TECHNOLOGY, JOBS AND SKILLS

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Abstract

There is a growing concern in advanced countries that the position of less skilled workers has deteriorated, either through their ability to secure jobs and/or their ability to earn a decent wage. Some have linked this decline to modern computing technologies. This paper surveys the evidence on the effects of technical change on employment (in total and by skill group) by examining the micro-econometric evidence coming out of activities associated with the TSER Network R&D, Innovation and Productivity. Most studies which use direct measures of technology rather than associating technology with a residual time trend. We first point to three basic methodological problems relating to endogeneity, fixed effects and measurement. To characterise our overview very crudely:

(i) There is a significant effect of technology on skills which appears reasonably robust to measurement issues and fixed effects

(ii) Product innovations appear to raise firm employment growth, but there is no clear evidence of a robust effect (either positive or negative) of process innovations or R&D on jobs.

(iii) The problems of endogeneity, linking micro evidence to macro events and the theoretical mechanisms underlying the econometric relationships are still poorly understood.

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1. INTRODUCTION

The effect of the development of tools on the evolution of human activity has long been a principal concern for students of social behaviour. Marx viewed the development of the productive means as the key force in his theory of history. The identity of the dominant class was determined by their ability to best muster the development of technology. In neo-classical economics, technological progress is also regarded as the driving force behind economic growth, a notion that is reinforced by endogenous growth theory. Given its role in economic growth, technical progress leads to higher standards of living on average. But how are the benefits of technical progress distributed across society? Who gets a 'share of the plunder'?

In the past, many commentators have worried that technology could lead to a 'de-skilling' of workers. The pin factory symbolises the destruction of skilled artisans and their replacement by workers who were required only to perform the most menial repetitive tasks (Braverman, 1973; Edwards, 1979). More recently, however, debates by economists have focused on whether modern technologies are generally biased towards more skilled workers. The participants are particularly vocal in the debate over the causes of the increasing inequality of wages and employment between the skilled and the unskilled. Although closely related to it, the existence of skill-biased technical change does not provide the explanation for recent changes in the wage and employment structure. To demonstrate that technology is biased towards more skilled labour is not sufficient (and some would argue not even necessary - see Leamer, 1994) to establish technical change as the dominant explanation for increases in inequality. We also have to consider the supply of skills, for example.

This paper surveys the evidence on the effects of technical change on employment (in total and by skill group) by examining the micro-econometric evidence coming out of activities associated with the TSER Network R&D, Innovation and Productivity. Most studies which use direct measures of technology rather than associating technology with a residual time trend.

The plan of the paper is as follows. Section 2 briefly discusses some theory which implicitly or explicitly forms the background of the empirical studies. Section 3 discusses empirical problems with implementing the theory. Section 4 discusses the results of the papers explicitly and Section 5 draws some conclusions.

2. THEORETICAL GUIDE[1]

2.1 The skill bias of technical change

We start with a general framework based within the context of a neo-classical model of production. For simplicity we consider the case of three variable factors (skilled labour, unskilled labour and materials) and two quasi-fixed factor (physical capital, denoted by *K*, and "technological capital", denoted by *R*). Consider a quasi-fixed translog cost function:

$$\ln C = \alpha_0 + \sum_h \sum_{i=B,W,M} \alpha_{hi} D_h \ln w_i + \sum_{i=B,W,M} \sum_{j=B,W,M} \beta_{ij} \ln w_i \ln w_j + \beta_q \ln q +$$
$$\sum_{j=B,W,M} \beta_{iq} \ln w_i \ln q + \beta_K \ln K + \sum_{j=B,W,M} \beta_{iK} \ln w_i \ln K + \beta_R \ln R + \sum_{j=B,W,M} \beta_{iR} \ln w_i \ln R$$
(1)

where C are the variable costs (`unskilled' blue-collar labour - *B*, `skilled' white collar labour - *W* and materials - *M*). The α parameters reflect own price effects. We allow these to differ in different 'units', indexed by D_h. (D = 1 if in unit *h*, etc). For example, we might allow the own price effects to vary in different industries or even different firms (fixed effects). The β parameters measure the effect on total cost of the other factor prices (*w*), the log of plant output (*q*), technological capital (*R*) and the fixed capital stock (*K*).

Since cost is homogeneous of degree one in prices, there are a series of restrictions as follows:

$$\sum_{j=B,W,M} \beta_{ij} = \sum_{i=B,W,M} \beta_{ij} = \sum_{i=B,W,M} \sum_{j=B,W,M} \beta_{ij} = \sum_{i=B,W,M} \beta_{iR} = \sum_{i=B,W,M} \beta_{iK}$$
(2)

These allow equation (1) to be normalised by one of the factors. Taking the materials price (w_M) as the unit of normalisation, we obtain a normalised translog cost function where costs (relative to materials price) are a function of the relative prices, output, capital, technology and their interactions. From Shephard's lemma, the variable cost share S_i for input *i* is given as:

Unskilled Workers

$$S_B = \alpha_B + \sum_{i=B,W} \beta_B \ln(w_i / w_m) + \beta_{Bq} \ln q + \beta_{BK} \ln K + \beta_{BR} \ln R$$
(3a)

Skilled Workers

[1] This section owes much to the exposition in Adams (1997).

$$S_W = \alpha_W + \sum_{i=B,W} \beta_W \ln(w_i / w_m) + \beta_{Wq} \ln q + \beta_{WK} \ln K + \beta_{WR} \ln R$$
(3b)

Note that the materials equation has been dropped because the cost shares sum to unity.

We can test for homotheticity of the structure of production (i.e. that the cost shares are independent of the levels of output and the quasi-fixed factors) by imposing the following restrictions:

$\beta_{iq} = -(\beta_{iR} + \beta_{iK})$, where $i = B, W$

If these can be accepted, the cost share equations simplify to:

Unskilled Workers

$$S_B = \alpha_B + \sum_{i=B,W} \beta_B \ln(w_i / w_m) + \beta_{BK} \ln(K / q) + \beta_{BR} \ln(R / q)$$
(4a)

Skilled Workers

$$S_W = \alpha_W + \sum_{i=B,W} \beta_W \ln(w_i / w_m) + \beta_{WK} \ln(K / q) + \beta_{WR} \ln(R / q)$$
(4b)

The elasticities of substitution and complementarity can now be calculated. In terms of the technology variable, if the coefficients $\beta_{WR} > 0$ and $\beta_{BR} > 0$, we would say that technology is labour-biased. If $\beta_{WR} > 0$ and $\beta_{BR} < 0$, then technology is clearly skill biased.

The formulation is often further simplified using value added (*VA*) rather than output. In this case the dependent variable is the share of skilled labour in the wage bill, and the factor demand equation is simply:

Skilled Workers

$$S_W = \alpha_W + \beta_W \ln(w_W / w_B) + \beta_{WK} \ln(K / VA) + \beta_{WR} \ln(R / VA)$$
(5)

Again, skill biased technical change would be indicated by a positive coefficient on β_{WR}.

