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Discussion Papers in Economics

THE GENDER DIMENSION OF TECHNICAL CHANGE AND TASK INPUTS

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ISSN: 1749-5075

The Gender Dimension of Technical Change and Task Inputs.

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January 2011

Abstract

Studies have shown technical change has led to job polarisation. A relatively unexplored aspect of this is whether there has been a gender bias. This paper shows gender bias in technology driven skill polarisation. Between 1997 and 2006 the demand for women shows hollowing out across education groups as a consequence of technical change. This was not the case for men. Overall, the demand for women has fallen relative to that for men as a consequence of technical change. This can be explained by a gender bias in the complementarities between computerisation and changes in task inputs. Numeracy skills are the largest complementarity to technical change and these help to explain the increase in the demand for highly skilled women. However, there are gender biased complementarities to technical change across a range of other non-routine tasks which can explain the fall in the demand for medium educated women and the overall increase in the relative demand for men. At the same time there was a fall in the gender pay differential. For moderate and complex computer users this fall is largely explained by changes in qualifications. However, there remains a large unexplained component suggesting that gender biased demand shifts towards numerate and computer literate women have significantly contributed to the closing of the gender pay gap.

Key words: Gender Pay, Task-Bias Technology Change, Skills.

JEL: J01,J16,J2,J31

Acknowledgement: Thanks to Stephen Machin for his advice, as well as Francis Green, Steve McIntosh, Andy Dickerson for their comments on an earlier draft. Thanks also to the UK Data Archive for making the data available. The usual disclaimer applies.

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1. Introduction

Recent research has shown that most Western economies have experienced substantial job polarisation in the last two to three decades.[1] The falling price of information technology has led to substitution of routine labour for physical capital. As routine tasks tend to be performed by jobs situated in the middle of the job quality distribution, economies with access to information technology have witnessed decreasing employment shares in the middle of the earnings distribution. Consequently, employment has polarized into high paid and low paid jobs and inequality has risen. This process has become known as task-biased technical change (TBTC). [2]

At the same time, gender wage differentials have fallen in many countries. Research has shown this to be mainly a consequence of education and experience changes.[3] Blau and Khan (1997) also show that inequality has impacted on the closing of the gender pay gap. The fall in the US gender pay differential between 1979 and 1988 would have been even larger if it were not for the widening of the male wage distribution over this period.[4] Breen and Salazar (2010) have also shown an increase in the correlation between the earnings of partners in two-earner households and suggest that increasing women's earnings may now be reinforcing inequalities.

It is therefore surprising that there has been little research investigating the role of changing skills or technology in explaining the fall in the gender pay gap. One exception is Black and Spitz-Oener (2008, 2010) who generate routine task measures to investigate the implications of task polarisation for the job content of German men and women. They show that women were over-represented in occupations that intensively involved routine tasks during the 1970s and consequently experienced larger reductions in routine task job content compared to men. This led to greater job polarisation for women.

This paper firstly investigates whether there are important gender differences in technology driven changes in relative demand. The aim here is to look for a gender bias in the polarisation of the demand for education. The paper also addresses the implications of technical change on the supply of female labour by decomposing the change in the gender pay differential into education and experience components, whilst building on the existing literature by also including measures for generic skills (using the task content of jobs), the routineness of job (using repetitive tasks in jobs) and technology change (using the complexity of computer usage). Hence the aim of the paper is to identify how changes in education and skills have interacted with the technology measures to explain the falling gender wage gap.

This is the first study to provide evidence of gender differences in the polarisation of demand for high, medium and low skilled women which is correlated with technical change, with no such evidence for men. Overall technical change has involved a male bias in labour demand because of complementarities between technical change and non-routine tasks that differ by gender. Industries that have increased computerisation have also increased their use of a number of non-routine tasks for men but only increased their use of numeracy tasks for women. This helps to explain why technical change has led to an increase in the demand for high skilled (numerate) women and a fall in the demand for moderately educated women (women with other non-routine skills), with an overall increase in the relative demand for men.

At the same time, the gender pay gap fell with skills and computer use measures being important explanatory factors in explaining the fall. Changes in education have only significantly lowered the gender pay differential for workers employed in moderate and complex computer use jobs. Changes in generic task use have actually increased the gender pay differential. However, even after conditioning on changes in qualifications and job tasks, a large part of the fall in the gender pay differential for moderate and complex computer users remains unexplained. Overall, the evidence suggests that the fall in the gender pay differential for computer literate women is a consequence of increased demand for their skills or explained by changes in non-measurable (perhaps non-cognitive skills) in the labour market.

The paper is organised as follows. The next section describes the data and provides some descriptive trends for pay and inequality. Section 3 describes the changes in the generic task and computer use content of jobs over this period. Section 4 uses industry level data to assess to what extent these changes can explain changes in the skill demand for men and women, whilst section 5 looks at the industry level correlation between computerisation and changes in tasks. Section 6 looks at the relative remuneration implications of technical change by decomposing the fall in the gender pay differential into composite observable and unobservable characteristics. The final section concludes.

2. Descriptive Trends and Data Description.

The backdrop to the issues studied in this paper is the changing labour market inequality. This section therefore describes trends in the UK labour market with regard to wage inequality and job polarisation, before going on to describe the various data sets used in the paper.

2.1 Changes in Inequality and Job Polarisation.

Figure 1 shows changes in UK wage inequality between 1970 and 2009 by comparing the wage at the 90^{th} and the 10^{th} percentile of the earnings distribution, separately for men and women.[5] There is an increasing trend in inequality for men and women, although this tends to flatten out towards the end of the period and especially for women. Rising wage inequality has been accompanied by changes in inequality within various groups of workers. For example, it is well documented that demand has shifted in favour of educated workers and this partially explains the rise in inequality.[6]

An explanation given in the early literature argues that skill biased technical change (SBTC), whereby technology changes have favoured highly educated workers and been detrimental to low educated workers, has been a key driver of inequality, see Machin (2003, 2004). More recently, studies have suggested that technical change has replaced the routine tasks that workers perform (TBTC) and that the workers who tend to perform more of these tasks are situated in the middle of the earnings distribution.[7] This has resulted in the displacement of routine task intensive jobs and polarisation in employment. Figure 2 shows the pattern of growth in UK employment shares across the job quality distribution from 1979 to 2008.[8] This provides clear evidence of polarisation in employment growth across the distribution, with positive growth in the top two deciles, hollowing out in the middle and growth in the bottom decile.[9] Similar patterns for employment growth have been found in the US by Autor, Katz and Kearney (2006), as well as across 16 European countries by Goos, Manning and Salomons (2008).

Figure 3 graphs the gender pay differential measured at the mean using data from the 1997-2009 Annual Survey of Hours and Earnings (ASHE).[10] This is fairly stable between 1997 (25.3 percent) until 2002 (25.2 percent) but then begins a marked decline thereafter (20.9 percent in 2009). The contribution of this paper, therefore, is to try to ascertain whether technical change can explain gender differences in job polarisation and the fall in the gender pay gap.

2.2 Data Description

The two data sets used in this paper are the UK Skills Surveys and the EU KLEMS data. The UK Skills Surveys are large cross sections of individuals in paid work and aged 20-60.[11] They provide rich information on human capital and socio-economic background but also contain questions on job skills and tasks performed. The EU KLEMS data provides detailed information on outputs and inputs at the two-digit industry level from 1970 to 2007.[12] They provide information on labour inputs, capital investments and compensation. The paper uses the 1997 and 2006 Skills Surveys for analysis at the individual level but also merges this with the EU KLEMS data to undertake analysis at the industry level.

The UK Skills Surveys are richer than data used in other existing TBTC studies as they contain information on both tasks and the complexity of computer use.[13] Technology is measured using computer use complexity and this consists of four categories: `none' `simple', `moderate' and `complex' use. Individuals are asked which of these four measures best describes the use of computers or computerised equipment in their jobs. Hence workers who report no computer use might be thought to be employed in relatively non-technical jobs. Simple computer use consists of straightforward use (eg printing out an invoice in a shop) whereas moderate computer use is for example word processing/spreadsheets or email. Complex computer use involves analysis or design, statistical analysis and programming.

