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THE GENDER DIMENSION OF TECHNICAL CHANGE AND THE ROLE OF TASK INPUTS

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The Gender Dimension of Technical Change and the Role of Task Inputs.

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Abstract

By 2011 the employment shares of UK graduate men and women had become equal for the first time. With no evidence of a significantly declining graduate female-male wage differential, this suggests that the relative demand for graduate women must have increased in order to accommodate the faster increase in their relative supply. However, gender clustering in degree subjects suggests that male and female graduates may not be perfect substitutes in production and therefore that gender biases may exist in the relative demand and supply of graduate labour. Consequently this paper investigates whether industry level skill demand shifts differ for men and women, focussing specifically on the role of technical change and job task inputs. The paper shows that despite the large growth in the percentage of women obtaining a degree, overall between 1997 and 2006 women lost out from technical change which is likely to be a consequence of their lower quality numeracy and literacy skills, as well as other skills required to undertake the tasks that are correlated with technical change, in highly computerised private sector industries like finance and machine manufacturing.

Key words: Gender Pay, Task-Biased Technical Change, Skills.

JEL: J01,J16,J2,J31

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1. Introduction

Recent research has shown that the US and UK experienced substantial growth in inequality over the last two to three decades.[1] This has led to an avenue of research investigating whether growing wage inequality can be explained through technical change. The idea is that 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.[2] This process has become known as task-biased technical change (TBTC). [3] Here routine tasks are thought to be substitutes, whilst non-routine tasks are thought to be complements with new technology.

Given the amount of the research on TBTC it is surprising that there has been little research investigating gender differences. 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. Weinberg (2000) also concludes that changes in computer use may have contributed to the substitutability between highly skilled women and less skilled men in the US during the 1970s and 1980s.

Following the existing literature, this paper investigates whether there are important gender differences in technology driven changes in labour demand. The main difference to the Black and Spitz-Oener study is that this paper adopts a different approach by estimating industry level cost-share equations. This paper also distinguishes between different types of computer use by talking into consideration computer use complexity. Finally this paper also focusses on the interaction between computer use and specific task inputs (like numeracy and literacy), as opposed to generating `routineness' measures by grouping tasks together in what has often been described to be an ad-hoc way.[4]

The paper finds that between 1997 and 2006, demand shifts in favour of UK skilled women that are correlated with technical change mainly occurred in the education and health sector, whist at the same time there was an increase in the supply of women with education and medical related degrees relative to men. In other high computer use sectors like finance and machinery manufacturing, the increase in the demand for skilled workers had a male bias. Overall women lost out from technical change since the increase in the demand for highly educated women was less than the fall in the demand for medium educated women during this period.

Numeracy task inputs are highly correlated with technical change and men possess higher levels of numeracy skills compared to women, especially amongst complex computer users. Men also seem to undertake a whole range of other task inputs that are positively correlated with changes in complex and moderate computer use, whereas women do not. This suggests that the quality of the skills men acquire from their degree programmes might differ to those of women, on average. Given that men are over-represented in physical science, mathematics, computer science, engineering, economics and business degrees this might suggest that these degree programmes are providing the skills that are complements to technical change.

The paper is organised as follows. The next section provides a background discussion on the existing empirical evidence on changes in the demand and supply of UK skilled and unskilled workers. This section also includes a deeper discussion on the gender differences that we can draw on from this literature, whilst also providing some contemporary descriptive analysis of changes in the relative demand and supply of women vis-à-vis men. Section 3 describes the data that will be used in the rest of the paper, whilst section 4 undertakes industry level analysis to estimate correlations between technical change and skill demand shifts. Section 5 looks at correlations between technical change and changes in task inputs, whilst also trying to explain any gender biases by comparing these to changing supply factors across men and women, such as differences in the quality of skills and subject of degree. The final section concludes.