Versions of this structure are very common in the literature. It seems a natural one given the difficulties in accurately measuring a user cost of physical or technological capital (especially one that varies exogenously across microeconomic units). Sometimes the physical capital factor is allowed to be variable and only the technological component is fixed (e.g. Duguet and Greenan, 1997).

Many researchers have estimated equation (5) in employment shares rather than cost shares. Although less appropriate from a theoretical point of view, this clearly has the advantage that it allows a statistical decomposition of the effects of technology into a relative wage component and a relative employment component.

This is only a framework for organising our thoughts over the effects of technology in a well-known neo-classical framework. Other models suggest different rationalisations for the correlation of technology with cost shares. For example, the neo-classical model here takes factor prices as exogenous, which is clearly a questionable assumption since wage-setting is not conducted in a competitive spot market. Models of bargaining would suggest that workers may be able to 'capture' some of the rents from innovation. If skilled workers are more able to do this than unskilled workers (because of higher turnover costs associated with more skilled employees, for example), then the technology-cost share correlation could be driven by relative wage movements rather than relative employment movements. This underlines the importance of analysing movements in factor prices and quantities.

The literature on the effects of technology on wages has been primarily motivated by attempts to assess the productivity effects of computers on highly skilled workers. Note that a competitive labour market would only have one wage for each skill type, so the underlying model behind these correlations is not entirely clear. We offer a critique of the innovation-wage relationship elsewhere (Chennells and Van Reenen, 1998; Harhoff, 1999).

The impact on labour demand can also be derived from the structure outlined above. One problem with this, of course, is that much of the effect of innovation might derive from increased output, which implies estimating the production function directly. In fact, researchers have tended to estimate simpler equations of employment based on aggregating across all workers and estimating employment growth equations (see 2.3 below).

There are, of course, serious difficulties in extrapolating results from the micro-level to produce macro-level implications. We have focused on the demand side, but the equilibrium effects of technological change will also depend on what is happening in other areas of the economy, and in particular to the supply of more skilled labour. Furthermore, reallocations of output and employment will occur within and between sectors that will tend to complicate the aggregate effects. The micro-econometric evidence is only a small part of the story, and researchers should resist extrapolating too much from these partial equilibrium results.

2.2 Skill bias and unemployment

In this section we consider what the implications of our model of skill biased technical change are for unemployment and jobs. There are a great number of complex interactions between innovation and employment but we begin with what we think is the most important route.

If technology is skill biased an exogenous increase in the stock of technological capital (a 'technology shock') will increase the demand for skilled labour relative to unskilled labour. This can be illustrated on the standard relative demand and relative supply diagram. As the relative demand curve shifts out, in equilibrium there is both a rise in the relative wages and the relative employment of the more skilled group.

Note that there is no unemployment in this model since the labour market clears. Now consider introducing some institutional limits to how far the wages of less skilled workers can fall. These could arise due to minimum welfare levels, minimum wages, trade unions or efficiency wage considerations. In this case there will be less of an increase in wage inequality, but there will be some unemployment for unskilled workers.

This is not a new idea. Solow (1966), for example, discussed it in his Wiskell lectures. More recently, the basic supply-demand analysis has become the dominant view of changes in the labour markets of the industrialised countries in the last 20 years, at least in the America. In the flexible labour market of the US, wage inequality has increased and unemployment has remained stable. In the relatively inflexible labour markets of Europe (outside the UK), wage inequality has been stable but unemployment has increased dramatically. Paul Krugman (1996) has christened US inequality and European unemployment as "two sides of the same coin".

The debate on these matters is fierce. As noted in the introduction, the existence of skill biased technical change and the question of whether technology is responsible for recent labour market trends are related, but quite distinct analytical issues. Explaining recent history is a far harder task than simply understanding skill bias. This is not least because of strong disagreement on the appropriate model of the labour market.

There are three key questions to be addressed.

1. Has the demand for skilled workers outstripped the supply of skilled workers? Or more accurately, has the demand/supply gap become greater over time?
2. If demand has accelerated relative to supply, is this due to technical change or some other factor, such as increased trade with less developed countries?
3. If the answer to both 1. and 2. is yes, how much of the change in unemployment and inequality can be accounted for?

Has the demand for skilled workers outstripped the supply of skilled workers?

Katz and Murphy (1992) and Autor, Katz and Krueger (1997) try to date the timing of the increase in demand for skills in the U.S. They use a weighted average of the growth of relative wages and employment, assuming that the labour market is in equilibrium with no unemployment. Given an assumption over the degree of substitutability between the skilled and the unskilled, it is possible to use a CES production function to estimate the relative employment changes. It is very hard, however, to date precisely the timing of the acceleration in demand, although both authors argue it exists (as does Machin, 1998, for the UK[2]).

More general methodologies have been proposed to take into account the unemployment in Europe and elsewhere. Nickell and Bell (1995), Jackman et al

[2] See Mishel and Schmitt, 1996, for a dissenting view

(1996), Manacorda and Manning (1997) argue that there has been relatively little increase in mismatch outside of the UK and US and that most of the increase in European unemployment has other roots.

Has the demand change been due to technical change?

There is greater agreement that, to the extent that demand has shifted towards the skilled, this is due to technology rather than trade. The methodologies used to reach this conclusion are based the fact that most of the change in skills has been a within industry phenomenon (see Berman et al, 1998, for more discussion of this debate).

How much can it account for?

This question needs a full general equilibrium analysis which has rarely been attempted (see Minford et al, 1997, for one attempt). Back of the envelope calculations in Machin and Van Reenen (1998) suggest that technological factors alone can only account for a third or less of the changes in the US and UK, but far more outside these two countries.

Katsoulacos (1996) argues that there is another question that should be considered. He puts forward the proposition that product innovation can increase labour supply. If we assume product innovation (in a general equilibrium context) has no effect on aggregate labour demand, one can still believe that the increase in the average quality and variety of goods stimulated by a faster rate of product innovation can change the leisure/work trade off. If wages are downwards rigid then this increase in labour supply could generate unemployment.

A problem with this argument is that participation and average hours worked have declined for men in the industrialised world since the end of the war. It is amongst women that participation has risen. Product innovations have clearly had a role in relieving women of the burdens of their traditional role as workers in home production. Examples would include technological improvements in domestic production (e.g. dish washers and micro-wave ovens) and in birth control (e.g. contraceptive pills). But (a) these are not the mechanisms Katsoulacos is focusing on, (b) there are a large number of other influences affecting female participation, (c) the implication that rising female participation could be a cause of increased male joblessness is highly controversial (which is not to say that the GE effects are an important area are that is insufficiently researched).

2.3 Technology, homogenous labour and employment

The debate of the previous section is a crucial one for policy makers. Yet there is another strand in the literature which asks whether technology is responsible for falls in jobs *even when it is not skill biased*. Although a great deal has been written on this topic, the literature and the surrounding policy debate are littered with confusions.