Following Green (2009), job tasks are aggregated to form eight generic task measures: literacy, numeracy, external communication, influencing communication, self planning, problem solving, physical and inspecting.[14] Literacy tasks consist of reading and writing activities, whilst numeracy contains mathematical procedures which range from making simple calculations (summation, subtraction, multiplication and division) to more advanced maths and statistical procedures. External communication tasks include sales, counselling and dealing with people, whilst influencing communication tasks includes teaching, instructing, influencing others and making presentations. Self planning is a measure of autonomy over time and task management, whilst problem solving consists of analysing and finding solutions to complex problems as well as identifying and fixing faults. Physical tasks include tasks that require strength, stamina, using tools and machinery and using hands or fingers. Inspecting tasks involve looking for mistakes and ensuring there are no errors. In order to provide a measure for the routine task content of a job, this analysis also includes a variable that directly measures repetitive-task job content.[15]

Pooling the 1997 and 2006 Skills Surveys provides data on 3174 men and 3100 women. Table 1 shows that the male/female hourly pay differential falls from 0.29 log percentage points in 1997 to 0.23 log percentage points in 2006 providing a fall in the raw gender hourly pay differential of 0.06 log points.[16] Table 1 also shows rising inequality for men since the standard deviation increased from 0.54 to 0.56, whereas this is not the case for women.[17] The final row of Table 1 shows in which percentile the average female would be in the male distribution for each year. This has increased from 28.9 in 1997 to 37.7 in 2006 clearly showing that women are improving their place in the male earnings distribution. Using the female average log wage in 2006 in the male earnings distribution for 1997 places them in the 42.6 percentile suggesting that women would have done better if earnings growth and male inequality had remained unchanged.

3. Task Changes Over Time.

A critical aspect of the TBTC literature is the measurement of technical change.[18] Therefore, I begin in Table 2 by providing information on gender differences in changes in the task intensity of jobs as well as changes in computer use. For men, literacy, communicating, influencing, self planning, problem solving and inspecting tasks have increased, whereas for women, all task measures except numeracy increased. Moreover, increases have been substantially larger for women relative to men in literacy, influencing, self-planning, physical and inspecting tasks. According to Green (2009), influencing and self planning tasks are largely non-routine in nature, whilst literacy are partly non-routine, which would suggest that TBTC may be increasing the non-routine content of women's jobs more so than men. However, the repetitive-task measure, intended to capture the routine task content of a job shows there to be equal increases for men and women, although levels are higher for women.

Technical change measured by computer usage is also important since the percentage of workers reporting moderate and complex computer use has increased, whilst no and simple computer use has fallen, for both men and women. Moreover, simple computer use has fallen equally for men and for women, although moderate computer use has fallen, whilst complex computer use has increased for men relative to women. So women are more likely to use computers for moderate tasks whereas men are more likely to use computers for complex tasks and these gender differentials have increased over time.

The TBTC hypothesis predicts that changes in task composition should occur within occupation and industry cells if they are a consequence of technical change.[19] Between occupation/industry changes suggest changes in the demand for products, perhaps through increased globalisation. Following Black and Spitz-Oener (2008), the gender-specific task changes over time can be decomposed into two components. The first is the changes in the task composition `within' occupations and industries, whilst the second is the changes in the distribution of men and women `between' occupations and industries. The `within' measures how much of the difference can be explained by the fact than men and women experience different task changes within occupation and industry cells. The `between' measures how much of the difference can be explained by differential shifts in employment across occupation and industry cells. This provides the following decomposition for each of the eight generic task measures, the routine task measure and the four computer use measures:

$$(\bar{Z}_M - \bar{Z}_W)_2 - (\bar{Z}_M - \bar{Z}_W)_1 = \left[\sum_j \bar{\alpha}_{Mj}(\bar{Z}_{M2j} - \bar{Z}_{M1j}) + \sum_j \bar{\alpha}_{Wj}(\bar{Z}_{W2j} - \bar{Z}_{W1j})\right] + \left[-\sum_j \bar{Z}_{Mj}(\alpha_{M2j} - \alpha_{M1j}) + \sum_j \bar{Z}_{Wj}(\alpha_{W2j} - \alpha_{W1j})\right] \quad (1)$$

where $\bar{Z}_{gtj}$ is the average value of tasks and α_{gtj} is the proportion, of gender g (M and W denotes men and women respectively) at time t in occupation/industry j. The first term in square brackets represents the fraction of the total change in the gender gap in a particular task that can be attributed to changes within cells, where the first of these terms evaluates at the average male task level and the second at the average female task level. The second term in square brackets is the fraction of the total change in the gender task gap that can be attributed to changes in the gender-specific employment composition of cells, where the first (second) term captures the proportion that can attributed to the changing employment share of men (women).

Table 3 decomposes the gender differences observed in the final column of Table 2 using equation (1) into `within' and `between' both 2 digit ISCO88 occupation and 2 digit SIC92 industry cells. The upper panel of Table 3 refers to occupational changes, whilst the lower panel refers to industry changes. Clearly Table 3 supports the TBTC hypothesis since the within cell changes are much larger than the between cell changes. For generic tasks, the within cell changes are generally larger for women than men. The exception is numeracy which is much larger for men, although the gender differential is insignificant.

The significant reduction in `no' and `simple' computer use which is fairly similar for men and women, is clearly a consequence of a reduction within cells. However, the relative increase in female moderate computer use is clearly a consequence of larger within cell changes for women, whilst the relative increase in male complex computer use is a consequence of larger within cell changes for men. Again these results are consistent with the idea of TBTC, but with a significant gender bias in the change in the technological content of jobs.

4. Technology, Changes in Skill Demand and Polarisation.

Following a similar approach to that used in Autor et al. (1998), this section uses industry level data to investigate to what extent the technical changes observed in Tables 2 and 3 are intrinsically associated with relative changes in labour demand for men and women. First, changes in high, medium and low skilled demand are considered, both for a pooled sample and then for separate samples of men and women. Following this, changes in overall female-male relative demand shifts are addressed.

Following the existing literature on skill upgrading, this involves the estimation of the following equation:

$$\Delta SHARE_j = \beta + \alpha \ \Delta \log(K/Y)_j + \gamma \ \Delta C_j + u_j \tag{2}$$

where, in the first instance, ΔSHARE$_j$ measures a change in the relative demand for high, medium and low education levels in industry j between 1997 and 2006.[20] This is calculated using wage bill shares taken from the 17 industries available in the 1997 and 2006 EU KLEMS data.[21] Following this, equation (2) is estimated again where ΔSHARE$_j$ measures a change in the demand for women relative to men. This is measured using the change in the female wage-bill share again taken from the EU KLEMS data.[22]

The Δlog(K/Y)$_j$ term is the change in the log of the capital-value added ratio. This imposes constant returns to scale (which is supported by the data) and given the small sample sizes, importantly increases the degrees of freedom. The capital stock and the value added measures are also taken from the EU KLEMS data.[23]

The ΔC_j term captures a change in technology for industry *j*. Technology is measured using industry level proportions of changes in computer use at work, as well as for changes in simple, moderate and complex computer use from the 1997 and 2006 Skills

Survey data. For relative demand shifts in highly educated workers, γ measures how relative demand has changed as a consequence of technical change, whilst the intercept β measures the growth in relative demand conditioning on changes in capital-value added and on technical change. A similar interpretation can be given for changes in the demand for moderate and low educated workers, as well as for male-female relative demand shifts

In Table 4 the dependent variable measures changes in the high, medium and low education wage bills respectively. The first column in each of the three equations shows there has been an increase in the demand for high education workers (0.067) and a fall in the demand for medium and low education workers, where the fall in the medium education workers (-0.046) was larger than the fall in low education workers (-0.021) suggesting a hollowing out of the education distribution in line with TBTC. Moreover, changes in moderate and complex computer use have increased the relative demand of high education workers (0.226), reduced the demand for medium education workers (-0.234) and had virtually no effect on the demand for low education workers. These show clear evidence of polarisation.[24] This is all being driven by moderate and complex computer use and therefore simple computer use is likely to be capturing what is now considered to be general purpose technology (like a cash register in a shop). The findings are very supportive of TBTC where technical change is predicted to complement high education workers and substitute for medium education workers through the replacement of routine tasks, see Autor, Levy, and Murnane (2003) for the US and Mieske (2009) for the UK.

Table 5 provides the split sample results for changes in relative high, medium and low education demand for men and women separately. Given the results from Table 4, changes in technology are only measured using changes in moderate and complex computer use. The first column in each category clearly shows polarisation for both men and women since the relative demand for high education workers has increased (0.026 and 0.041) whilst the demand for medium education workers has fallen (-0.033 and -0.014). Again there has been a small decline in the demand for low education workers (-0.007 and -0.013). However, the change in computer use variable shows significant gender differences exist. Polarisation explained by technical change has been for women, with virtually nothing being significant for men. For men, changes in computer use have actually significantly increased the demand for low education workers. For women, changes in computer use have increased the demand for high education workers (0.175) and reduced the demand for medium education workers (0.292) in line with TBTC.