2. Background: Changes in the Labour Supply of Men and Women.

It is well documented that demand has shifted in favour of more educated workers and this partially explains the rising income inequality.[5] US empirical evidence from Katz and Murphy (1992) as well as Card and Lemieux (2001) show that college graduates are not perfect substitutes for high school graduates in production. Lindley and Machin (2011) find a similar result using more recent US data with a smaller elasticity of substitution for postgraduates compared to college only graduates. Overall there is a consensus in the literature that increasing graduate wage differentials which have been accompanied by increased graduate labour supply in the US are a consequence of an increase in the demand for graduates. Lindley and Machin (2011) also show that similar patterns exist for Britain, although data limitations prevent canonical demand and supply models being estimated.

With this in mind, Figures 1 and 2 use Quarterly Labour Force Survey (QLFS) between 1994 and 2011 to plot the employment shares and wage differentials of UK graduates separately by gender.[6] The employment shares of male and female graduates have both increased (with women closing the gender gap entirely by 2011), whilst the graduate wage differential has increased for men (17.5 in 1994 to 22.5 percent in 2011) and remained relatively flat for women 31.4 in 1994 to 29.3 percent in 2011). Card and Lemieux (2001) suggest that the elasticities of substitution between US college graduates and high school graduates are fairly similar for men and women.[7] Figures 1 and 2 therefore suggest that recent demand shifts in favour of UK graduates have also been similar for men and women.

In the early literature, an explanation for the growth in the demand for graduates argues for skill biased technical change (SBTC), whereby technology changes have favoured highly educated workers and been detrimental to low educated workers, which 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.[8] This has resulted in the displacement of routine task intensive jobs and polarisation in employment. See Autor *et al*. (2006, 2008) for US evidence as well as for 16 European countries in Goos *et al*. (2009).

So far there has been relatively little research explaining the change in the relative supply and demand of women. To do this, one must first consider whether men and women are prefect or imperfect substitutes in production. If they are total imperfect substitutes in production then this implies that men cannot do the jobs of women and vice versa. They therefore operate in different labour markets. Using a similar methodology to that used in Katz and Murphy (1992) and Card and Lemieux (2001), Lindley *et al*. (2012) find for both Norway and the US that men and women are imperfect substitutes but that they have become more substitutable over time, with this process being slower in the US than in Norway. Unfortunately data limitations prevent this analysis being undertaken for the UK, owing to a too short consistent time series with sufficient sample size.

For graduates, it is likely that some men and women are more substitutable than others since gender clustering in some degree subjects may prevent perfect substitution across specialist graduate jobs. Table 1 shows gender clustering in subject of first degree amongst UK graduates both in 1994 and 2011, with little evidence of complete convergence (unlike the graduate employment shares). This suggests that some female graduates might not possess the skills required to do the jobs that male graduates can do and vice versa. Non-graduates may also be imperfect substitutes across gender as a consequence of occupational clustering that still exists from traditional gender roles.

Figures 3 and 4 again draw on the QLFS 1994-2011 to document the changes in female employment shares and wage differentials first for the full sample of men and women, but then again for graduates only and then finally for graduates who might be thought to possess more mathematical and technical skills compared to other graduates. Given the growing heterogeneity in the quality of graduates, as documented in Carneiro and Lee (2011), graduates with Science, Technology, Engineering and Maths (STEM) degrees are considered separately.[9]

In Figure 3 the female employment share increased from 0.485 in 1994 to 0.494 in 2011, where this change is larger for graduates 0.404 to 0.499, and even more so for STEM graduates 0.251 to 0.414. In Figure 4 we can see that the female-male pay differential narrowed from -25.46 in 1994 to -22.17 in 2011 closing the gender pay gap by 3.29 percentage points. However, the change is negligible for graduates overall at 0.37 percentage points (-16.82 to -17.19) suggesting that demand has shifted in favour of graduate women, given the substantial shifts in their relative supply. For STEM graduates the gender pay differential has widened by 2.28 percentage points (-13.26 to -15.55) perhaps suggesting that the relative supply increases may not have been completely absorbed by increases in relative demand.

Given these trends, it seems that that demand has shifted towards women to accommodate the faster increase in supply, but that this might not the case for all graduate women since the STEM gender pay differential has widened. Drawing on the existing methods used in the literature, the main aim of this paper therefore is to try to understand to what extent the changes in the demand and supply for male and female workers can be attributed to technical change. The paper also tries to investigate how changes in the demand for qualifications interact with technical change by looking for gender differences in the relationship between computer use and the implementation of the skills that qualifications embody through task inputs (like literacy and numeracy), rather than by grouping tasks together that are thought to be routine in nature.