Information and Communication Technologies (ICTs) have diffused rapidly in Europe over the last 20 years and unemployment has also risen. The temptation is strong to suggest that there is a causal link between the two. Yet waves of technology have passed over Europe in the past without creating persistent and structural unemployment. The debate over technological unemployment on the other hand has proved persistent. Similar arguments were being made in the 1960s over the introduction of automation, while in the 1930s Lord Kaldor (1932) commented:

"Today there is scarcely any political or journalistic observer of world affairs who does not attribute to the rapid growth of technical improvements one of the major causes of the present trouble".

Yet the fact remains that an examination of long-run unemployment trends shows no upward trend, despite the presence of technical change for several hundred years. If we examine U.K. and U.S. unemployment since the Nineteenth century we can see that the main difference is that unemployment was far more volatile pre-1945 than in the post war period. It is possible that technology has a temporary destabilising effect on employment, but it is difficult to believe that it is the major cause of the recent rise in European unemployment levels. Only technology combined with something else - such as wage rigidity - could be part of the cause.

What can economic theory tell us about the likely effects of technical change on employment? One form of technological change to consider is labour-augmenting process innovations. This case has been explored thoroughly in the literature. There are essentially two forces at work. For a given level of output, this type of technical change means that employment must fall since the same output can be produced with a lower level of inputs. To offset this, however, is the fact that output will increase as prices fall, because costs have fallen. This is the primary 'compensation mechanism' of technical change. It means that examining the impact of technology on output (the production function relationship) is fundamental to understanding the effects of technology on output.

In Appendix I we consider a simple model which shows how the effects of technical change work. This model leads us to the following results:

1. **Price elasticity of product demand.** The greater is the sensitivity of consumers to price changes the more likely it is that an innovation will raise employment. The higher is the price elasticity the greater the increase in output generated by an innovation.
2. **Substitution of capital for labour.** The easier it is to substitute the more likely it is there will be positive effects of labour augmenting technical change, since labour is now relatively cheaper than capital and the firm will substitute into labour. The opposite is true for capital augmenting technical change.
3. **Monopoly power.** If the firm has some degree of market power not all of the reduction in cost will be passed on in the form of lower prices. This will blunt the output expansion effect and make positive employment effects less likely.

Generalisations of the model lead to the consideration of further possible effects.

4. **Market share effects.** If the innovation does not diffuse immediately throughout the industry, the firm will have a cost advantage and so will tend to expand at the expense of its rivals. This will mean larger effects at the firm level in the short

run. It also means that researchers should be careful in generalising from the micro-results to the economy level.

5. **Union effects.** If some of the efficiency gains from innovation are captured by unions in the form of higher wages (or reduced effort, etc), this will also blunt the output expansion effects. The results are uncertain if the union also bargains over the employment level (see Ulph and Ulph, 1994).
6. **Product Innovation.** Product innovations will tend to have stronger output expansion effects and are therefore more likely to result in employment increases (see Katsoulacos, 1984, for a fuller analysis)
7. **Economies of scale.** These will tend to magnify the positive employment effects. See Dobbs et al. (1987)

3 ECONOMETRIC MODELS

We discuss some econometric problems focusing on fixed effects, endogeneity and measurement. Consider the basic equation to be estimated as the stochastic form of equation (5)

$$S_W = \alpha_W + \beta_W \ln(w_W / w_B) + \beta_{WK} \ln(K / VA) + \beta_{WR} \ln(R / VA) + u$$
(6)

where u represents a stochastic error term. This could be justified by allowing the α_W to be random across units, or due to measurement error or optimisation mistakes. It is unlikely, however, that the error term is uncorrelated with other right hand side variables. Some firms may have dynamic managers who employ both top quality workers and high quality technology. For this reason, controlling for **fixed effects** is important and researchers might estimate the equation in differences (or by including dummies if the time series is long enough):

$$\Delta S_W = \beta_W \Delta \ln(w_W / w_B) + \beta_{WK} \Delta \ln(K / VA) + \beta_{WR} \Delta \ln(R / VA) + \tau t + e$$
(7)

where Δ denotes the difference operator, τt denotes time dummies, and e the error term. Unfortunately, estimating this type of model usually requires panel data, which is rare in the firm level work. This is one reason why most research has focused until recently on the industry level.

A second fundamental problem is dealing with the issue of **endogeneity**. Even when unobserved heteroegeneity is removed, firms might still change their technology in response to a change in the make-up of skills available, rather than vice versa. If the 'technological' factor was truly fixed, this would not be an issue. But the factor is `quasi-fixed' meaning that it will move partially towards the long-run equilibrium in the short-run. Weak exogeneity (R is insensitive to current shocks this period, but may partially adjust next period) may be more plausible for R&D than for other technology proxies (such as computer use). The use of longer differences (used to mitigate such problems as measurement error) will exacerbate these problems of endogeneity. The only solution is to develop instrumental variables to deal with the fact that the technology and the skills decisions are being taken simultaneously. Unfortunately, such instruments are not easy to find, and researchers have been rightly reluctant to use the standard approach of using lags because of concerns that they are weak instruments.

A related issue is the interpretation of the coefficients on the relative wage terms. These terms are directly involved in the construction of the dependent variable. It is doubtful how much of the inter-firm or inter-industry variation in relative wages is due to changes in the price of labour, rather than due to changes in the quality mix of labour which is imperfectly captured by observable skill. An intellectually respectable solution would be to use credible instruments for relative wages. One commonly encountered short cut in the literature is to argue that time dummies will capture the real variation in wages, and to include these instead of the relative wage terms.

The third and perhaps the most basic issue, however, is the problem of **measurement** of technology. This is a very serious problem, since the technology input is a far more nebulous concept than the input of, say, labour, which in itself is difficult enough to measure. The traditional approach is simply to use time trends. The problem here, of course, is that the trends are likely to be picking up a lot more than just technical change, such as unmeasured price movements, changing demand conditions, cost shocks and so on. These criticisms are well known from the debate on how suitable total factor productivity (TFP) is as a measure of technology.

Researchers have turned to a variety of alternatives in seeking observable measures of technology. We can distinguish crudely between three types of measure, which correspond to inputs into the knowledge production function, outputs from the knowledge production function and subsequent diffusion of these outputs around the economy.[3] Inputs are generally measured by R&D activities. R&D expenditure has the advantage that it is measured in many databases over time, across countries and in a reasonably standard way[4] - at least by comparison with the alternatives. Also, R&D is measured in terms of a unit of currency, which provides a natural weighting, whereas other innovative measures are more qualitative. A big disadvantage of using R&D as the technology measure is the existence of spillovers. A firm might invest in large amounts of R&D without receiving any benefit from it, if the R&D does not produce any outputs (either in the form of innovation for the firm, or in the form of acquiring the ability to learn from other firms' innovations). There are long and unknown variable lags between the act of investing in R&D and reaping useful output from it.[5] The transmission mechanisms for knowledge to spill over from one firm to another are also poorly understood. For example, the R&D spending of Intel has dramatically affected the development of computer technologies used by other firms all over the world, but the process by which this knowledge has been absorbed by other firms is unclear, and rarely addressed in the literature.