Given that we can only observe technology changes over a ten year period and for 17 industries, one concern with the estimates presented in Table 5 is the potential for measurement error. The change in moderate and complex computer use is therefore instrumented with nominal gross fixed capital formation for information and communication technology (ICT) in 1990 and the change in ICT gross fixed capital formation between 1980 and 1990.[25] The two-stage least squares (2SLS) estimates are provided in Table 6. These are roughly twice as large as the OLS coefficients in Table 5 although the story is still the same. These results suggest the presence of measurement error whereby OLS under-estimates the importance of technical change in explaining changes in the demand for education and the differential extent of polarisation between men and women.

Table 7 provides the results for equation (2) where the dependent variable now measures the change in the female-male wage bill share. The first column shows without technical change, the change in the demand for women has outstripped the demand for men (0.014). Changes in computer use at work, however, have reduced the demand for women relative to men (-0.233). The growth in the relative demand for women would have been larger (0.039) if not for the changes in computer use. The final column again shows that this is all working through changes in moderate and complex computer use (0.180).[26]

Overall, women suffer at the expense of men as a consequence of technical change and experience greater polarisation.[27] Table 5 shows that the demand for highly educated women increased (0.175) but the demand for medium educated women fell by more than this (-0.292) as a consequence of technical change. This was not the case for men and Table 7 shows that as a consequence of technical change, overall the demand for women fell relative to men (-0.180). These results are consistent with the existing literature but also suggest computer-skill complementarity for women. Mieske (2009) finds hollowing out of the UK skills distribution as a consequence of TBTC, whilst Autor, Levy, and Murnane (2003) find the same for the US. Black and Spitz-Oener's (2008) find evidence of greater job polarisation for women as a consequence of technical change in Germany.[28]

5. Computerisation and Task Changes

This section estimates a model for the within-industry relationship between computerisation and task changes. Following Autor, Levy and Murnane (2003), the aim is to understand how changes in computer use have affected different task requirements. This involves estimation of the following equation

$$\Delta T_j = \beta + \gamma \Delta C_j + u_j \qquad (3)$$

where ΔT_j is the change in the average value of each task and ΔC_{kj} again captures the change in technology (using moderate and complex computerisation) for industry *j*. Data are taken from the 1997 and 2006 Skills Survey data and are aggregated to the same 17 industry level as in the previous section. Unlike in previous studies, equation (3) is here estimated across only moderate and complex computerisation, but also ΔT_j is measured separately by gender. [29] Hence equation (3) is estimated separately by gender and for each of the eight generic tasks and the routine task measure (repetitive task content) as discussed in sections 2 and 3.

The first row in Table 8 provides the estimates of equation (3) for the routine task measure. These are significantly positive for men and negative but insignificant for women. Although this is contrary to Autor, Levy and Murnane (2003) who find a negative relationship between computer use and changes in routine tasks, Table 9 shows that replacing moderate and complex computer use with simple (or routine) computer use provides a negative and significant correlation for the routine task measure for men (-

2.34), though this is statistically insignificant for women. Of course, simple computer use is likely capturing general purpose technology which is a substitute for routine tasks, whilst moderate and complex computer use is capturing technology that is complementary to non-routine tasks.

The subsequent rows in Table 8 provide estimates of equation (3) separately for the eight generic tasks. For men, industry computerisation is positively correlated with changes in numeracy (2.61), literacy (1.14), self-planning (1.29), problem solving (1.02) and inspecting (1.45) task inputs. Indeed this supports the existing literature since Autor, Levy and Murnane (2003) show a positive relationship exists between changes in computer use and changes in non-routine tasks between 1970 and 1990. However, it is also clear from Table 8 that numeracy is the main complementarity to technical change.

For women, however, computerisation is only positively correlated with numeracy (1.29) and is negatively correlated with self-planning (-0.841). This helps to explain the results in the previous section. As a consequence of technical change male non-routine task inputs have increased across a variety of skill levels. However, for women, only numeracy skills are complements to moderate and complex computerisation. Table 9 shows that, for women, self-planning and problem solving are complements only to simple computerisation.

So there has been a male bias in the change in task inputs associated with computerisation. Only women with numeracy skills are complements to moderate and complex computer use and women with self-planning and problem solving skills are complements to simple computer use. For men, numeracy, literacy, self-planning, problem solving and inspecting are complements to moderate and complex computer use whilst repetitive tasks are substitutes for simple use. This helps to explain the fall in the demand for medium educated women and also why the demand for highly skilled women has increased. Overall, this also helps to explain why the relative demand for women is negatively correlated with technical change in Table 7.

Table 10 estimates equation (2) again where $\Delta SHARE_j$ measures a change in the demand for women relative to men and the technical change variable (ΔC_j) is now replaced by the change in the eight generic tasks and repetitive tasks, again using the relative female wage-bill share from the EU KLEMS data. This clearly shows that the change in the relative demand for women is negatively correlated with changes in numeracy (-0.06), literacy (-0.07), external communication (-0.08) and inspecting task inputs (-0.14), with self-planning (-0.06) and problem solving (0.07) also being negative but not quite statistically significant. Changes in physical tasks and repetitive tasks are positive and statistically insignificant. Combined with the results in Table 8 this suggests that numeracy, literacy, self-planning, problem solving and inspecting task use has reduced the relative demand for women through technical change, although none are as large as changes in computer use at work (-0.23). External communication use is also negatively correlated with the relative demand for women although this is not working through technical change.

6. Focussing on the Decline in the Gender Pay Gap

This section investigates to what extent can the -6.44 percentage point fall in the gender pay differential observed in Table 1 can be explained by the task changes and polarisation observed to be key drivers of relative demand shifts in sections 4 and 5. To do this, the 1997 and 2006 Skills Survey micro data and the Juhn, Murphy and Pierce (1993) decomposition methodology are used. The question is whether gender-biased task changes can explain the fall in the gender pay differential, conditioning on other human capital and socio-economic characteristics. These are highest qualifications (four dummy variables), experience (employment tenure in months), the eight generic task dummy variables, the dummy for routineness of the job and three computer use complexity variables. Other controls include age, sector of employment (9 dummy variables), and binary dummy variables to measure marital status, the presence of children, union membership, whether work in the public sector or whether a temporary worker.[30]

Following Blau and Khan (1997) the change in the gender pay gap between 2006 (year 2) and 1997 (year 1) can be written as ΔY_2-ΔY_1. This can be decomposed into the change that can be explained by changes in endowments namely the difference in the predicted gap (ΔE) and the change that can be explained by changes in the unexplained component or the difference in the residual gap (ΔU):

$$\Delta Y_2 - \Delta Y_1 = \left[\Delta X_2 \beta_2 - \Delta X_1 \beta_1\right] + \left[\Delta \theta_2 \sigma_2 - \Delta \theta_1 \sigma_1\right] = \mathit{\Delta E} + \mathit{\Delta U} \qquad (4)$$

where ΔX_t is the change in human capital and socio-economic characteristics, β_t is a vector of male coefficients, $\Delta\theta_t$ is the change in the standardised residual and σ_t is the residual standard deviation, observed in time t.

The ΔE term in equation (4) can be further decomposed into composite effects that capture the change in the observed quantities effect (ΔQ) which measures the change in the gender pay gap that can explained through a change in the characteristics of men and women and also the change in the observed prices effect (ΔP) which captures the change in prices of observed characteristic effects for men. Similarly ΔU in equation (4) can be further decomposed into the gap effect (ΔUQ) which measures the effect of changing differences in the relative wage positions of men and women after controlling for observed characteristics, and the unobserved prices effect (ΔUP) which captures the effect of differences in residual inequality between 1997 and 2006. The ΔUQ term gives the contribution to the change in the gender pay gap that would result if the level of the residual male wage inequality had remained the same and only the percentile rankings of the female wage residuals had changed. The ΔUP term measures the contribution to the change in the gender pay gap that would result if the percentile rankings had stayed the same for the female wage distribution and only male wage inequality had changed. Hence equation (4) can be written as

$$\Delta Y_2 - \Delta Y_1 = \Delta Q + \Delta P + \Delta UQ + \Delta UP$$

or

$$\Delta Y_2 - \Delta Y_1 = (\Delta X_2 - \Delta X_1)\beta_2 + \Delta X_1(\beta_2 - \beta_1) \ +$$

$$(\Delta\theta_2 - \Delta\theta_1)\sigma_2 + \Delta\theta_1(\sigma_2 - \sigma_1) \qquad (5)$$

Following Blau and Khan (1997) ΔQ and ΔUQ provide the full effect of the gender-specific factors whilst the sum of the ΔP and ΔUP terms reflect the change in the wage structure for men and women and might therefore be thought of as the discrimination component. Blau and Khan (1997) find the first term to be negative and the second term to be positive using US data for 1979 and 1988. This shows that the change in the male wage structure has increased the change gender pay differential over and above that which it would have been based on changes in gender-specific factors alone. Hence women were improving relative to men and the gender differential was falling but because of growing wage inequality for men they were swimming upstream and dropping back down the male earnings distribution.

