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COMPUTERS AND THE DEMAND FOR SKILLED LABOUR: INDUSTRY AND ESTABLISHMENT-LEVEL PANEL EVIDENCE FOR THE UNITED KINGDOM

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NON-TECHNICAL SUMMARY

Many OECD countries seemed to have experienced a fall in the demand for unskilled workers in recent years. At the same time, computerization has become a vital feature of industrial technology. This paper investigates whether computerization and the fall in unskilled demand are linked. It uses two panel data sets, at the establishment and the industry levels that enable us to go beyond work that has already been done on this issue.

We look at data on computerization over the 1980s, when computers were increasingly introduced into British manufacturing. In 1981, around 45% of UK manufacturing used some sort of chip at the workplace. By the end of the 1980s that figure had risen to over 80%. Of course, some industries have always used computers, notably the car industry who have been using robots and computerized machine tools since the 1970s. Computerization increased in these industries, however, and spread to new sectors, such as textiles, which increasingly began to use computers in the production process, especially computer-aided design.

What about the fortunes of the workers in these industries? We divide the workforce into manual and non-manual and then skilled and unskilled. We then compare the economic fortunes of these two groups in the relatively computer-intensive industries, like engineering, and in less computerized sectors, like footwear. In the computer-intensive sectors, the wage and employment position of the skilled non-manuals was significantly improved, whilst the unskilled manuals did significantly worse. In the less computerized industries, by contrast, both groups performed more or less the same. This suggests that computerization has tilted labour demand away from unskilled manual workers.

But is it true that computerization has hurt only this group? We then looked at the fortunes of skilled manuals. These workers are in an interesting position. They typically have jobs like foremen and skilled machinists. So they are usually experienced and trained. As manual workers, however, they are potentially vulnerable to being displaced by machines. Our data indicated that computerization had effected these workers too. So the key to understanding the computer revolution is that it has effected manual industrial workers regardless of whether they are skilled or not.

We then investigated the robustness of these findings. We used data on around 20,000 establishments for which we had information on skill upgrading, capital deepening and computerization. The computerization results were robust to this. We also used data on different types of computers, but could not find any significant effects of differing types. We tested to see if the computerization effect is simply reflecting human-capital upgrading within industries, but found the computer effect was robust to this. Finally, we found the computer effect was robust to the endogeneity of computer introduction.

Computers and the Demand for Skilled Labour:
Industry and Establishment-Level Panel Evidence for the UK

1. Introduction

The collapse of demand for unskilled workers is now a major topic of research. In an influential paper using US data, Berman, Bound and Griliches (1994) documented the decline in unskilled labour and found that computerisation had moved demand away from unskilled labour. Similar industry-level findings were reported in Autor, Katz and Krueger (1997) and Berndt et al (1992). This paper uses two new UK panel data sets to investigate this issue.

Our first data set is the *ACOP Respondents Database* (ARD) data set, comprising of the establishments underlying the industry averages published in the UK *Annual Census of Production*. The ARD data consists of around 15,000 establishments per year who report employment and wages of non-manuals and manuals, investment, output etc. Each establishment has a unique reference number which enables the identification of survivors, entrants and exitors. We use these data to decompose skill-upgrading into the contributions of changes within firms, between firms and of entry and exit. For 1986 and 1988 we also have computerisation information and so can study the computers/upskilling link. To the best of our knowledge, this is the first use of the UK Census data in this area[1] and one of the few studies to use establishment-level data.

Although this data set has a wealth of detail it raises some problems common to other studies. First, the only skill data available is non-manuals and manuals. This restricts computerisation to have an equal effect on occupational groups that span differences in education and skill levels (e.g. "manuals" includes skilled fitters and unskilled cleaners). Second, researchers have recently grown suspicious of correlations between computers and labour market variables.[2] In the labour demand context there are two particular problems with computers: (a) they may be endogenous and (b) they may be correlated with some omitted factor that also affects labour demand e.g. technological opportunities or worker skill upgrading/sorting. Third, computerisation can take many different forms, robots, computer-aided design etc. Yet there has hardly been any investigation of whether different types of computerisation have different effects.