Patents are a widely available and standard way to measure the outputs of knowledge. The problem with patents is that a large number of them appear to be of very low

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[3] This roughly corresponds to the Schumpeterian triad of invention, innovation and diffusion.

[4] In OECD statistics most countries follow the guidelines of the Frascati manual (1993). Within countries accounting regulations often define how R&D is to be reported (e.g. in the USA under FAS and in the UK under SSAP13(Revised).

[5] Of course the same is true of the standard way in which the physical capital stock is measured. The main difference here is that the degree of uncertainty involved with R&D investments is much greater, and there is usually a method of benchmarking the physical capital stock in a particular year.

value and there is no obvious method of weighting them to take account of this.[6] In some countries expert innovation surveys exist, which can be viewed as a method of cutting off the lower tail of low value patents. The UK Science Policy Research Unit (SPRU) Innovation Survey is a good example of this, since industry experts were asked to list the most important innovations in their field, in order to weed out the innovations with little value. Output measures such as patents suffer from some of the problems of R&D – such as spillovers and variable time lags – and add new problems – such as the difficulties of dealing with count data.

Diffusion measures seem to be closely related to what is usually thought of as technology. A common example would be the use of computers in a firm. Researchers are usually faced with the problem of which technologies to include: what sort of computers (word processors, mainframes); whether also to include production-based technologies (lasers, robots, NC, CADCAM); how to weight the usage (the proportion of people using the computer is a common form of weighting). The most satisfactory method seems to be constructing the capital stock of information technology (IT), although since IT is hardwired into more and more modern organisations, separating out this component becomes increasingly difficult. Measuring the diffusion of a particular technology is difficult in any time series context, since the passage of time changes the significance of using a particular type technology. For example, in 1978 an indicator of whether a computer was extensively used within the firm gave a very different signal to that same indicator in 1998. Diffusion-based measures of technology are more likely to suffer more from simultaneity problems than, say, R&D. Current changes to a firm's environment will have less of an effect on something like R&D than on the decision whether or not to postpone investing in more computers. This is primarily because of the greater adjustment costs attached to restructuring or cancelling a research programme than in purchasing a new piece of hardware.

The measurement of skills is a less controversial issue, and the problems associated with it are well known. There are two main methods of measuring skills. Perhaps the most common in the literature is to use an indicator of occupation, often simply by dividing the population into manual (production) and non-manual (non-production) workers. Such categorisations can be criticised, since many non-manual occupations require very low levels of skill. Education-based measures are more closely tied to ideas of levels of human capital, but face the problem that even highly educated workers may not be employed doing very skilful jobs. Some authors have developed measures based on job content, where an occupation is broken down into different levels of task complexity (see Wolff, 1997). In studies that have compared them, these measures all tend to be highly correlated across industries (e.g. Gera et al, 1997). Nevertheless, there are real worries that the categories chosen are not comparable over time and across countries.

Another measurement issue relates to double counting. Innovative activities tend to be labour intensive and involve skilled workers. R&D is a good example, since typically about half of all R&D is staff costs and only 10% capital costs. This will automatically generate a positive correlation between the level of skilled (i.e. better

[6] Some current ideas include renewal fees, number of countries where the patent is registered, surveys of inventors and citations.

paid) employees and the level of R&D. Correcting for this ‘double counting’ has been found to be important in the productivity literature. The problem reappears here in many guises.

Finally, there are issues to be grouped under ‘selectivity’. The usual problems of sample response and survivor bias are encountered, but there are particular problems relating to the use of R&D expenditure. In most European countries, disclosure in company accounts of the amount of R&D carried out is not compulsory. This means that researchers have to be aware that excluding, or setting to zero, those companies which do not disclose any R&D is likely to introduce a selectivity bias.

4. RESULTS FROM TSER STUDIES

4.1 Skills

4.1.1. Industry Level Studies

Berman, Bound and Machin (1998) use the UN General Industrial Statistics Database to provide some basic decompositions of the changes over time in the skill distribution across the manufacturing sectors of 14 different industrialised countries since 1970. In each country there has been an upgrading in the skill structure (as measured by the employment or wage bill share of non-production workers). This has been accompanied by an increase in wage inequality in some (notably the US and UK), but not all, countries.

They then decompose the change of skilled employment share into a `within industry’ and `between industry’ component.

$$\Delta P = \sum_i \Delta S_i \overline{P_i} + \sum_i \Delta P_i \overline{S_i}$$

Where P = proportion of skilled workers, S = share of industry *i* in total employment, a bar denotes a mean over time and the is the difference over the same two time periods.

The between industry contribution arises because the less skilled industries (such as textiles) have been declining as a share of total manufacturing employment. This effect of industrial restructuring is relatively minor,, however. The vast majority of skill growth has occurred `within’ industries. It appears that the within industry growth has occurred more in some industries than others. They find that chemicals, computers and non-electrical machinery and printing and publishing are particularly large contributors to the within component, and this tends to be true across all countries (the rank correlation coefficients tend to positive across countries). Since these are also industries which have has a lot of technical change, the authors argue that their results suggest that technological factors may be behind the upskilling evident in the data.

An important drawback of the Berman et al study (and the earlier studies which focused on the U.S.[7] using a similar methodology) is that there are no direct measures of technology. **Machin and Van Reenen** (1998) estimate a version of equation (7). They use 15 two digit manufacturing industries from 7 OECD countries (Denmark, France, Germany, Japan, Sweden, UK and US) between 1973 and 1991. The data was based on the OECD STAN/ANBERD dataset combined with occupational data from the UN dataset used by Berman et al. Information on educational sources was obtained by aggregating individual datasets from the different countries. This latter task was very time consuming and was done with the collaboration of fellow TSER colleagues in France, Germany and elsewhere.

Their measure of technology was R&D as a proportion of value added. There was a positive and significant association of skill upgrading and R&D intensity in almost every specification. This was robust to different measures of skill, conditioning on capital and output, using employment shares as the dependent variable, including industry wage differentials as a control variable or using either first- or four-year differences. They conclude that direct measures of technical change are important in explaining the upgrading of the skill structure, although stress that technology accounts for different proportions of the change in different countries (for example, the proportion `explained' in the US and the UK is far smaller than elsewhere).

Goux and Maurin (1997) probe the decomposition of sectors into within and between components in more detail for France. They find that in contrast with most other countries most of the change in skill shares in France are due to between industry movements and these movements are driven by changes in domestic demand rather than import/export patterns. Part of the reason for this difference with the results from other countries is that the supply of qualifications has expanded very rapidly in the 1970-1993 period in France and was accompanied by falls in wage inequality. A second reason may be that they look at non-manufacturing sectors instead of just the manufacturing sector. The within sector changes tend to be larger in manufacturing than services (although as **Desonqueres et al,** 1998, and Autor, Katz and Krueger, 1998, show in the US and UK, at least the within sector movements also dominate).