3. Data Description

The rest of the paper draws upon two main datasets. These are the UK Skills Surveys and the EU KLEMS data. The paper uses the 1997 and 2006 Skills Surveys for information on computer and job tasks and merges this with the EU KLEMS data to undertake analysis at the industry level.

The UK Skills Surveys are large cross sections of individuals in paid work and aged 20-60.[10] They provide rich information on human capital and socio-economic background but also contain questions on computer use and job tasks. The EU KLEMS data provide detailed information on outputs and inputs at the two-digit industry level from 1970 to 2007.[11] They provide information on labour inputs, capital investments and compensation.

Pooling the 1997 and 2006 Skills Surveys provides data on 3174 men and 3100 women.[12] 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 the factor analysis undertaken in Green (2009), job tasks are aggregated to form eight specific task measures: literacy, numeracy, external communication, influencing communication, self planning, problem solving, physical and inspecting.[13] 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.

4. Technology, Changes in Skill Demand and Polarisation.

Following a similar methodology to that used in Autor *et al*. (1998), this section investigates to what extent technical change (measured here by computer use) is intrinsically associated with relative changes in labour demand. The analysis differs to previous studies by considering men and women separately, assuming two extremes for gender substitutability and allowing men and women to be considered both perfect and then total imperfect substitutes in production (as in Card and Lemieux (2001)).

4.1 Cost-Share Equations

The existing literature on skill upgrading involves the estimation of the following cost-share equation:

$$\Delta SHARE_j = \beta + \alpha \ \Delta \log(K/Y)_j + \gamma \ \Delta C_j + u_j \tag{1}$$

where $\Delta SHARE_j$ measures a change in the relative demand for high, medium and low education levels in industry j.[14] The $\Delta SHARE_j$ variable measured using changes in the high, medium and low education wage bills and is calculated using wage bill shares taken from the consistently defined 17 industries available in the 1997 and 2006 EU KLEMS data.[15]

The $\Delta \log(K/Y)_j$ term is the change in the log of the capital-value added ratio. This specification imposes constant returns to scale and given the small sample sizes used in this analysis, importantly increases the degrees of freedom.[16] The capital stock (K) and the value added (Y) measures are also taken from the EU KLEMS data.[17] The ΔC_j term captures a change in technology for industry *j*.[18] This is measured using the computer use information from the skills survey as described above.

Estimating equation (1) on a pooled sample of men and women treats men and women as if they are perfect substitutes in production. Including the industry female employment share in equation (1) will give us some idea of how the supply increases in female employment (shown in figure 3) may have interacted with skill demand shifts. At the other extreme, equation (1) can be estimated separately by gender which treats men and women as total imperfect substitutes in production. In reality the substitutability of men and women is likely to lie somewhere between these two extremes.

Table 2 provides the estimates of equation (1) estimated for high, medium and low skilled wage bill share changes, for the pooled sample of men and women. The first column shows that there has been an increase in the wage bills shares for high education workers (0.067) and a fall 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 which is consistent with TBTC and job polarisation.[19] Moreover, changes in moderate and complex computer use have increased the relative wage bills shares of high education workers (0.226), reduced wage bills shares for medium education workers (-0.234) and had virtually no effect for low education workers. These show clear evidence of polarisation.[20] 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). Michaels *et al*. (2010) use the EU KLEMS data with a different measure of technical change but show a very similar polarisation pattern for 11 countries.[21]

The polarisation pattern for technical change is fairly robust to including the industry change in the female employment share in equation (1). The change in the female employment share exhibits an unskilled biased technical change pattern whereby industries that have increased their share of female employment have reduced their medium education wage bill shares (-0.513) and increased their low education wage bill shares (0.378), with the change in the high education wage bill shares not being statistically different than zero. This highlights the import role of technical change in terms of its correlation with skill demand shifts.