To address these questions we use our second data set which is based on a series of computerisation surveys on a stratified sample of UK manufacturing establishments during the 1980s conducted by the *Policy Studies Institute*. They surveyed overall computer use and also the use of robots, computer-aided design, computer-numerically controlled machines etc. They also asked about the extent of training for computer use, consultation with workers on its introduction and the technological scope for

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1 See Dunne, Haltiwanger and Troske (1996) for similar US analysis.

2 Studies of computerisation and the *wage* (see eg. Allen (1996), Autor, Katz and Krueger (1996), Bartel and Sicherman (1996), DiNardo and Pische (1997), Krueger (1993) for the US and Chennels and van Reenen (1996) for the UK) face the problem that since the wage is the outcome of demand, supply and/or institutions, many aspects of which are hard to measure, such equations are particularly subject to omitted variable bias. We therefore stick to estimating labour demand only.

computer introduction.[3] We have matched these data with data on wages and employment by skill and occupational group using the New Earnings Survey Panel Dataset. Owing to strict confidentiality requirements, these data are unfortunately only available at industry level. However, it can shed light on some of the questions raised above. Since we have data on both different types of worker and different types of computer, we can test whether aggregation across worker and computer types is acceptable. As for endogeneity, we mimic our UK industries with suitably aggregated data from the US *Annual Survey of Manufacturing,* and use these US industry data as instruments for the UK variables. As for technological opportunities and skill upgrading, we have survey data on the scope for computer use and on the extent of computer-related training undertaken at the workplace.

Our paper is of course related to a number of other studies in the literature on skill upgrading and computerisation. We are only aware of three establishment/plant-level studies. Dunne, Haltiwanger and Troske (1996) use the US LRD (analogous to the ARD) and find a significant role for within-firm skill upgrading which in turn is correlated with various technology measures.. For the UK, Machin (1994) uses two cross-sections of 398 UK establishments drawn from the WIRS survey and finds a positive effect of a yes/no computer investment dummy on the employment share of high skilled workers. As he acknowledges, since there is no satisfactory data on wages, capital or output this is a very restricted specification of factor demand. Doms, Dunne and Troske (1997) use a US plant-level panel of data on different computer and worker types in selected industries and find no relation between changes in the non-manual wage bill share and computer introduction; however, they only have computer data for one year.

At the industry level, for the US, Berman, Bound and Griliches (1994) find computer investment biases demand towards non-manuals, but they do not use different worker or computer types nor examine the possible endogeneity of computers. Berndt, Morrison and Rosenblum (1992) find that "high-tech" capital raises the demand for educated white-collars, see also Autor, Katz and Krueger (1996). Although these studies cover different worker types they do not address the endogeneity problem nor do they use establishment-level data as we do. Machin, Ryan and Van Reenen (1996) use industry data to study the effects of R&D on non-manuals and workers of different education types, but have only a single cross-section of information on computers.

The rest of this paper briefly describes the data and presents our estimates. Our main findings are as follows. First. most of the aggregate skill upgrading is due to upskilling within continuing plants. Second, computerisation appears to have reduced the demand for manuals, irrespective of their educational level. Our findings therefore suggest that aggregating over these groups is legitimate and that computerisation has changed the production process to the detriment of manuals, who are predominantly poorly educated. Third, computerisation effects are significant even controlling for endogeneity, human capital upgrading and technological opportunity. Fourth, we can detect no significant difference in the

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[3] The PSI survey formed the basis for the computer questions asked in the UK Workplace Industrial Relations Survey (WIRS). For analysis of that data see Chennells and van Reenen(1996). Haskel(1996) and Machin(1996).

impact of computers of different computer types, although we do have some collinearity/degrees of freedom problems here.