Goux and Maurin (1995) complement their decomposition analysis with some direct measures of technical change. They estimate a version of equation (7) for higher and lower professional share of the wage bill between 1982 and 1993 for 35 sectors (aggregated from Enquete Emplois) but replace the technology variable (R/VA) by a set of industry fixed effects. They then regress these fixed effects against cross sectional measures of technical change drawn from the TOTTO surveys. Computer utilisation is found to be associated with significantly greater skill upgrading in these estimates. This is quite consistent with US and UK studies (e.g. Machin and Van Reenen). More surprisingly, however, they do find that a measure of the utilisation rate of industrial technologies (e.g. robots) has a negative correlation with skill upgrading. One suspects that these measures of diffusion may be subject to some sort of definitional problem. Industries with a lot of industrial technologies are likely to be more reliant on manual workers. Sectors with a growing number of white collar workers are more likely to have computers. Although R&D intensity is less likely to

[7] For example, Berman, Bound and Griliches (1994) and Bound and Johnson (1992).

be endogenous (at least in the short run when it is relatively fixed) Machin and Van Reenen attempt to control for this problem by explicitly instrumenting R&D with government subsidies for R&D (assumed exogenous). They did not find evidence of endogeneity bias in their sample.

Fitzenberger (1996) takes a slightly different approach in his analysis of German skill patterns between 1970 and 1990. He follows Leamer (1996) in criticising labour economists for working with an overly simplistic model which underestimates the importance of trade vis-à-vis technology. Using a three skill group approach he shows that in Germany both the more qualified and less qualified had faster wage growth than the middle group (broadly, those with only an apprenticeship training). The unemployment of the least skilled group had risen faster than that of the other groups, however. This is consistent with a view that the demand for the most skilled has been increasing relative to the other groups as both their wage and employment relativities rose. The declining position of least skilled is a combination of lower demand and wage increases generated by union power.

The trade approach focuses on the sector bias of technical change. If technical change is faster in the skill intensive sectors then this `mandates' a growth in the skilled-unskilled wage differential. Fitzenberger cannot find a clear pattern in the data when he examines TFP growth across different sectors. Some work does suggest some sector bias towards the more skilled sectors in the US, but there is no consensus[8]. Part of the difficulty is undoubtedly in estimating TFP which is subject to a range of problems being an indirect residual from a postulated production function.

Another study which focuses on Germany is by **Falk and Koebel** (1997). They take a quite aggregate approach dividing the economy into 5 sectors. Using bi-annual data from 1977 to 1994 they estimate factor demand equations for three groups of workers, materials and capital. They assume that capital is variable and take technology to be simply a common time trend[9]. They also find that technology is the main factor in explaining skill upgrading. Unfortunately, the study is also subject to the criticism that there are no direct measures of technology.

4.1.2 Enterprise Level Studies

Aggregation may be a serious problem for these industry studies, so we now consider analyses based at the level of the enterprise (both firm and plant).

Duguet and Greenan (1997) use an innovations survey to estimate cost share equations for a large panel of French manufacturing firms 1986-1991 in long differences (there are almost 5000 companies). They jointly model the 5 technical change variables (product improvements, new products, product imitations, process improvements, process breakthroughs) alongside the share equations (two types of labour and capital). So capital is treated as variable and innovations as quasi-fixed.

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[8] For different conclusions see Sachs and Shatz (1994), Lawrence and Slaughter (1993), Haskel and Slaughter (1998), Desjonqueres et al (1998).

[9] They use the normalised quadratic cost function rather than the translog which gives rise to a slightly different functional form for the factor demand system than that represented in equation (7).

They find that skilled workers are not as easily substitutable for capital as unskilled workers. Furthermore, they find evidence for skill bias and argue that it comes primarily from the introduction of new products, although their results here are mixed. There appear to be differences in the different sorts of innovation but with not systematic pattern.

One problem with subjective innovations surveys is the comparability of the notion of innovation across different firms. Different firms may have of what counts as `innovation'. An interesting extension, given the increasing availability of this type of innovation survey (e.g. CIS), would be to use the longitudinal aspect of the panel when the question is asked to the same firms in future. If the same individual is questioned over time then differencing can remove the `permanent' component of the measurement error.

Greenan, Mairesse and Topel-Bensaid (1998) also use a large sample of French firms (about 11,000) producing in both the manufacturing and non-manufacturing sectors (combining the Enquete Structure des Emplois with the BIC). They have information for three years (1986, 1990 and 1996) and estimate a variety of long differenced models. They use an unusual measure of IT capital intensity derived from the firm's balance sheet expenditure on office and computing equipment. This includes computers but also less advanced equipment (such as photocopying machines). They are also careful to avoid double counting expenditure on IT personnel. Using four skill groups and a version of equation (7) they identify significant negative effects of IT capital on the share of blue collar workers, but only in the manufacturing sector.

Machin (1996) uses the British Workplace Industrial Relations Survey (WIRS) panel 1984-1990 of 402 establishments, which contains information on the presence of computing technologies. He distinguishes between the employment proportions of five occupational groups. The introduction of computers has a significantly negative effect on the least skilled groups and a significant positive effect on the most skilled group.

Machin's measures of computing are rather crude (basically a binary dummy). **Caroli and Van Reenen** (1998) extend the UK analysis by using a more sophisticated set of variables to measure the impact of computing. They also find that the establishments which have more intensive use new technology reduce the proportion of the least skilled workers to a much greater extent than other plants. A further finding is that plants who introduced major organisational changes in the early 1980s were more likely to shed unskilled workers in the later 1980s than plants who do not introduce organisational innovations. They compare these results to the Enquete Reponse, the French equivalent of WIRS. Following about 1000 of these establishments over time, they also find that the plants with the highest levels of technological and organisational innovation between 1989-1992 had the fastest falls in unskilled employment in the 1992-1996 period.

Another paper which stresses the importance of organisational influences is **Aguirrebriria and Alonso-Borrega** (1997). They use rich Spanish firm level panel data between 1986-91 (over 1000 firms). They are able to distinguish between 5 types of labour and three types of capital (fixed, R&D, and "bought-in" innovations). They estimate employment (not cost share) equations along the lines of equation (7) treating the capitals as quasi-fixed. The equations are first differenced and right hand side variables are instrumented by their own levels in t-2 using the Arellano and Bond (1991) GMM procedure. Since some of the innovation variables are zero they also use introduction dummies. Their most interesting result is that they obtain strong negative impacts of the introduction of technological capital on the least skilled group. Smaller incremental changes in the stock variables do not have significant impacts on the demand for skills. This paper is admirable for its attempt to deal with endogeneity and probe the innovation relationship more deeply that most other studies. Nevertheless, difference based GMM methods for dealing with endogeneity have come in for much recent criticism due to the `weak instruments' problem (e.g. Blundell and Bond, 1998; Mairesse and Griliches, 1997). Also the exact definition of "technological capital" is rather unclear in the paper.

Data constraints have hampered establishment level analysis in German studies. A notable exception is **Kaiser** (1998). She focuses on a sample of firms in the German business-related services' sector. Her employment measure is the managerial forecast of what she expects the change in net employment to be for each of four different skill groups over the next two years. Using ordered probit techniques a positive impact of current IT capital intensity is detected for employment growth of the most skilled group and a negative and significant impact revealed for the least skilled group. The main criticism of the study is the lack of any real longitudinal element to the data and the fact that employment is measured in qualitative rather than quantitative terms.