The first two columns of Table 11 decomposes the -6.44 percentage point fall in the gender pay differential between 1997 and 2006 using equations (4) and (5). This table only contains the results for key drivers that explain the fall in the gender pay differential. Table A2 in the Appendix provides a full set of results.

In line with the existing empirical evidence, the first column shows that changes in education and experience endowments mainly explain the fall in the gender pay differential between 1997 and 2006. However, comparing the first and second columns shows that including generic task measures, routineness and computer use reduces the contribution of both of these. This is quite a substantial fall for highest qualifications (-

4.43 to -2.32). Changes in the endowments of the routineness variable (repetitive task content) has lowered the gender pay gap (-0.21) almost as much as the total change in generic tasks (-0.28), both of which are mainly as a consequence of changes in quantities rather than prices. As shown in Table A2 of the Appendix, the largest of the changes in generic tasks is numeracy, which is working in favour of men (1.44) and all working through male biased changes in prices rather than quantities (-0.06), although changes in physical tasks are working in favour of women (-1.42).

Including task and computer use measures also increases the change in the residual gap from -0.98 to -3.08. This fall in the residual component suggests that women have upgraded their unobservable skills and/or discrimination has declined. Changes in male wage inequality observed in Table 1 significantly increased the gender pay differential since the sum of the gender-specific component is less than the raw differential (-7.06) even when task measures are included. This is supportive of Blau and Khan (1997) who used data for the US, although the effect here is much smaller. Widening male wage inequality between 1997 and 2006 has increased the gender pay gap, on average, but the effect is relatively small (0.62).[31] This is not surprising given that Table 1 shows very little change in inequality for men.

The final four columns of Table 11 decompose the fall in the gender pay differential by computer use complexity. Clearly there are important interaction effects between task use and the technological content of jobs that explain the fall in the gender pay gap. The key drivers for the fall in the gender pay differential for workers in jobs with no or simple computer use are not changes in education or employment tenure endowments. Also, there is virtually no role for changes in generic task use or routineness of job.[32] The fall in the gender pay differential for these workers largely remains unexplained. It is likely that these workers were more affected by the introduction of the minimum wage in 1999.[33] Given the average wage for women was £5.25 in non-computerised jobs in 1997 and £7.39 in simple computer use jobs, compared to £7.46 and £9.02 for men respectively, this could partially explain the unexplained fall in the gender pay gap.[34]

Contrariwise, changes in education and employment tenure endowments do explain a large part of the fall in the gender pay differential for moderate and complex computer users. Moreover, changes in generic tasks appear to be increasing the gender pay differential for the moderate and complex computer users (2.47 and 1.62), whereas Table A2 of the Appendix shows this is mainly being driven by numeracy (2.22) for complex users and by communication and influence (2.66) for moderate users. The routineness of work has reduced the gender pay differential for moderate users (-2.31) and increased it for complex users (1.05). This provides further evidence of gender bias in the wage effects from the interaction of technical change with numeracy, communication skills and the routineness of work.

The Blau and Khan (1997) result, whereby the decline in the gender pay differential would have been much larger if it were not for changes in the male wage structure, only applies to women who used computers for moderate procedures and those who do not use computers at all. These `swimming upstream' effects are small relative to those found in

Blau and Khan (1997). For workers who used computers for simple procedures, women were swimming downstream, since women did better at the expense of changes in the wage structure. For complex computer users, changes in the wage structure have contributed to the fall in the gender pay differential (-2.26) but do not fully explain it (-6.64), given the gender-specific component (-4.47).

In summary, section 4 showed greater polarisation in the demand for women relative to men as a consequence of technical change. This was accompanied by a fall in the gender pay differential, the main reason for which largely remains unexplained for moderate and complex computer users (-4.41 and -6.31). This suggests that these women have upgraded unobservable (perhaps non-cognitive) skills outside those measured in the data and/or that the demand for these computer literate women increased. The latter explanation is consistent with the previous sections since Table 5 shows the demand for highly educated women increased even though the demand for medium educated women fell by more than this as a consequence of technical change. Table 8 showed that changes in a number of non-routine task inputs (specifically self-planning and problem-solving) are explaining this overall fall in the relative demand for women, which has occurred as a consequence of technical change. Changes in numeracy are male biased but to a lesser degree, and are the only complementarity to moderate and complex computer use for women. This helps to explain why the demand for highly educated (numerate) women has increased as a consequence of technical change, whilst the demand for medium educated women (with other non-routine skills) has fallen.

6. Conclusion

One focus of this paper is whether the changes in the task content of jobs differed for men and women using a unique data set that contains information on job tasks. The percentage of workers employed in non-technical and technically routine jobs has fallen, whilst for more skilled technical jobs (involving moderate or complex computer tasks) percentages have increased. However, both computer use and the generic skill content of jobs have changed over time but with a gender bias. The percentage of women employed in moderate computer jobs has increased relative to men, whilst the percentage of women employed in complex computer use jobs has fallen relative to men. Literacy, influencing communication, self-planning, physical and inspecting tasks have increased for female job content relative to male job content. These changes have occurred within rather than between occupation and industry cells suggesting gender biased TBTC.

The paper also shows recent polarisation between changes in the demand for highly educated women and moderately educated women which is correlated with technical change, whereas for men this has not been the case. For men, hollowing out across the skill distribution exists but it has not occurred as a consequence of technical change. Overall the relative demand for women has fallen as a consequence of these technology driven relative demand shifts. These relative demand shifts are a consequence of a gender bias in the complementarities between computerisation and non-routine task inputs. The results are consistent with the general literature on TBTC although this is the first paper to provide direct evidence of a gender bias in the demand for labour alongside evidence of gender bias in the complementarities between computer use and specific non-routine tasks such as literacy, numeracy, self-planning, problem solving and inspecting.

The decomposition analysis shows that changes in qualifications, generic tasks and computer use have played a significant role in explaining the gender pay gap. Contrary to the findings of Blau and Khan (1997) however, there is little evidence that British women were swimming upstream during the 1997-2006 period. Further analysis shows that the key drivers for the fall in the gender pay differential are education and experience, but only for moderate and complex computers. There is also evidence of gender bias in the wage effects from the interaction between routineness of job and technical change. However, a large part of the fall in the gender pay differential remains unexplained even after conditioning on qualification and generic task changes.

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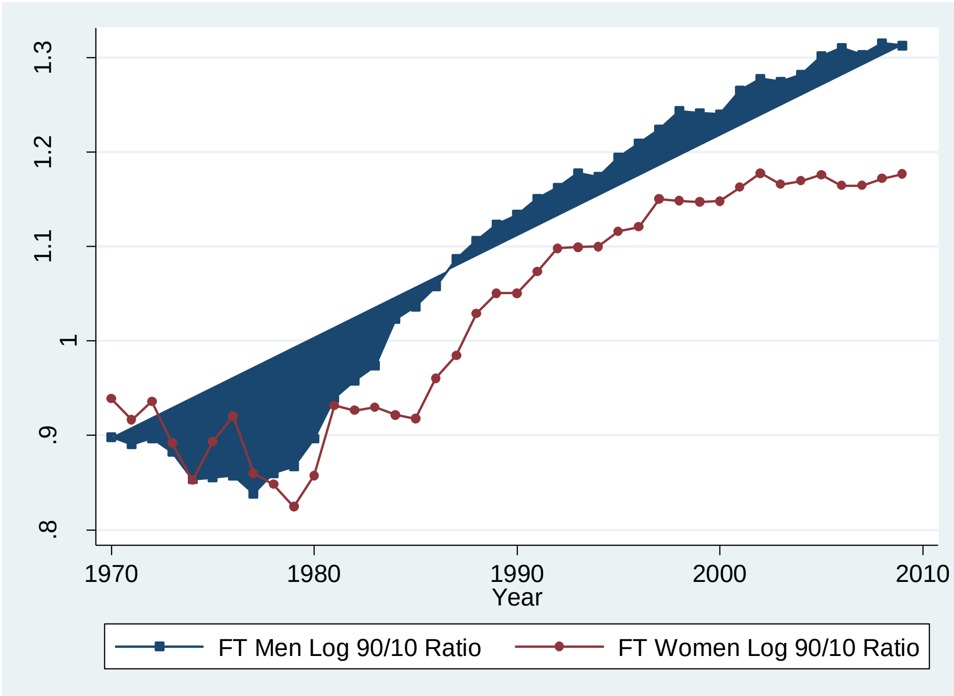
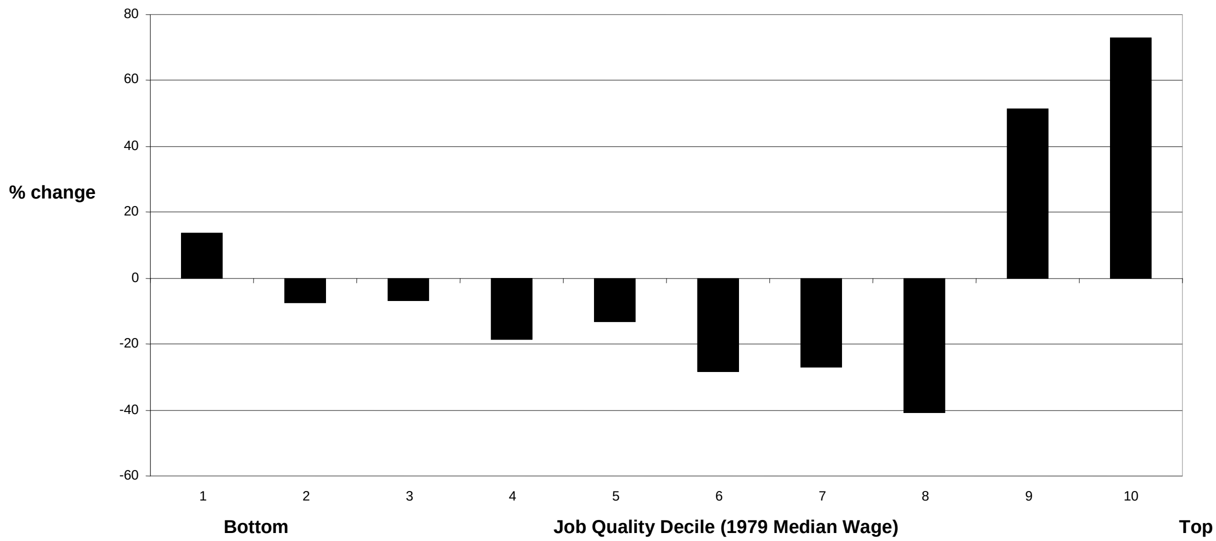
Figure 1: The 90-10 log weekly earnings ratios, full-time men and women, 1970-2009