Table 3 provides the split sample results for changes in relative high, medium and low education wage bills shares for men and women separately. Given the findings in Table 2, 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 wage bills shares for high education workers has increased (0.026 and 0.041) whilst that for medium education workers has fallen (-0.033 and -

0.014). Again there has been a small decline in the wage bills share for low education workers (-0.007 and -0.013). Notice that the wage bills share shift towards highly educated women is much larger than for highly educated men.

The change in computer use variable also shows significant gender differences.[22] Over this period, polarisation as a consequence of technical change has been for women, with virtually nothing being significant for men. For men, changes in computer use have actually significantly increased the wage bills shares of low education workers. For women, changes in computer use have increased the wage bills shares for high education workers (0.175) and reduced the wage bills shares for medium education workers (0.292) which is consistent with TBTC. Note however, that this increase for highly educated women is less than the fall for medium educated women which implies that overall women lost out from computerisation during this period. These results are consistent with the existing literature since Black and Spitz-Oener (2008) also found evidence of greater job polarisation for women as a consequence of technical change in Germany.

4.2 Where are the Gender Biases in the Industry Skill Demand Shifts?

Figure 5 plots the 1997 initial level of high education wage bill shares by the initial level of computer use for men and women across the 17 industries.[23] Overall, within industry skilled wage bill shares were higher for men than women in 1997, but both demonstrate a positive correlation, as we would expect. But this suggests that skilled men displayed larger complementarities to technical change than skilled women in 1997.

Figure 6 plots the raw correlations between the change in high education wage bill shares and the change in computer use by gender between 1997 and 2006. The OLS regression line only shows a positive relationship between the change in computer use and the change in high education wage bill shares for women and not for men. Most of the industries have increased their industry share of computer use over the period, but the largest increases are in the health and education sectors. This has led to greater increases in the demand for public sector skilled women than men, where this is especially large in the education sector, since the change in the high skilled wage bill share for men is virtually zero (-0.002) whilst for women it is the largest industry to increase its high skilled wage bill share (0.069). Other noticeable differences are for the finance and machinery manufacturing sectors since these have increased their demand for high skilled men much more than for high skilled women.

Given the patterns found in Table 3, Figure 7 plots the change in the medium education wage bill shares and the change in computer use. From this we can see that it is the education and health sectors that are mainly explaining the fall in the demand for medium educated women, with this being less so for men. Together Figures 6 and 7 suggest that the education and health sector are replacing medium education women with high education women. Indeed removing the education and health sectors altogether in Figure 9 shows that a clear bias in favour of highly educated men in industries that have increased their use of technology and that this is mainly in the finance and machinery manufacturing sector. Estimating the cost-share equation (1) again excluding the education and health sectors (Table A3 in the Appendix) shows that the female polarisation patterns observed in Table 3 are now much smaller for women compared to those for men. The increase in the demand for highly educated men (0.166) is almost twice that for highly educated women (0.095). This helps to explain how UK women lost out from technical change overall, because the fall in the demand for medium educated women in the health and education sectors was not as large as the increase in the demand for high skilled women in these and other sectors.

5. Computerisation and Task Changes

We now turn our attention to explaining the observed demand side gender biases by looking for gender biases in the task inputs that are correlated with technical change. In a similar way to Autor *et al*. (2003), the aim is to understand how changes in computer use are correlated with changes in job task inputs. The difference in this paper is that the focus is on generic job tasks like numeracy and literacy rather than on routine tasks and also that men and women are considered separately. This involves estimation of the following equation

$$\Delta T_j = \beta + \gamma \Delta C_j + u_j \qquad (2)$$

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 again 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 (2) is estimated across only moderate and complex computerisation, but also ΔT_j is measured separately by gender. [24]

Table 4 shows that 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 *et al*. (2003) show a positive relationship exists between changes in computer use and changes in non-routine tasks between 1970 and 1990 in the US. However, it is clear from Table 5 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 suggests that the skills workers possess that are required to perform tasks may differ across men and women. For example, female self-planning task inputs have increased in industries that have reduced their computer use, whereas for men they have increased in industries that have increased computer use. This alludes to gender occupational segregation within industries and perhaps that self-planning task implementation, on average, differs for men and women because of a difference in the quality of the underlying skills that men and women possess.