4.1.3 Summary

We end this sub-section with three general comments.

First, there does appear to be considerable support for the notion of skill-biased technical change from TSER research. This occurs across a range of studies, and these are usually robust to controlling for fixed effects. This is bolstered by findings from other research in the US (Doms et al, 1997, Dunne et al, 1997; Berndt et al, 1992; Autor et al, 1998, Mishel and Bernstein, 1998; Goldin and Katz, 1997; Bartel and Lichtenberg, 1987; Osterman, 1986; Adams, 1997; Wolff, 1996) and in other countries (Hansen, 1995, on Sweden; Gera et al , 1998, on Canada; Vainiomaki, 1998, on Finland).

Secondly, there have been few attempts to find instrumental variables to deal with the potential endogeneity of technology. Candidates could include government-induced schemes to alter the incentives to accumulate technological capital (such as R&D tax credits, government grants etc).

Thirdly, there are surprisingly few studies which try to analyse the mechanisms by which technological change translates into higher demand for skills. One mechanism is through organisational changes such as delayering, decentralisation and giving greater autonomy to workers. These organisational factors have been found to be important in the case study evidence and in the literature on the productivity paradox (investigating why computers have not raised measured productivity by as much as might have been expected). Some of the most interesting work discussed above suggests that this organisational restructuring could be the link between technology and labour demand (cf. Bresnahan et al. (1997)).

4.2 Employment

There are fewer econometric studies of the relationship between overall employment and technology. Those which do exist tend to be mainly descriptive in character and focused on specific industries (e.g. Dosi and Soete, 1983). The analysis in Blechinger et al. (1998) captures some of the salient points. An examination of the OECD STAN/ANBERD database (which covers manufacturing) reveals that the high technology industries (those with higher R&D intensity) expanded more quickly (contracted less slowly) than the medium or low technology industries.

TSER Research has focused on company level panel data.

Van Reenen (1997) examines 598 firms listed on the UK Stock Exchange. Companies are not required to disclose information about the skill composition of their workers. He examined a dynamic employment equation:

$$LnN_{it} = f_i + \sum_{k=0,\dots 6} b_k\, INNOV_{it-k} + a_1 lnN_{it-1} + a_2 lnN_{it-2} + g_1 ln(W_{it}) + g_1 ln(K_{it}) + d'x_{it} + time\ dummies + v_{it}$$

(8)

Where N = total employment, $INNOV$ is a count of firm level innovations, W = average wage, K = fixed capital, f = a fixed effect and x includes other controls such as the number of industry innovations, i = firm.

This model is derived from the first order conditions for a CES production function. (see Appendix I). The user cost of capital is proxied by the fixed effects and time dummies. The innovation measures are drawn from the SPRU innovations survey (see section 4 above). These are headcounts of the first commercialisation of technologically important innovations identified by expert surveys in 1983, 1980 and 1970.

Equation (8) was estimated in first differences using the same standard GMM technique of Arellano and Bond (1991) that were used in the study by Aguirrebriria and Alonso-Borrega (1997) discussed above. Lagged employment was always instrumented and in some of the specifications firm wages and capital stocks were also treated as endogenous. The sample period runs 1976 through 1982.

Throughout the paper significantly positive effects of innovation were identified on firm employment. These were stronger for product innovations rather than process innovations. Over time the impact of innovations died away, presumably as other firms imitated the leading edge firm.

Martinez-Ross (1999) estimates a similar model for Spanish firms 1991-1995. She also finds it important to allow for second order dynamics in the employment equation. Her measure of innovation is drawn from a survey of Spanish firms were firms are asked if they have introduced new technologies, and if so, how many (similar to the Community Innovation Surveys). She criticises the Van Reenen study for assuming that the innovation measures were weakly exogenous. Instrumenting innovations by lagged innovations leads to a far lower (and insignificant) effect when compared to the OLS results.

The Van Reenen study argued that the rarity of SPRU innovations (compared say to the Spanish survey) would make lagged innovations an extremely poor instrument for current SPRU innovations. If patents only effect employment when they are commercialised as innovations, then past patent stocks become legitimate instruments. When using lagged patents as an instrument for innovations, he could find no evidence of endogeneity bias.

Blechinger, Kleinknecht, Licht and Pfeiffer (1998) use panel data from a large sample of Dutch firms in both the manufacturing (772 companies) and services sectors (836). They relate employment growth over the 1988-1992 period to characteristics of the firm in 1988. Essentially these controls include the size of the firm and indicators of technology. They found that office automation had a significantly positive effect in the service sector and production automation had a significantly positive effect in the manufacturing sector. The authors recognised the potential endogeneity problem. There are many unobservable reasons why firms may be growing faster in 1988-1992 and these shocks could induce firms to innovate in order to capture the higher demand. They try to control for these by including an inverse Mills ratio in the manner of Heckman (1979). This procedure is formally close to instrumenting the endogenous variable. It is still the case that one requires a variable that will shift the probability of innovating that is uncorrelated with the residual term in the employment growth equation. Unfortunately there are no obvious identifying instruments in this study and much then relies on the particular functional form.

The Blechinger et al study also examines the impact of the lagged proportion of R&D personnel on employment growth. Again, a positive effect of the innovation proxy is identified. Other studies using R&D have not found the same result. **Klette and Førre** (1998), for example, uses data from Norweigan manufacturing plants and industries to investigate whether R&D intensity is associated with above average employment growth. The data is extremely rich and comprehensive being essentially the population of firms with over 20 employees. R&D is measured as firm R&D intensity in the same line of business as the plant.

Klette found that R&D intensive establishments had lower net job creation than their less R&D intensive counterparts. This was robust to controls for size, sector and business cycle. Furthermore, the high tech sectors themselves fared worse in employment terms than other sectors (although not significantly so). A worry concerning his study is that the Norweigan economy suffered from a series of negative shocks arising from the oil-sector and banking sector. Nevertheless, Klette claims that his results are not driven by a few disastrous cases associated with these shocks but are a more general phenomenon. It is important to replicate Klette's extremely careful study in other countries to see if his results are a specific feature of a small open economy in crisis or a more general phenomenon.

A novel approach to the question of the impact of computers on employment is offered in **Entorf, Gollac and Kramarz** (1997). French individual workers are followed for 5 quarters in the Enquete Emplois. By matching these employees with other surveys (e.g. TOTTO, DMMO, EET) the authors can examine the employment profile of workers who use different forms of new technology and compare their employment trajectories with those who did not use these devices. Using multinomial probit techniques and controlling for a host of observed (gender, education, experience, part-time, region, occupation, establishment turnover and age, etc) and unobserved factors they find that computer use reduces the probability of unemployment in the very short run (one quarter) but not the long-run (one year). Although the authors make extensive attempts to control for selectivity one is still left wondering whether the results could be driven by the fact that employers are unlikely to give advanced tools to workers who are likely to leave in the near future. Still, this is one of the most sophisticated attempts to examine the problem in our current batch of research.