2. Establishment-level results from the ARD data[4]

The ARD data set is the establishment-level data underlying the published industry averages in the UK Census of Production. We have drawn data for 1972-1992. Roughly 15,000 firms per year are sampled out of all UK manufacturing firms: each establishment has a unique identifier. Firms with over 100 employees are always sampled, firms with less than 20 never. From 1972-77 all firms with over 20 were sampled; since then the sampling fraction for most years has been 20-49 employees: 25%, 50-99 employees: 50%.[5] Data is collected on output, investment, manual/non-manual employment and wages etc. for every year. Our decomposition uses this full sample. Over the whole period there were 5,060 stayers, 8,555 entrants, and 16,563 exits. In 1986 and 1988 firms were asked to report computer spending, so our regression sample consists of 10,220 and 10,074 establishments in 1986 and 1988 and 6,986 establishments in the underlying panel.

2a. Decomposition

To examine the effects of entry, exit and survival on skill-upgrading we decompose the aggregate change in the share of non-manuals ΔNM_t as (this follows Dunne, Haltiwanger and Troske, 1996)

$$\Delta NM_t = \sum_{stayers}\left(\frac{L_{it-1}}{L_{t-1}}\right)\Delta NM_{it} + \sum_{stayers}(NM_{it} - NM_{t-1})\left(\frac{L_{it}}{L_t}\right) + \sum_{stayers}\Delta\left(\frac{L_{it}}{L_t}\right)\Delta NM_{it} + \sum_{entrants}\left(\frac{L_{it}}{L_t}\right)(NM_{it} - NM_{t-1}) - \sum_{exits}\left(\frac{L_{it-1}}{L_{t-1}}\right)(NM_{it} - NM_{t-1}) \qquad (1)$$

where $NM = L^{skilled}/(L^{skilled} + L^{unskilled})$, L denotes employment, i denotes establishment and L_t total employment. The first three terms relate to continuing firms between t-1 and t. They will be positive if, respectively, skill upgrading takes place within firms, employment moves between firms to establishments of above average skill-intensity and the covariance between skill upgrading and the changing employment share is positive. The last two terms reflect the contributions of entry and exit.[6] Table 1 sets out the terms in (1) for four subperiods. Between 1972 and 1986, skill-intensity rose steadily, with the within component accounting for around 50% of the rise and the between about 20%.

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[4] For more details on the data results see Haskel and Heden (1998). Establishments can be comprised of plants, but plant-level information is only provided on employment and investment.

[5] For complete sampling information see table 1 in Oulton (1997). As he notes, since all large firms are sampled, the ARD covers the vast majority of manufacturing employment (88% in 1993).

[6] It must be emphasised that since our data are a sample entry and exit could refer to birth and death of firms but also to the entry or exit of firms from the sampling frame. So there is probably "too much" entry and exit which could understate the role of survivors. Since most entry and exit are of small firms we suspect this effect is small.

From 1986-92 the within effect accounts for almost all of the rise.[7] This suggests that we should concentrate on within-establishment upgrading to explain much of total skill-upgrading at least in the late 1980s.

Table 1
Decomposition of Non-production Labour Share Changes, 1973-1992

Sample used	Total	Within	Between	Covariance	Net Entry
1973-1977	**0.0170**	0.0081	0.0029	-0.0018	0.0078
1977-1980	**0.0190**	0.0099	0.0040	-0.0013	0.0064
1980-1986	**0.0259**	0.0145	0.0028	-0.0010	0.0097
1986-1992	**0.0241**	0.0187	-0.0035	-0.0012	0.0100

2b. Regression results.

To examine skill-upgrading we estimate the following regression

$$\Delta S_{int} = \beta_{1i} + \beta_{2i}TIME_t + \beta_{3i}\Delta COMPUTERS_{nt} + \sum_j \gamma_{ij}\Delta\ln\left(\frac{W_{jnt}}{W_{knt}}\right) + \delta_{1i}\Delta\ln K_{nt} + \delta_{2i}\Delta\ln Y_{nt} + \varepsilon_{int} \tag{2}$$

where S_{int} is the wage bill share for worker type i, in industry n at time t, $TIME$ is a time dummy, $\Delta COMPUTERS$ is the computer measure, W is the wage, K is capital and Y is output and Δ denotes a first difference. This follows Bartel and Lichtenberg (1987) and Berman et al (1994) and can be derived from a restricted cost function, where K is fixed factor, i types of labour are variable and homogeneity is imposed by normalising on wages of worker group k. If $\beta_{3i} > 0$ then technology is biased toward that factor i. β_{1i} measures the worker group-specific bias, assumed constant across years and $TIME_t$ denotes a time dummy.