Overall it seems that there are a whole range of tasks complementary to technical change undertaken by men but not by women. This helps to explain the results in the previous section and why overall women lost out from technical change. One interpretation is that there are gender differences in the quality of the skills required to undertake these tasks (in particular numeracy) which are driving the greater skill demand polarisation for women.

To look for gender differences in the quality of skills Table 5 compares adult numeracy and literacy test scores with computer use and complexity using the 2004 wave of the British Cohort Study (BCS) when respondents were age 34.[25] The first row shows that men have higher numeracy test scores on average (13.62) than women (12.57) where this male bias is statistically significant (1.05). For literacy, test scores are in favour of women but this differential is small (-0.163). There is clear evidence of a male bias in numeracy test scores which is much larger for workers who use their computer for data analysis (2.46). A similar result holds for literacy where again, the male `data analysis' computer users exhibit significantly higher test scores compared to women (0.771). Overall, this suggests that men who use computers for moderate and complex procedures have much better numeracy and literacy skills compared to their female counterparts.

Revisiting Table 1 we can again look at the gender differences in the supply of graduates by subject of degree. The male biased skilled demand shifts observed in the finance sector may well be a consequence of the over-representation of men with mathematics, economics and business degrees. Similarly the female biased skilled demand shifts in the education and health sectors were clearly a consequence of female over-representation in the education and medical related degrees (which have both grown over the last 17 years).[26] Other gender biases in the demand for skilled workers in the other sectors are more difficult to link to technical change through supply constraints but we might conjecture that the better quality numeracy, literacy, self-planning, problem solving and inspecting skills than men appear to possess must in part come from their over-representation in physical science, mathematics, computer science, engineering, economics and/or business degrees. Notice however, that these are not the STEM group of degrees. To presume that STEM degrees are the most correlated with economic growth through technical change may therefore be misleading.

6. Conclusion

The UK supply of female skilled workers has grown, equalising the employment shares amongst graduate men and women by 2011. At the same time there were important gender biases in the demand for skilled labour. Between 1997 and 2006 the demand for skilled women in the education and health sectors increased, where these sectors also increased their technology use more than other industries. Probing further however reveals that women lost out from technical change because these demand shifts in favour of skilled women were not large enough to offset the fall in the demand for medium educated women in these sectors. It turns out that there are gender biases in the task inputs that are correlated with technical change (the largest being for numeracy) and this helps to explain why women lost out overall, especially in the technologically rich private sector industries such as finance and machine manufacturing.

On the supply side, men are over-represented in physical science, mathematics, computer science, engineering, economics and business undergraduate degrees relative to women. These are all relatively mathematical degrees and therefore we might assume that these are the subjects delivering the skills to men that are complementary to technical change. The overrepresentation of women in education and medical related degree subjects were clearly feeding the increased demand for skilled computer literate women in the education and health sectors, but this was not enough to stop them losing out overall. Reducing existing gender biases in the supply of skills like numeracy might therefore facilitate economic growth by utilising female labour to its full capacity in technologically advancing private sector industries.