4.2.3 Summary

The TSER research findings are comparable with other parts of the literature on innovation and employment. Overall, there appear to be consistently positive effects of proxies for product innovations on the growth of employment (e.g. Konig et al. (1995), Entorf and Pohlmeier (1995), Smolny (1998) for German firms; Leo and Steiner (1994) for Austrian firms). The results for process innovations are very mixed – although usually insignificant, several examples of positive effects exist (e.g. Blanchflower and Burgess (1997) for UK and Australian plants; and Regev (1995) for Israeli firms). In an interesting study of French data, Greenan and Guellac (1996) find that process innovations have a strong positive effect at the firm level, but this washes out at the industry level. The story is reversed for product innovations. When measures such as R&D are used, negative correlations frequently arise. (e.g. Brouwer et al. (1993) for Dutch firms.). Hall (1987) find different effects for small U.S. firms (positive) than large U.S. firms (negative). The most plausible explanation for these results is that the effects of innovation depend critically on the type of innovations being produced

In general, existing employment studies have rarely been conducted with as detailed an eye to the econometric problems involved as those investigating wages and skills. This perhaps reflects the greater theoretical ambiguity involved in estimating the relationship (and policy interest in the microeconomic results). The econometric problems are particularly difficult in these studies however, and future work needs to address these more seriously.

5. CONCLUSIONS

In this paper we have focused on studies in the TSER Network R&D, Innovation and Productivity which relate to the impact of technical change on employment. We distinguished between studies which distinguished between different types of skills and those that focused on total employment. Most studies have been micro-econometric so relate indirectly to the macro question of the causes of aggregate unemployment.

In any survey it is difficult to reach definitive conclusions, aside from methodological ones. Nevertheless we hazard the following stylised description of our brief survey.

First, there is considerable evidence of a positive correlation of various measures of technology with the skill structure suggesting that technology is, on average, biased towards skilled labour. Secondly, the evidence on total employment is more mixed, with most measures suggesting a positive association (notably product innovation), but some others (notably R&D-based) being more negative. On balance, innovation at the micro level is probably associated with employment growth.

The three main methodological problems with these results is the presence of unobserved heterogeneity, endogeneity and measurement problems. Most of the studies here have recognised the problem of heterogeneity and have turned to panel data where one can make attempts to control for fixed effects. There are well known problems in this but we feel that this is a huge improvement over earlier work examining cross sectional correlations.

There are fewer attempts to deal with the issue of the endogeneity of technology. Some authors have relied on GMM approaches which identify based on an assumed serial correlation structure. A more satisfactory approach would be to use some of the empirical work on the determination of innovation. The large numbers of public policies towards stimulating innovation may offer some hope for identification in this respect. These policy changes may in many cases be regarded as natural experiments which exogenously shift the innovation measure independently of shocks in current employment and skills.

Another area for future work is the theoretical framework for analysing technology effect. The basic neo-classical model needs to be supplemented by a richer understanding of technological adoption in a tractable manner. There are a plethora of theoretical models; the task is to translate them into an empirically coherent form for implementation and testing. In particular, examining the role of organisational change in translating the effects of technology into labour demands should be a key area of future research (Caroli (1998)).

Finally, the links between micro-economic analysis and macro-economic outcomes are still very crude. We re-iterate that the existence of skill biased technical change is not the same as saying that technology is responsible for unemployment. Linking the empirical results here with simple GE models must be another important avenue of future research.

Appendix I

The micro-economics of technology and employment : a simple example

A special case of the translog cost function is when there is a constant elasticity of substitution between the factors (the translog allows for more general patterns of substitution and complementarity). To simplify the discussion we will work with this form. Write the production relationship as:

$$VA = T[(AN)^{(\sigma-1)/\sigma} + (BK)^{(\sigma-1)/\sigma}]^{\sigma/(\sigma-1)}$$
(A1)

Where K = capital, N = labour, VA = value added. T represents a neutral technology parameter, A is labour augmenting technology and B is capital augmenting technology. If a firm maximises profit then the labour demand equation is:

$$\log N = \log VA - \sigma \log(W/P) + (\sigma - 1)\log A$$
(A2)

The elasticity of labour demand with respect to a change in labour augmenting technical progress is given by:

$$\frac{\partial \log N}{\partial \log A} = \left(\frac{\partial \log VA}{\partial \log P}\right)\left(\frac{\partial \log P}{\partial \log MC}\right)\left(\frac{\partial \log MC}{\partial \log A}\right) + (\sigma - 1)$$
(A3)

or more succinctly,

$$\frac{\partial \log N}{\partial \log A} = \eta_P \mu \theta + (\sigma - 1)$$
(A4)

where the effect of technical change on labour demand is now written as a function of four factors: the price elasticity of product demand[10] (η_p), the mark-elasticity (a measure of market power, μ), the ‘size’ of the innovation as measured by its effect on marginal cost (θ) and the elasticity of substitution between capital and labour (σ) .

The interpretation of all of these results is quite intuitive and discussed in the text. Some points to note are that:

- When there is perfect competition (θ =1), and no substitution between labour and capital (e.g. if labour is only factor of production σ = 0) then for a normalised innovation (θ =1) the effect on labour demand will hinge on whether demand is

[10] We are assuming the elasticity between value added and output is unity.

elastic. If product demand is elastic ($\eta_p>1$) then employment will rise, if it is inelastic ($\eta_p<1$) then employment will fall.

- Since it is difficult to know the effect of any given measure of innovation on marginal cost, it is very difficult to compare different studies to determine the quantitative effect of an innovation – there is no natural scale of normalisation.

For further discussion of these points see Van Reenen (1997).

Table 1: The effect of technology on skill structure

A. Industry level					
Study	**Method**	**Data**	**Proxy for technology**	**Controls**	**Result**
Falk and Koebel (1997)	5 Equation System from normalised quadratic cost function; 3 types of labour, capital and materials; SUR	5 sectors in Germany: manufacturing, energy, water & mining, construction, wholesal & retail, banking & insurance; bi-annual 1977-1994;	time trend	prices of all factors (all assumed variable)	No capital skill complementarity; wage elasticity of demand greater for least skilled; trend dominates explanation for increase in skilled proportion
Fitzenberger (1997)	Leamer Method; Regression of output prices changes and TFP changes on initial factor shares (3 skill groups). TFP growth slowest for the middle group; weighted OLS	1970-1990 West German sectors (36 traded and 13 non-traded); national accounts, IAB-BST data: 1% sample of Social Security records	TFP with 3 labour inputs (estimates sensitive to the factor share weights used).	Capital	
Goux and Maurin (1997)	Decomposition analysis of aggregate skill changes based on extension of Katz and Murphy methodology	FQP (Enquete sur la formation et la qualification Personnelle) 1970, 1977, 1985, 1993; National statistics;	Mainly implied from the testing methods; Computer use, industrial technologies from TOTTO		Most of the change in skills due to shifts in domestic demand between industries; two types of technology (computers and production technologies) accoutn for a maximum of 15% of 1970-93 labour demand shifts