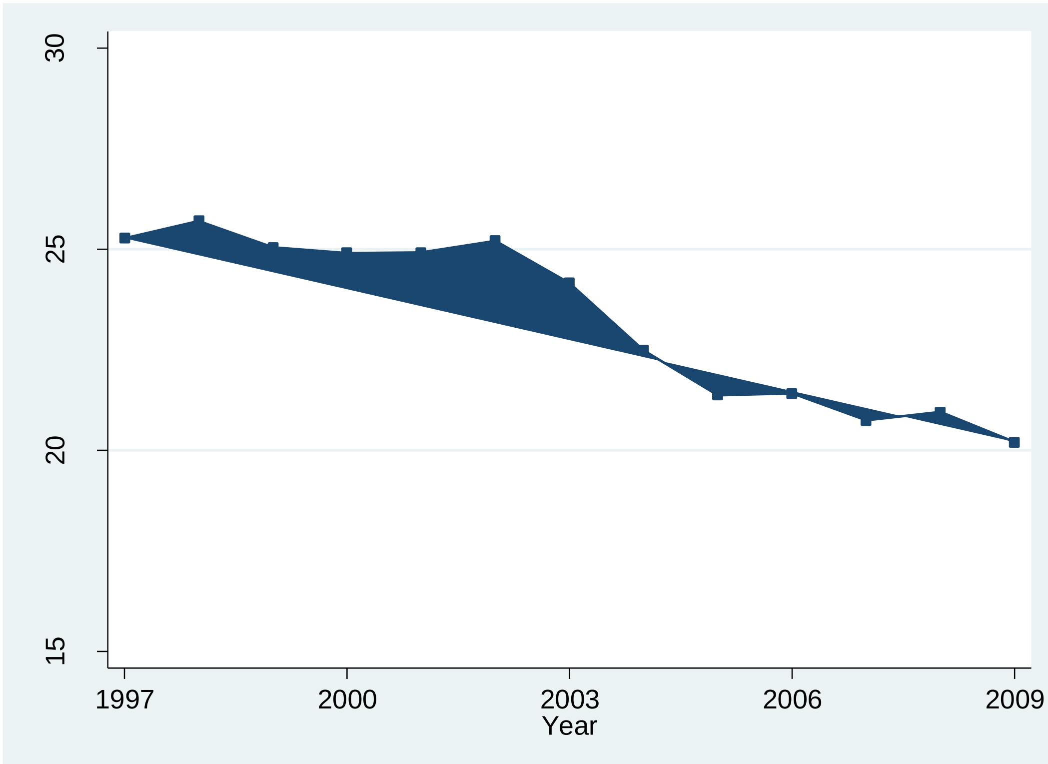
Source: Machin (2010), 1968-1996 New Earnings Survey (NES) and 1997-2009 ASHE.

Figure 2: Polarisation of the UK labour market, 1979-2008



Source: Mieske (2009).

Fig 3: The gender pay gap for all male and female workers, 1997-2009.



Source: National Equality Panel Analysis, 1997-2009 ASHE.

Table 1: Changes in mean log hourly pay by gender, 1997-2006

	1997	**2006**
Men	2.28 (0.54)	2.39 (0.56)
Women	1.99 (0.50)	2.16 (0.50)
Gender Differential	-0.29	-0.23
MWP	28.9	37.7

Notes: Standard deviations are in parentheses. Using weighted UK Skills Survey data 1997-2006.
MWP denotes the mean women's percentile of the average women's wage in the men's distribution.

Table 2: Changes in tasks and computer use, 1997-2006.

	Men				Women					
	1997	**2006**	**Δ**	**SE**	**1997**	**2006**	**Δ**	**SE**	**DiD**	**SE**
Generic task measures:										
Literacy	3.27	3.44	0.17	0.04*	3.20	3.50	0.30	0.05*	-0.13	0.06*
Numeracy	2.91	2.98	0.07	0.05	2.57	2.59	0.02	0.05	0.05	0.07
Communication: External	3.50	3.57	0.07	0.04**	3.56	3.71	0.15	0.01*	-0.08	0.05
Communication: Influencing	3.04	3.19	0.15	0.04*	2.91	3.17	0.26	0.04*	-0.11	0.05*
Self Planning	3.92	4.03	0.11	0.03*	3.78	4.06	0.29	0.04*	-0.18	0.05*
Problem solving	3.86	3.94	0.08	0.04*	3.55	3.70	0.15	0.04*	-0.07	0.05
Physical	3.16	3.12	-0.04	0.01	2.68	2.77	0.10	0.04*	-0.14	0.06*
Inspecting	4.28	4.34	0.06	0.03*	4.19	4.33	0.14	0.03*	-0.08	0.04**
Repetitive task content	3.12	3.23	0.11	0.04*	3.36	3.43	0.07	0.04**	0.04	0.06
Computer use:										
No use	33	23	-9	1.61*	33	21	-11	1.66*	2	2.31
Simple computer use	24	19	-5	1.48*	27	21	-6	1.63*	1	2.19
Moderate computer use	24	31	7	1.64*	28	41	14	1.85*	-7	2.47*
Complex computer use	19	27	8	1.55*	12	16	4	1.38*	4	2.09**
N	1141	2033			1061	2039				

Notes: **Δ** represents the change over time.
DID denotes the difference in the male and female differentials, **Δ**.
SE denotes standard deviations, whilst * and ** implies statistically significant at the 5 and 10 percent level respectively.

Table 3: Decomposing changes in tasks and computer use into within and between occupation and industry cell changes, 1997-2006. Where DiD = $W_M - W_W + B_M - B_W$.