With two worker groups the system (2) reduces to one equation where S is the wage bill share of non-manuals. Since we have no data on changes in the computer capital stock we follow Berman et al (1994) and replace $\Delta COMPUTERS$ with the ratio of computer investment to total investment *(C/I)*. They argue that the cross-sectional variation in *(C/I)* proxies the variation in capital stock due to differences in the underlying technological potential for computerisation across technologies. With no data on K we measure ΔlnK by investment and ΔlnY by real net output, both deflated by industry price deflators.

Table 2 sets out establishment-level estimates of (2). Columns 1 and 2 estimate (2) for 1986 and 1988 cross-sections the pooling across establishments. The *C/I* coefficient is of very similar sign in both cases, although significant at 10% in the 1988 cross-section. The relative wage term is highly significant with an implied elasticity of substitution of 1.53 which is in line with other estimates (Hamermesh, 1993). Dropping the relative wage gave t-statistics of 2.12 and 1.45 on the *C/I* term, similar to table 2. Column 3 pools over both years, which strengthens the significance of *C/I*.

[7] These data are very similar to Dunne et al (1996) for the US. Over the period as a whole, net entry is quantatively more important since entrants cumulate employment. Dunne et al show that within entrant skill upgrading is most important.

Column 4 combines the two cross-sections into a balanced panel and estimates including fixed effects and a time dummy which should control for an establishment-specific factor, e.g. technological opportunity, which might cause both computer investment and skill upgrading. This panel is of course a selected sample of the cross-sections since it conditions on survival from 1986 to 1988.[8] The computer term hardly changes in sign although has fallen in significance (significant at the 6.5% level). Other signs and coefficients are not much changed. In this column the fixed effects were jointly insignificant and so the final column reports the pooled balanced panel without fixed effects: *C/I* falls here in significance. One is tempted to conclude that the computers/skill upgrading differs by entrant/exitor and survivor, but measurement error in the right hand side variables might be obscuring the results in these one-year differences.[9]

Table 2
Change in wage bill share regressions, (ARD)
(Dependent variable: Δ wage bill share of non-manual workers)

	Cross section 1986	Cross section 1988	Pooled 1986 and 1988	Balanced panel, F.E.	Balanced panel
C/I	0.0094	0.0082	0.0088	0.0108	0.0061
	(2.264)	(1.609)	(2.712)	(1.843)	(1.746)
$\Delta \log(W_{n\text{-}m}/W_{man})$	0.1263	0.1262	0.1262	0.1238	0.1268
	(35.680)	(38.688)	(52.596)	(45.525)	(66.240)
Δ log of real net output	-0.0063	-0.0108	-0.0086	-0.0133	-0.0104
	(2.037)	(3.626)	(4.005)	(-4.817)	(5.535)
Log of real net investment*	-0.0563	-0.0138	-0.0347	-0.1823	0.0022
	(1.504)	(0.368)	(1.312)	(2.077)	(0.073)
Observations	10220	10074	20294	13612	13612

Notes: Heteroscedastic consistent absolute t-statistics in brackets. Equations include constant and in the last three columns time dummies. * denotes variable multiplied by 100.

3. Industry-level results from the PSI data

To investigate further these correlations, we turn to our second data set. PSI carried out a stratified survey of new technology use in 1,200 UK manufacturing establishments 1981, 1983, 1985, and 1987. For our purposes the key question asked was *"are you at present using the new microelectronics technology*[10] *in your production process?"* PSI publish average use for 10 manufacturing industries, averaging over sampled establishments. The data does not give the fraction of workers at the establishment who are using

[8] With only two cross-sections we cannot meaningfully form an unbalanced panel, since a fixed effects regression would simply dummy out all the unbalanced elements in the panel.