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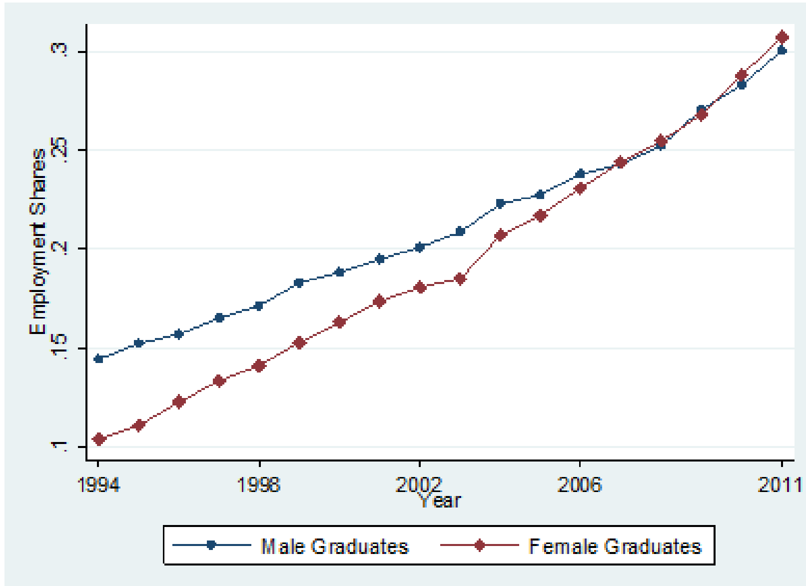
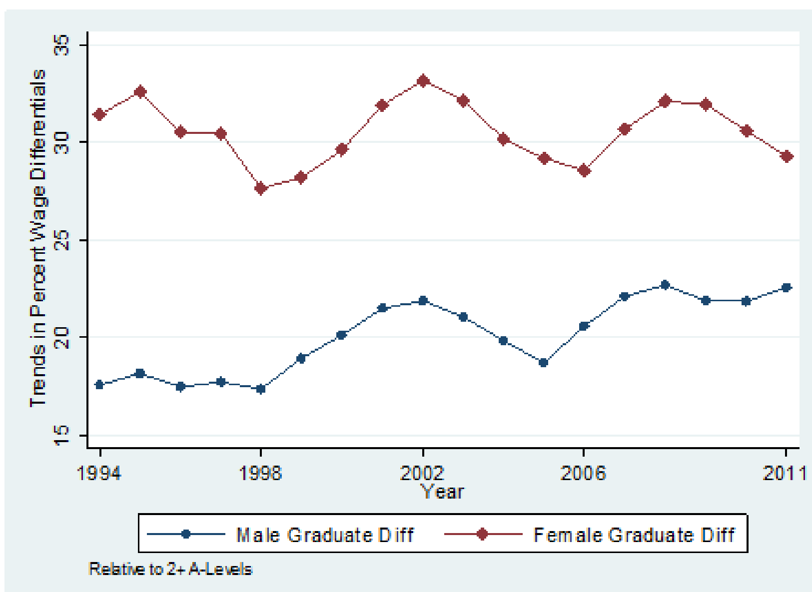
Figure 1 Changes in Employment Shares for Graduate Men and Women, 1994-2011



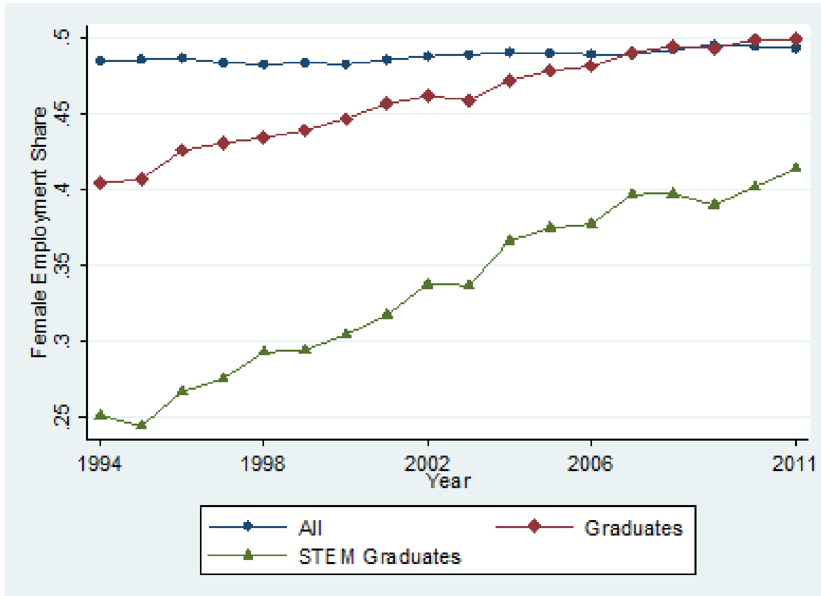
Notes: Data are from the QLFS 1994-2011. The sample contains all employed men and women age between 21 and 60.

Figure 2 Changes in Conditional Percentage Wage Differentials, 1994-2011.