	DiD	**Within Men (W_M)**	**Within Women (W_W)**	**Between Men (B_M)**	**Between Women (B_W)**
	$(\bar{Z}_M - \bar{Z}_W)_2 - (\bar{Z}_M - \bar{Z}_W)_1$	$\sum_j \bar{\alpha}_{Mj}(\bar{Z}_{W2j} - \bar{Z}_{M1j})$	$\sum_j \bar{\alpha}_{Wj}(\bar{Z}_{W2j} - \bar{Z}_{W1j})$	$\sum_j \bar{Z}_{Mj}(\alpha_{M2j} - \alpha_{M1j})$	$\sum_j \bar{Z}_{Wj}(\alpha_{W2j} - \alpha_{W1j})$
Occupation N=26					
Generic task measures:					
Literacy	-0.13*	0.18	0.24	-0.02	0.06
Numeracy	0.05	0.11	0.04	-0.04	-0.03
Communication: External	-0.08	0.05	0.10	0.02	0.04
Communication: Influence	-0.11*	0.15	0.18	0.003	0.09
Self-Planning	-0.18*	0.11	0.23	0.001	0.05
Problem Solving	-0.07	0.13	0.13	-0.05	0.02
Physical	-0.13*	0.01	0.08	-0.04	0.01
Inspecting	-0.08**	0.11	0.16	-0.05	-0.02
Repetitive tasks	0.04	0.12	0.16	-0.01	-0.08
Computer use:					
No computer use	0.21	-1.13	-1.15	-0.20	0.02
Simple computer use	0.07	-0.45	-0.61	-0.54	0.03
Moderate computer use	-0.68*	0.80	1.41	-0.14	-0.06
Complex computer use	0.40**	0.78	0.38	-0.007	-0.02
Industry N=60					
Generic task measures:					
Literacy	-0.13*	0.11	0.25	0.05	0.05
Numeracy	0.05	0.08	0.03	-0.01	-0.02
Communication: External	-0.08	0.05	0.13	0.02	0.01
Communication: Influence	-0.11*	0.12	0.23	0.03	0.04
Self-Planning	-0.18*	0.07	0.25	0.03	0.03
Problem Solving	-0.07	0.06	0.15	0.02	0.001
Physical	-0.13*	-0.01	0.11	-0.03	-0.01
Inspecting	-0.08**	0.05	0.14	0.01	0.001
Repetitive tasks	0.04	0.13	0.10	-0.02	-0.03
Computer use:					
No computer use	0.21	-0.91	-1.11	-0.02	-0.02
Simple computer use	0.07	-0.43	-0.59	-0.07	0.02
Moderate computer use	-0.68*	0.59	1.32	0.08	0.04
Complex computer use	0.40**	0.75	0.39	0.02	-0.03

Notes: **DID** denotes the difference in the men and women differentials from Table 2.
* and ** imply statistically significant at the 5 and 10 percent level respectively.

Table 4: Change in high, medium and low education wage bill shares, 1997-2006.

N = 17		High Education			Medium Education			Low Education	
Constant	0.067* (0.008)	0.051* (0.013)	0.033* (0.015)	-0.046* (0.008)	-0.036* (0.014)	-0.011 (0.016)	-0.021* (0.005)	-0.015** (0.008)	-0.022** (.012)
Changes in % Using Computer at Work[a]		0.185 (0.124)			-0.120 (0.135)			-0.065 (0.081)	
Changes in % Using Computer at Work For Moderate and Complex Tasks[b]			0.226* (0.091)			-0.234* (0.095)			-0.008 (0.068)
R Squared	0.57	0.31	0.32	0.13	0.17	0.39	0.14	0.18	0.14

Notes: Dependent variable is change in high, medium and low education wage bill share; All regressions include the change in log(capital/value added); All regressions weighted by average of industry employment shares across the relevant time periods; Standard errors in parentheses. * and ** imply statistically significant at the 5 and 10 percent level respectively. Test statistics show that we cannot reject the null for CRS H_0: $\beta_{\Delta\log(K)} = -\beta_{\Delta\log(Y)}$ in all cases.

a consists of simple, moderate and computer use.

b imposes the restriction that H_0:$\gamma_{\Delta simple} = 0$ and H_0: $\gamma_{\Delta moderate} = \gamma_{\Delta complex}$ which are supported by the data.

Table 5: Change in high, medium and low education wage bill shares for men and women using OLS, 1997-2006.

	Men						Women					
N=17	High Education		Medium Education		Low Education		High Education		Medium Education		Low Education	
Constant	0.026* (0.005)	0.018** (0.010)	-0.033* (0.007)	-0.041* (0.017)	-0.007* (0.003)	-0.018* (0.006)	0.041* (0.005)	0.015 (0.009)	-0.014** (0.007)	0.029* (0.010)	-0.013* (0.003)	-0.004 (0.006)
Changes in % Using Computer at Work For Moderate and Complex Tasks[a]		0.051 (0.061)		0.057 (0.099)		0.072** (0.038)		0.175* (0.055)		-0.292* (0.062)		-0.063 (0.038)
R Squared	0.24	0.28	0.02	0.04	0.19	0.35	0.33	0.61	0.08	0.64	0.02	0.30

Notes: The dependent variable is the change in the high, medium and low education wage bill share. All regressions include the change in log (capital/value added). All estimates are weighted by industry employment shares. Standard errors are in parentheses. * and ** imply statistically significant at the 5 and 10 percent level respectively. Test statistics show that we cannot reject the null for CRS H_0: $\beta_{\Delta \log(K)} = - \beta_{\Delta \log(Y)}$ in all cases.
a imposes the restriction that H_0:$\gamma_{\Delta simple} = 0$ and H_0: $\gamma_{\Delta moderate} = \gamma_{\Delta complex}$ which are supported by the data.

Table 6: Change in high, medium and low education wage bill shares for men and women using 2SLS[a], 1997-2006.

	Men						Women					
N=17	High Education		Medium Education		Low Education		High Education		Medium Education		Low Education	
Constant	0.026* (0.005)	0.009 (0.012)	-0.033* (0.007)	-0.049* (0.024)	-0.007* (0.003)	-0.018* (0.008)	0.041* (0.005)	-0.0002 (0.012)	-0.014** (0.007)	0.066* (0.030)	-0.013* (0.003)	-0.007 (0.009)
Changes in % Using Computer at Work For Moderate and Complex Tasks[b]		0.114 (0.091)		0.116 (0.154)		0.072 (0.050)		0.277* (0.080)		-0.538* (0.187)		-0.041 (0.065)
R Squared	0.24	0.22	0.02	0.02	0.19	0.35	0.33	0.52	0.08	0.25	0.02	0.17

Notes: The dependent variable is the change in the high, medium and low education wage bill share. All regressions include the change in log (capital/value added). All estimates are weighted by industry employment shares. Standard errors are in parentheses. * and ** imply statistically significant at the 5 and 10 percent level respectively. Test statistics show that we cannot reject the null for CRS H_0: $\beta_{\Delta\log(K)} = -\beta_{\Delta\log(Y)}$ in all cases.

a The instruments for change in moderate and complex computer tasks are KLEMS nominal gross fixed capital formation for information and communication technology (ICT) for 1990 and the change in ICT gross fixed capital formation between 1980 and 1990. An F test on significance of the instruments provides an F statistic of 2.79 with the joint probability of rejection of Prob>F=0.098.

b Imposes the restriction that H_0:$\gamma_{\Delta simple}$ =0 and H_0: $\gamma_{\Delta moderate} = \gamma_{\Delta complex}$ which are supported by the data.

Table 7: Changes in women-men wage bill shares, 1997-2006.

N=17	Constant & Δ log(K/Y)	With Δ Computer Use	
Constant	0.014* (0.006)	0.034* (0.008)	0.041* (0.011)
Changes in % Using Computer at Work[a]		-0.233* (0.081)	
Changes in % Using Computer for Moderate and Complex Tasks[b]			-0.180* (0.068)
R Squared	0.10	0.44	0.40

Notes: The dependent variable is the change of the women-men wage bill share.
All regressions include the change in log (capital/value added).
All estimates are weighted by industry employment shares. Standard errors are in parentheses.
* and ** imply statistically significant at the 5 and 10 percent level respectively.
Test statistics show that we cannot reject the null for CRS H_0: $\beta_{\Delta \log(K)} = -\beta_{\Delta \log(Y)}$ in all cases.
a consists of simple, moderate and computer use.
b imposes the restriction that H_0:$\gamma_{\Delta simple} = 0$ and H_0: $\gamma_{\Delta moderate} = \gamma_{\Delta complex}$ which are supported by the data.

Table 8: Moderate and Complex Computerisation and Task Intensity, 1997-2006.

N = 17	Intercept		Changes in % Using Computer at Work For Moderate and Complex Tasks	
	Men	**Women**	**Men**	**Women**
Δ Repetitive Tasks	-0.006	0.112	1.305**	-0.234
	(0.138)	(0.068)	(0.64)	(0.363)
Δ Literacy	-0.059	0.179*	1.138*	0.386
	(0.062)	(0.069)	(0.495)	(0.448)
Δ Numeracy	-0.254*	-0.141	2.611*	1.285*
	(0.115)	(0.094)	(0.46)	(0.484)
Δ External Com.	-0.711	0.119	0.634	0.065
	(0.093)	(0.082)	(0.516)	(0.381)
Δ Influencing Com.	-0.007	0.267*	0.787	-0.249
	(0.064)	(0.058)	(0.471)	(0.302)
Δ Self-Planning	-0.118	0.386*	1.293*	-0.841*
	(0.074)	(0.069)	(0.510)	(0.409)
Δ Problem Solving	-0.089**	0.189*	1.023*	-0.331
	(0.049)	(0.066)	(0.367)	(0.189)
Δ Physical	-0.046	-0.078	0.631	0.802
	(0.094)	(0.139)	(0.732)	(0.658)
Δ Inspecting	-0.125	0.026	1.454*	0.419
	(0.096)	(0.042)	(0.577)	(0.254)

Notes: The dependent variable is the change of mean tasks.
All estimates are weighted by industry employment shares. Standard errors are in parentheses.
* and ** imply statistically significant at the 5 and 10 percent level respectively.