[9] We re-ran the regressions industry by industry to check that the implicit pooling across industries with possibly different technology is acceptable The C/I effect was typically positive but not typically well determined.

[10] A detailed definition of "the new microelectronics technology" was provided.

computers, since a firm with only one computer and another with 100 both answer yes to the question. Size-weighted data however gave very similar results, so used these unweighted averages.[11]

Although there are a relatively small number of observations the data is of interest due to some other questions. The users of computers are also asked *"are you at present using microelectronics in the following applications:...."* after which robots, computer numerically controlled (CNC) machines, computer aided design (CAD) etc. are offered as alternatives. Concerning training, establishments are asked *"about how many of your engineers have been on microelectronics training courses in the last two years?"* and the same question is asked for technical staff. Establishments are also asked about consultation; *"when microelectronics technology was first introduced, was there consultation with the workforce/unions?"* and technological opportunity: *"do you think there is potentially scope for using microelectronics in your production process?"*

Congruent industry-level information on skilled, unskilled, manual and non-manual wages, hours and employment is generated using successive years of the UK *New Earnings Survey Panel Data Set* (NESPD) where we use standard conventions to allocate occupations according to whether they are manual and non-manual and then skilled or unskilled (see Haskel and Heden, 1997). Thus we have four worker groups. Importantly, if the occupational classification simply reflects whether the worker uses a computer or not, then there will be a mechanical correlation between computers and occupational changes. This is not the case here. The occupational groups (e.g. toolmaker) refer to the tasks a worker undertakes rather than the means with which the task is performed. These four groups correspond closely to educational levels; 45% of unskilled manuals have no qualifications whilst 1% have a degree or above, whilst the figures for skilled non-manuals are 6% and 32% respectively.[12] Skilled non-manuals are the most experienced on average (22 years) whilst skilled manuals are slightly more experienced than unskilled manuals.

We shall also require data on capital and output. We have four different measures of capital; a gross capital stock series derived from the Blue Book, a net capital series calculated by ONS, a series that attempts to adjust for premature scrapping in the early 1980s and a series for equipment and machinery. Output is industry gross output from the Census of Production deflated by industry prices.

3a. Regression results on PSI data.

Concerning the empirical implementation of (2) there are a number of points to be made. First, since computers are part of *K*, if *K* in (2) is measured well enough β_i should pick up the computer effect. *K* is notoriously badly measured but this does raise the possibility that β_{3i} might understate the computer effect. Second, our PSI computer data (*%COMPUTERISED*) is a measure of the proportion of the industry using computers. With fast upgrading of computers this level is likely to proxy changes in computer stock. Indeed, the correlation between *% COMPUTERISED* and the industry-average computer introduction

[11] We have no data on the quality (e.g. speed) of computers in use or on the deprecation of past computer stock. We address this below.

[12] The figures for unskilled non-manuals are 17% and 4% and for skilled manauls 22% and 1% (source: Labour Force Survey, data for 1993).

measure from WIRS in 1983 was 0.77 (the correlation with the difference in *% COMPUTERISED* was 0.21). So we shall use this level term initially for *ΔCOMPUTERS* in (2); in any case our results are robust to including the change terms as well. Third, we identify our equations as demand curves by using the employer wage in S_{int} and W_{int} where the employer wage is the annual wage plus employer taxes plus employer expenses (pension and health contributions etc.).

Table 3 sets out our results. Panel (a) omits the relative wage terms. Column 1 reports the coefficients on computerisation and *Δln(K/Y)* with the change in non-manual wage bill share as dependent variable. The *% COMPUTERISED* term is strongly significant, suggesting that non-manuals are compliments in production to computers as in other studies for the US (Berman et al, 1994). Column 2 shows the results using *ΔS* for the skilled as a dependent variable. The coefficient on *%COMPUTERISED* is significant, but around half the coefficient in column 1, suggesting the computer effect varies between skill and occupational groups.

