 counts), office occupations (141 counts) and (associate) professional occupations (a combined 111 counts) are also being offshored relatively often.[47]

A weakness of this approach is that it does not take into account *how many* jobs of an occupation are being offshored, although this number may vary significantly among

[47] Note that the standardized values of offshorability presented in the main text are slightly different because there, the same value is assigned to occupations 12 and 13.

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

Table D1. Number of cases of offshoring by ISCO occupation

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

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

Appendix E: ECHP and EU-SILC

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

We use the gross monthly (weekly for the UK) wage, and weight it by persons employed and hours worked to obtain two wage measures. Table E1 shows how many individual observations we have for each country-year cell summed over all occupations, whereas Table E2 shows the average number of observations for each country-occupation cell across years. Although sample sizes are small (except for the UK), we find that the wage ranking of occupations is very stable both across time within a country – see Table 5 in the main text – as well as across countries over time – see Table E3.

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

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

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

Table E1. Number of wage observations by country and year

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

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

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

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

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

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

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

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

Appendix F: Country and industry heterogeneity in the impacts of technological change and offshoring

Table F1 shows that the negative employment estimated for routine intense occupations is not driven by a small subsample of countries: only Finland has a positive (albeit insignificant) employment impact for more routine intense occupations. This table also shows that the employment impact of offshoring is less homogeneous, with both positive (5 countries) and negative (11 countries) impacts found, and effects generally being less precisely estimated than the impact of technological change.

The interactions of routine intensity and offshorability with industry dummies are reported in Table F2. The estimated employment impact for routine intensive jobs is negative within all industries with the exception of persons employed in private households.[48] The highest employment decreases for routine intense jobs are found in manufacturing, financial intermediation, wholesale and retail and health and social work; whereas lower impacts are found in hotels and restaurants, and construction. This seems broadly consistent with larger percentage impacts for industries that employ larger shares of routine labor. The estimated employment impacts of offshoring by industry are largely negative, but less precisely estimated.

[48] The imprecision for this estimate reflects the fact that there is little variation in the routine intensity of employment in this industry- the predominant occupations being the non-routine personal and protective service workers and sales and service elementary occupations.

Table F1. Country heterogeneity in the conditional impacts of technological change and offshoring
Dependent variable: log(hours worked/1000)

	Routine task intensity	Offshorability
Task measure interacted with timetrend for Finland	0.59	−0.65
	(0.64)	(0.48)
Deviation for:		
Austria	−3.59*	−0.45
	(0.88)	(0.74)
Belgium	−1.67*	0.54
	(0.72)	(0.56)
Denmark	−1.55*	−0.34
	(0.73)	(0.58)
France	−1.17	−0.63
	(0.84)	(0.60)
Germany	−1.65*	0.77
	(0.69)	(0.53)
Greece	−2.00*	−0.06
	(0.76)	(0.66)
Ireland	−1.63*	0.32
	(0.82)	(0.77)
Italy	−3.06*	1.14
	(0.87)	(0.91)
Luxembourg	−2.80*	1.04
	(0.75)	(0.58)
Netherlands	−1.75*	0.44
	(0.73)	(0.61)
Norway	−2.08*	−0.02
	(0.86)	(0.76)
Portugal	−1.41	1.46
	(0.82)	(0.85)
Spain	−2.64*	0.31
	(0.74)	(0.63)
Sweden	−2.78*	1.28
	(0.88)	(0.80)
United Kingdom	−1.98*	1.22
	(0.79)	(0.68)
R^2	0.96	

Notes: Years 1993–2006; 3,910 observations for each regression. The regression includes dummies for industry-occupation-country cells. Task importances and offshorability have been rescaled to mean 0 and standard deviation 1. All point estimates and standard errors have been multiplied by 100. Standard errors clustered by industry-occupation-country. *Significant at the 5% level or better.

Table F2. Industry heterogeneity in the conditional impacts of technological change and offshoring
Dependent variable: log(hours worked/1000)

	Routine task intensity	Offshor-ability
Task measure interacted with timetrend for manufacturing	-1.48* (0.24)	0.01 (0.23)
Deviation for:		
Electricity, gas and water supply	-0.07 (0.51)	-1.07 (0.56)
Financial intermediation	-0.23 (0.64)	-0.76 (0.62)
Real estate, renting and business activity	0.22 (0.42)	-0.42 (0.53)
Transport, storage and communication	-0.86 (0.48)	0.00 (0.45)
Construction	0.59 (0.46)	-0.68 (0.43)
Wholesale and retail	0.09 (0.42)	0.24 (0.37)
Health and social work	-0.89 (0.46)	-0.34 (0.42)
Other community, social and personal service	0.25 (0.45)	-0.31 (0.45)
Hotels and restaurants	0.84 (0.58)	-0.69 (0.58)
Persons employed in private households	2.28 (1.23)	1.05 (1.70)
Fixed effects	ijc, ict	
R^2	0.96	

Notes: Years 1993-2006; all countries; 3,910 observations for each regression. The regression includes dummies for industry-occupation-country cells. Task importances and offshorability have been rescaled to mean 0 and standard deviation 1. All point estimates and standard errors have been multiplied by 100. Standard errors clustered by industry-occupation-country. *Significant at the 5% level or better.

Appendix G: OECD STAN Database for Industrial Analysis

The OECD STAN Database for Industrial Analysis is the source for measures of country-industry-year specific output; country-industry-year specific industry marginal costs; country-year specific income; country-industry-year specific price indices; and country-industry-year specific gross capital stock. STAN uses a standard industry list for all countries based on the International Standard Industrial Classification of all Economic Activities, Revision 3 (ISIC Rev.3). The first two digits of ISIC Rev.3 are identical to the first two digits of NACE Rev.1, the industry classification used in the ELFS. Since the ELFS only contains major groups for NACE, this is identical to ISIC. However, in the STAN database, data on NACE industry P (Private households with employed persons) is often missing or not reliable - we have therefore dropped it altogether except for the France, Portugal, Spain and the UK, where it is included in NACE industry O (Other community, social and personal service activities).

The STAN data then covers all 16 countries in our sample except Ireland; and after imputing a very small number of missing observations as described in the main text, the period 1993-2006 is covered.

The measure of output we use is value added (which is valuated at basic prices), available in STAN as the difference between production (defined as the value of goods and/or services produced in a year, whether sold or stocked) and intermediate inputs. In the STAN documentation value added is recommended as a measure of output rather than production, since production includes any output of intermediate goods consumed within the same sector. We deflate the value added data using country-industry-year specific deflators[49], and convert them into 2000 Euros using real exchange rates.

We calculate industry marginal costs as the difference between net operating surplus and production, divided by production: this gives a measure of average (capital

[49] Our results are robust to instead using country-year specific inflators, which is available for a larger sample of countries.

and labor) cost per unit of output which in our model is identical to industry marginal cost. Here we use production to account for the fact that intermediate goods are a part of production costs- in fact, the STAN methodology counts any capital costs from equipment that is rented (rather than owned) by a firm as an intermediate good. Intermediate goods also include the cost of offshoring.

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