Table 9: Simple Computerisation and Task Intensity, 1997-2006.

N = 17	Intercept		Changes in % Using Computer at Work For Simple Tasks	
	Men	**Women**	**Men**	**Women**
Δ Repetitive Tasks	0.032	0.045	-2.335*	-0.612
	(0.113)	(0.045)	(1.218)	(0.595)
Δ Literacy	0.059	0.243*	-0.553	0.213
	(0.056)	(0.058)	(0.974)	(1.027)
Δ Numeracy	-0.012	0.025	-1.81	-0.078
	(0.117)	(0.135)	(1.29)	(1.918)
Δ External Com.	0.025	0.086	0.194	-0.705
	(0.076)	(0.089)	(0.914)	(1.205)
Δ Influencing Com.	0.103*	0.222	0.093	-0.193
	(0.046)	(0.063)	(0.803)	(0.843)
Δ Self-Planning	-0.006	0.368*	-1.024	1.609**
	(0.061)	(0.058)	(0.923)	(0.791)
Δ Problem Solving	-0.008	0.249*	-0.946	1.775**
	(0.045)	(0.055)	(0.729)	(0.771)
Δ Physical	-0.015	-0.029	-0.901	-1.004
	(0.056)	(0.087)	(1.111)	(1.035)
Δ Inspecting	0.006	0.097**	-1.083	0.259
	(0.077)	(0.046)	(1.143)	(0.714)

Notes: The dependent variable is the change of mean tasks.
All estimates are weighted by industry employment shares. Standard errors are in parentheses.
* and ** imply statistically significant at the 5 and 10 percent level respectively.

Table 10: Changes in women-men wage bill shares, 1997-2006.

N = 17	Intercept	Changes in Generic Task Inputs
Δ Repetitive Tasks	0.012 (0.007)	0.029 (0.053)
Δ Literacy	0.025* (0.009)	-0.067* (0.040)
Δ Numeracy	0.020* (0.006)	-0.061* (0.026)
Δ External Com.	0.022* (0.007)	-0.083* (0.044)
Δ Influencing Com.	0.019 (0.011)	-0.029 (0.051)
Δ Self-Planning	0.023* (0.011)	-0.058 (0.057)
Δ Problem Solving	0.021* (0.007)	-0.071 (0.041)
Δ Physical	0.013** (0.007)	0.015 (0.043)
Δ Inspecting	0.027* (0.006)	-0.141* (0.039)

Notes: The dependent variable is the change of the women-men wage bill share.
All regressions include the change in log (capital/value added).
All estimates are weighted by industry employment shares. Standard errors are in parentheses.
* and ** imply statistically significant at the 5 and 10 percent level respectively.

Table 11: The key drivers that explain the fall in the gender pay differential, 1997-2006.

	Full Sample		**No PC**	**Simple PC**	**Moderate PC**	**Complex PC**
ΔY_2-ΔY_1	-6.44	-6.44	-9.22	-1.45	-5.15	-6.64
$\Delta E=[\Delta X_2\beta_2$- $\Delta X_1\beta_1]$:	-5.46	-3.36	-3.01	-3.75	-0.73	-0.33
Highest Qualification	-4.43	-2.32	-0.43	0.65	-4.03	-3.29
Employment Tenure	-1.32	-0.90	-1.28	0.44	-0.60	0.10
Total Generic Tasks:		-0.28	-1.96	-1.16	2.47	1.62
Repetitive Task Content		-0.21	-0.35	-0.43	-2.31	1.05
Simple Use		0.17				
Moderate Use		-0.65				
Complex Use		-0.01				
Other Controls	0.29	0.85	1	-3.24	3.74	0.19
$\Delta Q=[\Delta X_2$-$\Delta X_1]\beta_2$:	-4.32	-3.27	-5.29	2.45	-2.12	1.14
Highest Qualification	-4.01	-2.23	-2.07	0.42	-2.92	-2.94
Employment tenure	-0.84	-0.59	-0.97	-0.27	-0.23	0.90
Total Generic Tasks:		-0.65	-2.42	0.01	0.14	0.53
Repetitive Task Content		-0.16	0.32	-0.17	-2.01	0.96
Simple Use		0.05				
Moderate Use		-1.26				
Complex Use		0.94				
Other Controls	0.53	0.61	-0.15	2.47	2.89	1.94
$\Delta P=\Delta X_1[\beta_2$-$\beta_1]$	-1.14	-0.09	2.28	-6.19	1.39	-1.75
$\Delta U=[\Delta\theta_2\sigma_2$-$\Delta\theta_1\sigma_1]$	-0.98	-3.08	-6.21	2.30	-4.41	-6.31
$\Delta UQ=[\Delta\theta_2$-$\Delta\theta_1]\sigma_2$	-2.74	-3.79	-4.88	1.72	-4.58	-5.61
$\Delta UP=\Delta\theta_1[\sigma_2$-$\sigma_1]$	1.76	0.72	-1.34	0.58	0.16	-0.71
Sum Gender Specific	-7.06	-7.06	-10.17	4.17	-6.70	-4.47
Sum Wage Structure	0.62	0.63	0.94	-5.61	1.55	-2.46
N	6274	6274	1625	1366	2052	1231

Notes: Where ΔY_2–ΔY_1 is the difference in the log pay differential in 2006 and 1997, β is a vector of male coefficients, ΔE is the difference in the predicted gap, ΔQ is the observed endowment effect, ΔP is the observed price effect, ΔU is the difference in the residual gap, ΔUQ is the unobserved gap effect and ΔUP unobserved price effect. See Blau & Khan (1997). Table A2 in the Appendix provides a full set of estimates for the generic task measures and other controls.

Appendix

Table A1: The Composition of the generic task measures from the UK Skills Surveys.

Task	Variables and description from the UK Skills Surveys
Literacy:	READFORM: reading written information, eg forms, notices or signs READSHORT: reading short documents eg letters or memos READLONG: reading long documents eg long reports, manuals, etc WRITFORM: writing material such as forms, notices or signs WRITESHORT: writing short documents, eg letters or memos WRITLONG: writing long documents with correct spelling/grammar
Numeracy:	MATHS1: adding, subtracting, multiplying or dividing numbers MATHS2: calculations using decimals, percentages or fractions. MATHS3: more advanced mathematical or statistical procedures
Communication: External:	PRODUCT: knowledge of particular products or services SELLING: selling a product or service CLIENT: counselling, advising or caring for customers or clients PEOPLE: dealing with people
Communication: Influence:	INSTRUCT: instructing, training or teaching people PERSUADE: persuading or influencing others SPEECH: making speeches or presentations PLANOTH: planning the activities of others LISTEN: listening carefully to colleagues
Self-Planning:	OWNACT: planning your own activities OWNTIME: organising your own time AHEAD: thinking ahead
Problem Solving:	FAULT: spotting problems or faults CAUSE: working out the cause of problems or faults PROBSOLVE: thinking of solutions to problems ANALYSE: analysing complex problems in depth
Physical:	STRENGTH: physical strength eg, carry, push or pull heavy objects STAMINA: work for long periods on physical activities HANDS: skill or accuracy in using your hands or fingers
Inspecting:	TOOLS: use or operate tools, equipment or machinery MISTAKE: noticing when there is a mistake CHECK: checking things to ensure that there are no errors DETAIL: paying close attention to detail

Notes: Based on Green (2009).

Table A2: Decomposing the change in the gender pay differential, 1997-2006.