Table 3
Change in wage bill share regressions, (PSI)

Panel	change in wage bill share of:	Non-manuals	Skilled	Non-manuals Skilled	Non-manuals Unskilled	Manuals Skilled	Manuals Unskilled
(a)	%COMPUTERISED*	0.79	0.44	0.57	0.13	-0.09	-0.51
		(4.50)	(2.33)	(3.40)	(1.18)	(1.24)	(3.03)
	Δln(K/Y)	0.05	0.04	0.03	0.01	-0.02	-0.03
		(0.90)	(1.20)	(0.62)	(0.36)	(0.38)	(0.46)
(b)	%COMPUTERISED*			0.47	0.19	-0.22	-0.44
				(3.06)	(1.96)	(1.38)	(2.80)
	Δln(K/Y)			0.04	0.01	-0.02	-0.03
				(1.07)	(0.35)	(0.50)	(0.64)
(c)	% COMPUTERISED*			0.81	0.51	-0.65	-0.67
				(2.78)	(1.82)	(2.74)	(1.86)
(d)	% COMPUTERISED*			0.77	0.24	-0.28	-0.73
				(3.36)	(1 '1)	(1.19)	(2.86)
	NOSCOPE			0.05	0.03	-0.03	-0.06
				(0.60)	(0.62)	(0.40)	(0.66)
(e)	% COMPUTERISED*			0.38	0.20	-0.14	-0.44
				(2.06)	(1.70)	(0.85)	(2.46)
	(R&D)/Y**			0.35	-0.10	-0.71	-0.18
				(3.08)	(1.77)	(0.57)	(1.48)

Notes: Absolute heteroscedastic-consistent robust t statistics in brackets. * denotes variable multiplied by 1000, **multiplied by 100. All equations include constant and time dummy; the time dummy was restricted to be the same across years in each worker group (this restriction always acceptable). Subscript s denotes skilled, u unskilled, n non-manual, and m manual. Equations estimated by maximum likelihood as a system over 4 cross sections and 10 industries, except panel (a) columns (1) + (2) which are single equations.

The rest of the columns in panel (a) estimate (2) for the four worker groups. Computers have a positive effect for both non-manual groups and negative for non-manuals. The pattern of signs is reasonable with a steadily decreasing sign as one goes down the skill groups, but the skilled non-manuals and unskilled manuals are the best determined. Panel (b) includes the relative wage terms (not reported). The computer effects are robust in magnitude and significance. The relative wage terms are of mixed significance, but just jointly significant $\chi^2(6)=14.6$ (critical value 12.6).[13]

To what extent does a two-way manual/non-manual or skilled/unskilled split restrict the data? A Wald test for the equality of the computer effect between the non-manual groups rejects the hypothesis that they are the same $\chi^2(1)=5.2$, (critical value 3.84) for the specification without relative wages but only just fails to reject the hypothesis for the specification with relative wages, $\chi^2(1)=3.3$. For the manual groups, we fail to reject equality for both specifications $\chi^2(1)=1.8$ and 0.8 respectively.[14] So assessing the computer effect by combining the manual groups seems acceptable. The result for the non-manual groups is just on the margin, although the rejection of combination is on the basis of an equation that is strictly speaking misspecified.

These results are of interest since they suggest that (at least for manuals) computers are <u>not</u> simply complements to more educated workers. Our worker groups differ by educational attainment yet computers bias demand away from skilled manuals as much as unskilled manuals. This is consistent with DiNardo and Pische (1997) who found that the effect of computers on the wage depended critically on controlling for occupation. So computers seem to be altering the production process away from <u>manuals</u> (who on average are less educated) rather than away from all less educated workers.