Goux and Maurin (1995)	Wage bill share of higher and lower grade professionals, administrators and officials; regress industry fixed effects against technology measures	35 French industries (all sectors) each year 1982-93; Enquete Emploi wage and educational data; National statistics; 1987 and 1993 TOTTO surveys of technology	Computer use, industrial technologies (e.g. robots, NC machine tools, telewatching)	Capital, output, time dummies	Industry fixed effects positively correlated with computer use, but negatively correlated with 'industrial technologies'
Machin and Van Reenen (1998)	Changes in wage bill (and employment) share of skilled employees (occupation and education)	1970-89; 2 digit manufacturing industries in Denmark, France, Germany, Japan, Sweden, UK, US (15)	R&D intensity	Capital, value added, time dummies, imports (OECD and non-OECD)	Skill upgrading faster in high R&D industries in all countries

B. Enterprise level

Study	**Method**	**Data**	**Proxy for technology**	**Controls**	**Result**
Aguirregabriria and Alonso-Borrega (1997)	Factor demand equations for 5 types of labour, and 3 types of capital (total, R&D, bought-in technology); first differences; GMM; attempts to control for selectivity through propensity matching	CBBE; Balanced panel of 1,080 Spanish manufacturing firms 1986-91	R&D, expenditure on technological capital - "successful innovations generated externally to the firm"	Output, capacity utilisation, white collar-blue collar wage differential, time dummies	No effect of R&D and stock of technological capital has an unskilled bias; but dummy for introduction of 'technological capital' has strong negative effects on blue collar workers; most change in downturns
Caroli and Van Reenen (1998)	OLS regressions of change in share of skilled	(a) (a) 402 British establishments from	(a) % of workers affected by micro-	(a) organisational change, total	(a) technology significant effects

	workers	WIRS panel 1984-1990; 6 occupational groups (b) 992 French establishments Enquete Reponse 1992-1996; 5 occupational groups	electronic, computer intro, industry level computer use (b) computer use	employment growth, 1984 plant characteristics (b) org change (delayer), total emp growth, 1992 plant characteristics	(negative effect on least skilled and positive effect on most skilled); OC has negative signif effect on least skilled (b) no effect of technology in panel (but some in cross section); OC has signif negative effects on least skilled
Duguet and Greenan (1997)	I Probits of long-differenced innovations data (for five types of innovation); II Trans-log cost share equations in long-differences	Panel of 4,954 French manufacturing firms, 1986 and 1991	Five types of innovation: product improvement; new product; product imitation; process breakthrough; and process improvement	I Firm size, market share, diversification, industry dummies, cost shares of 'conception' and 'execution' workers; II Both types of workers, capital, production volume	Skill bias in favour of 'conception' labour, and 'execution' labour a stronger substitute for capital. Reduction in demand for execution labour largely due to new product innovation
Greenan, Mairesse and Topiol-Bensaid (1998)	Essentially cross sectional and 4 year differences of the occupational structure (aggregated into 4 groups)	c. 11,000 observations on French firm-years in three time periods (1986, 1990, 1996) - whole economy; from combining ESE, BIC; correct for double counting using measure (b) (see right)	(a) IT capital from firms balance sheet: basically office and computing (inc. photocopying equipment, etc); (b) use numbers of IT workers - computer staff/electronics specialists/research staff/analysis staff	Capital, value added, sector dummies	Strong correlations in cross section, but only the negative effect of IT on lowest skilled group robust in time series
Kaiser (1998)	Ordered probit for expected net employment change (3 categories) for 4 groups of skills 1995-1997	German firms in 'business related service industries' 1995; 1059 firms	IT investment as a share of total investment	Total investment per capital, number of employees in each skill group, sales, credit rationing, export status	Positive and significant effect on most skilled group; negative and significant effect on least skilled group.

Machin (1996)	Employment change for 6 occupational groups	UK WIRS panel data 1984-90; 402 plants; all industries	Introduction of any computers between 1984 and 1990	Dummy for fall in total employment, any manuals 1984	Positive for most skilled groups (managers and technicians) and negative for least skilled group (unskilled manuals)

Table 2: The effect of technology on total employment

Study	Method	Data	Proxy for technology	Controls	Result
Blechinger, Kleinknecht, Licht and Pfeiffer (1998)	I. OLS static conditional labour demand equations separately for each country	I. Manufacturing firms in Germany (1,821), Denmark (528), France (3,600), Norway (743), Spain (1,998), Luxembourg (241), Belgium (557), Italy (16, 374) in 1992 only	I. Community Innovation Survey (CIS) - subjective question; whether firm performs any R&D; whether R&D directed at product or process	I. Sales, sales squared, labour costs (industry level), qualitative indicators of barriers to innovation, exports, subsidiary status	I. Innovation indicator insignificant in every country except Italy (more small firms); R&D has a positive correlation (probably due to fixed effect)
Blechinger et al (1998) - cont.	II. Employment growth 1988-92 on 1988 characteristics; separate estimation for mnfg and services; attempt to control for survival bias using Heckman method	II. 772 mnfg and 836 service firms in Netherlands	II. Product and process R&D personnel %; indicators for office and production automation	II. Dummies for size class	II. R&D has positive effect in both sectors (process stronger than product); office automation positive effect in services; production automation positive effect in mnfg
Entorf, Gollac and Kramarz (1997)	Multinomial logit of individual employment paths, with individual fixed effects, controlling for economic conditions in some specifications	EE, the French household-based labour force survey; TOTTO, the 1993 technology supplement to the labour force survey; EET, the quarterly follow-up to the EE; and DMMO, an establishment based survey of labour turnover	Computer use, computer experience, use of other types of new technology (e.g. robot, video, fax)	I Gender, education, region, part-time indicator, occupation, size and status of employer, experience, firm age; II establishment turnover rates, experience, firm age, part-time indicator, retirement rate	Computer use protects workers from unemployment in the very short run, but not in the long run

Greenan and Guellec (1997)		Unbalanced panel of up to 13,000 firms 1984-91 in France	Indicator of intensity of process and product innovations in 1991		Innovating firms create more jobs; product innov.s create more jobs at sector level; process innov.s create more jobs at firm level (zero at sector level)
Klette	Norweigan manufacturing plants 1983-1992;	micro data of population firms > 20 employees	R&D by firm in the same line of business as the plant	size, industry, time	Slower growth of Norweigan high R&D firms compared to low R&D firms; industries with high R&D intensity had (insignificantly) lower employment growth;
Van Reenen (1997)	Dynamic employment growth model; OLS and GMM;	Unbalanced panel of 598 quoted UK manufacturing firms 1976-82	Major innovations (SPRU) counted at firm and industry level (expert survey); firm level patents (taken in U.S.)	2 lags of employment, wages, capital, industry innovation, time dummies, long lags of innovation and patents	Innovations (esp. product) have large effects on employment; patents effects not robust to fixed effects

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