	Full Sample		No PC	Simple PC	Moderate PC	Complex PC
ΔY_2-ΔY_1	-6.44	-6.44	-9.22	-1.45	-5.15	-6.64
$\Delta E=[\Delta X_2\beta_2$- $\Delta X_1\beta_1]$:	-5.46	-3.36	-3.01	-3.75	-0.73	-0.33
Age & Age^2	0.16	0.51	0.13	0.09	1.71	-0.14
Highest Qualification	-4.43	-2.32	-0.43	0.65	-4.03	-3.29
Employment Tenure	-1.32	-0.90	-1.28	0.44	-0.60	0.10
Generic Tasks:		-0.28	-1.96	-1.16	2.47	1.62
Literacy		0.26	-0.16	-1.05	0.87	-0.41
Numeracy		1.44	1.28	0.04	0.77	2.22
Communication: External		0.57	1.55	1.71	-0.08	1.05
Communication: Influence		-0.68	-0.91	-0.36	2.66	2.04
Self-Planning		-0.45	-2.61	-0.04	-0.10	-0.55
Problem Solving		0.06	-0.63	0.32	-0.72	-0.85
Physical		-1.42	-1.00	-1.70	-1.22	-1.82
Inspecting		-0.06	0.52	-0.08	0.29	-0.06
Repetitive Task Content		-0.21	-0.35	-0.43	-2.31	1.05
Simple Use		0.17				
Moderate Use		-0.65				
Complex Use		-0.01				
Sector (9)	0.86	1.68	3.04	-5.39	5.78	2.22
Other Controls	-0.73	-1.34	-2.17	2.06	-3.75	-1.89
$\Delta Q=[\Delta X_2$-$\Delta X_1]\beta_2$:	-4.32	-3.27	-5.29	2.45	-2.12	1.14
Age & Age^2	-0.35	0.02	-0.40	-0.67	0.70	-0.16
Highest Qualification	-4.01	-2.23	-2.07	0.42	-2.92	-2.94
Employment tenure	-0.84	-0.59	-0.97	-0.27	-0.23	0.90
Generic Tasks:		-0.65	-2.42	0.01	0.14	0.53
Literacy		0.33	0.04	0.05	0.85	0.03
Numeracy		-0.06	0.16	-0.06	0.01	-0.68
Communication: External		0.28	1.43	0.29	-0.14	0.001
Communication: Influence		-0.75	-1.05	-0.75	0.99	1.55
Self-Planning		-0.53	-2.57	-0.19	-0.68	-0.20
Problem Solving		-0.45	-0.69	0.16	-0.38	-0.15
Physical		0.57	-0.04	0.58	-0.55	0.06
Inspecting		-0.04	0.30	-0.07	0.04	-0.08
Repetitive Task Content		-0.16	0.32	-0.17	-2.01	0.96
Simple Use		0.05				
Moderate Use		-1.26				
Complex Use		0.94				
Sector (9)	1.27	1.13	0.91	1.56	0.39	2.83
Other Controls	-0.39	-0.54	-0.66	1.58	1.80	-0.73
$\Delta P=\Delta X_1[\beta_2$-$\beta_1]$	-1.14	-0.09	2.28	-6.19	1.39	-1.75
$\Delta U=[\Delta\theta_2\sigma_2$-$\Delta\theta_1\sigma_1]$	-0.98	-3.08	-6.21	2.30	-4.41	-6.31
$\Delta UQ=[\Delta\theta_2$-$\Delta\theta_1]\sigma_2$	-2.74	-3.79	-4.88	1.72	-4.58	-5.61
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Notes: Where ΔY_2–ΔY_1 is the difference in the log pay differential in 2006 and 1997, β is a vector of male coefficients, ΔE is the difference in the predicted gap, ΔQ is the observed endowment effect, ΔP is the observed price effect, ΔU is the difference in the residual gap, ΔUQ is the unobserved gap effect and ΔUP unobserved price effect. See Blau & Khan (1997). Other controls are: marital status, children, union member, public sector and temporary worker.

[1] See Goos and Manning (2007), Goos, Manning and Salomons (2009), Autor, Katz and Kearney (2006) and Spitz-Oener (2006).

[2] This concept was first introduced by Autor, Levy, and Murnane (2003) in their more refined treatment of skill bias technical change (SBTC). For a survey of the literature on SBTC see Katz and Autor (1999).

[3] See Altonji and Blank (1999) for a broad discussion on this literature.

[4] Harkness (1996) finds very similar results for the UK using various data sources for 1973-1993.

[5] From Machin (2010). Data are taken from the 1970-1996 New Earnings Survey (NES) and 1997-2009 Annual Survey of Hours and Earnings (ASHE) data

[6] See Katz and Murphy (1992), Autor, Katz and Kearney (2008) for the US and also Machin (2010) for the UK.

[7] See Autor, Levy, and Murnane (2003) and Autor and Dorn (2009).

[8] From Mieske (2009). Data are taken from the Labour Force Survey (LFS). Job quality is measured using 3 digit occupational median hourly wages from the 1979 NES. Percent changes are for the entire period.

[9] Employment in the bottom decile of job quality increased from 8.7% of total share in 1979, to 9.9% in 2008The 95% confidence interval for this change is 0.86 to 1.54 percentage points, so this is significantly different from zero at the 5% level.

[10] Taken from National Equality Panel (2010).

[11] Full details of the sampling methods can be found in Felstead et al (2002).

[12] See http://www.euklems.net/ for further information.

[13] Sample weights are used throughout the analysis to ensure that the sample is nationally representative according to the standard socio economic categories as checked by comparison with the quarterly Labour Force Survey (QLFS).

[14] Following Green (2009) 32 job tasks are used to generate 8 generic measures of tasks by averaging the scores of the component tasks. Table A1 in the Appendix provides detailed descriptions of these task measures and their composition.

[15] This measure is based on a five point scale for the question `how often does your job involve carrying out short repetitive tasks'.

[16] The gender pay differentials are higher than those shown in Figure 3 but are consistent with the Quarterly Labour Force Survey (QLFS). Using QLFS data in 2006 prices provides a gender pay differential of 0.28 in 1997 and 0.24 in 2006.

[17] The growth in male inequality is lower than that found in Blau and Khan (1997), who use US data for 1979 and 1988 and find a standard deviation increase of 0.50 to 0.55 for men and 0.49 to 0.54 for women.

[18] Green (2009) uses changes in the use of computers and computerised equipment to capture technical change. This paper further classifies this measure into the complexity of use.

[19] See Autor, Levy, and Murnane (2003) and Spitz-Oener (2006).

[20] This is based on a translog cost function for men (M) and women (W) in industry j at time t of the form $C[\log(W^{W})_{jt}, \log(W^{M})_{jt}, \log(K)_{jt}, \log(Y)_{jt}, C_{jt}]$. See Machin & Van Reenen (1998).

[21] Since equation (2) uses first differences, the smaller sample sizes from the skills surveys would only exacerbate measurement error. The EU KLEMS wage bill shares are

calculated using male and female labour compensation. The survey provides high, medium and low compensation data separately for men and women. High, medium and low education are defined by KLEMS according to ISCED one digit. This allows the construction of separate wage bill shares by gender and education level.

[22] All equations are weighted by industry employment shares using the EU KLEMS data. These are based on a weighted average using the Annual Employment Survey (AES) for 1997 and the Annual Business Inquiry (ABI) for 2006.

[23] Capital stock is measured using nominal gross fixed capital formation excluding that for information and communication technology. Value added is measured using gross value added at current basic prices.

[24] As a robustness check the initial share of high, medium and low skills are included as controls in order to test for mean reversion. The results do not change very much with parameters (standard errors) on change in moderate and computer use of 0.225 (0.098), -0.242 (0.099) and -0.017 (0.056).

[25] An F test on significance of the instruments provides an F statistic of 2.79 with the joint probability of rejection of Prob>F=0.098.

[26] If the change in moderate and complex computer use is instrumented with ICT fixed capital formation in 1990 and the change in ICT fixed capital formation between 1980 and 1990, this provides a second stage IV estimate for the change in moderate and complex computer of -0.302 with a standard error of 0.10.

[27] The correlation between the change in moderate and complex computer use and the KLEMS change in ICT fixed capital formation 1997-2006 is 0.54 which is statistically significant at the 5 percent level. However, replacing the computer use variables with the

KLEMS measure of ICT capital formation provides qualitatively similar results but which are not statistically significant.

[28] Further analysis of the EU KLEMS data showed significant anomalies for some countries when data were compared to micro data collected directly from the source countries. This has prevented further research on cross country comparisons using the EU KLEMS.

[29] Equation (3) is the same as collapsing the data by industry, year and gender and estimating the change in task use on computer use separately for men and women. Chow tests for parameter stability support this specification compared to that which includes a gender dummy and computer-use/gender interaction as estimated in Black and Spitz-Oener (2010).

[30] Initially a part-time variable was included as a control. However, this complicated the interpretation of the results since the numbers of part time men are often small. Estimating separately for full time and part time workers complicates the overall picture and the ability to link the results to the previous section. However hourly wages are used which should alleviate this issue somewhat.

[31] Compared to Blau and Khan (1997) for the US in 1979-1988 of 6.8.

[32] Table A2 in the Appendix shows that it is mainly sector of employment and other controls that explain the fall in the gender pay gap for no and simple computer users.

[33] The national minimum wage was introduced in April 1999. Robinson (2002) provides evidence that the introduction of the minimum wage only explains a small part of the fall in the gender pay differential.

[34]Average wages for men and women were £12.06 and £9.29 for moderate computer users and £13.20 and £10.07 for complex computer users, respectively.