We then carried out a number of other tests. First, it might be argued that *%COMPUTERISED* (or indeed $\Delta\ln(K/Y)$) are endogenous. Computerisation presumably depends on the profitability of adoption, which in turn depends on the price of computers, the wage and number of skilled workers who will use or install the computer and technological opportunity. Assuming computer prices are exogenous two potential biases arise. With the respect to the wage/number of skilled workers, if computer introduction required more "skilled" workers the coefficient on *%COMPUTERISED* in (2) is biased above its true value. On the other hand, if high skilled wages make firms less likely to introduce skill-complimentary technology then the coefficient is biased down. As for technological opportunity; the problem here is that since (2) is a technological relation technological opportunities appear there and in the underlying computer introduction equation. So textiles for example may have a technological attribute that lowers both the wage bill share of non-manuals and the propensity to introduce computers.[15]

To generate suitable instruments we constructed congruent US industry classifications and generated US data on $\Delta(\ln(K/Y))$. We have however no computer data. We therefore estimated (2) on US data, without the computer terms, using the non-manual wage bill share as dependent variable and relative non-manual/manual wages. We then generated the residuals for each industry and used these as

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13 The implied price and substitution elasticities gave sensible results, see Haskel and Heden (1997).

14 Combining the skilled groups was rejected, $\chi^2(1) = 6.4$ for the null of equality of the computer effect between skilled non-manuals and skilled manuals and $\chi^2(1) = 15.6$ for unskilled non-manuals and unskilled manuals.

15 Note too that if this were the case US computerisation would be an invalid instrument since it would be correlated with UK technological opportunity.

instruments for *%COMPUTERISED* (other instruments using other specifications made no difference to the results).

The results of this exercise are set out in table 3, panel (c). All the computer effects remain statistically significant. The positive effects of non-manuals rise and the negative effects fall suggesting that the OLS coefficients are biased downwards. This is consistent with effects from wage-induced technical change although we have to be careful about concluding too much from IV equations in small samples.

We deal with technological opportunity using the answers to the question *"do you think there is potentially scope for using microelectronics in your production process?"* We take the proportion of industry answering *"no"* (*NOSCOPE)* to measure lack of technological opportunity. As table 3 panel (d) shows, entering this term *NOSCOPE* left *%COMPUTERISED* largely unaffected. So our results are unaffected by omitted technological opportunity.

Second, spurious correlation would arise if workers are upgrading their skills as computers are being introduced or if computers are complementary to more "able" workers within each group so that increased computerisation causes unobservable sorting. To the extent different amounts of sorting occur in different skill groups the wage shares change to differing extents. Such upgrading and sorting would be controlled for at least to some extent by the wage, constant and time dummies,[16] but to explore this we entered the data by industry and year on the number of engineers and other technical staff sent by firms for microprocessor training. This should capture computer-related human capital upgrading (although it is not training for each of our worker groups), and sorting (conditional on the hypothesis that firms send for training those with highest computer abilities). The skilled non-manual *%COMPUTERISED* coefficient and *t*-statistic (not reported) were slightly reduced, hinting that the raw *%COMPUTERISED* effect captures an element of upgrading/sorting. However, the training variables were not jointly significant, $\chi^2(6)= 5.6$.

Third, we entered different computer types.[17] There are two features of these data which makes us wary of the regression evidence here. First, the data are quite collinear; industries introducing a lot of computers are generally introducing many different types as well. Second, these data were not collected in 1981 and so we have only data for 1983, 85 and 87 which is 30 observations. All computer types were jointly insignificant, $\chi^2(9)=8.5$ (critical value 16.9) and made little difference to the coefficient on computers.

Fourth, an alternative measure of technological change used for example by Machin (1994), Berman et al (1994) and Mincer (1991) is R&D intensity. As table 3, panel (d) shows, R&D significantly raises S_{int} for the skilled non-manuals and lowers it for skilled manuals. This is consistent with the

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16 So that any of these sorting-type effects would have to be over and above (a) the average level of upgrading/sorting for each worker group over time and (b) common changes over all groups for each time period.

17 Firms are asked whether they use computers or not and conditional on use what type of computer they use. Since the data on different types is not exhaustive we enter the overall use and the use by type together. So the coefficient on the use by type estimates the effect of the type additional to the overall effect of computers. Hence, an insignificant coefficient on computer-type does <u>not</u> suggest that the type has an insignificant effect, but rather that its effect is insignificantly different from the overall effect.