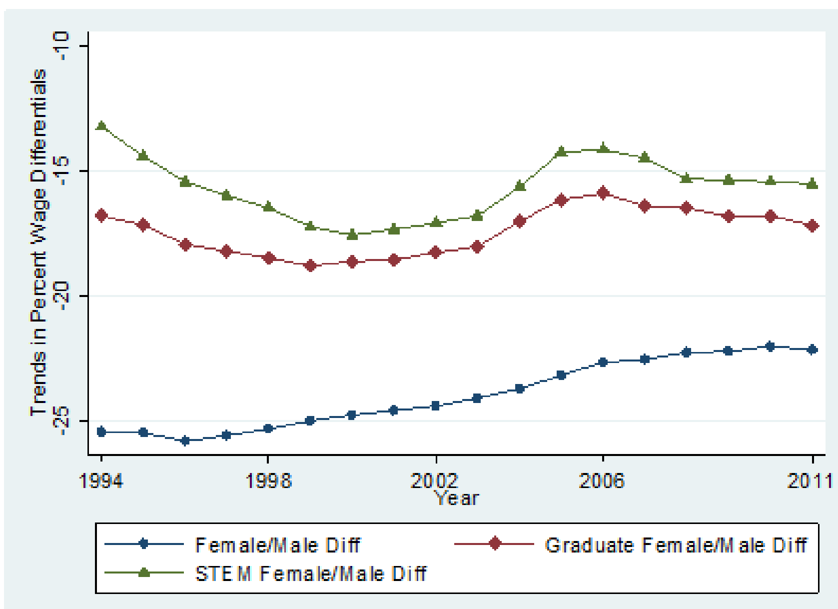
Notes: Data are from the QLFS 1994-2011. The sample contains full time men and women age between 21 and 60. Estimates are taken from separate log weekly wage equations for men and women where these contain additional controls for age and age squared, as well as a dummy variable for whether the individual lives in London.

Figure 3 Changes in the Female Employment Shares, 1994-2011



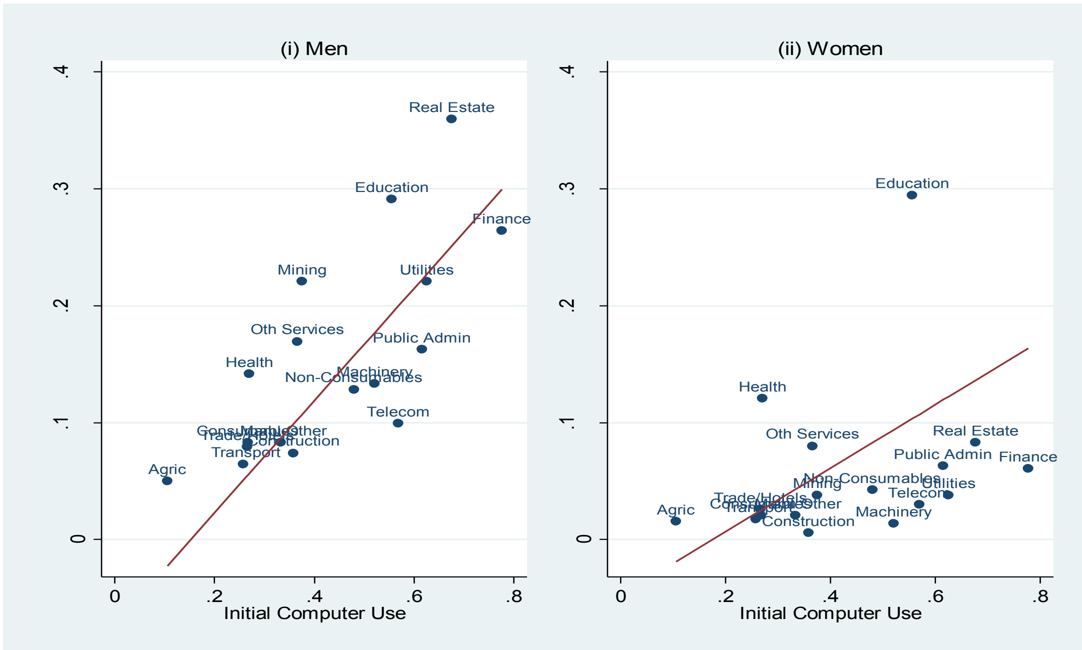
Notes: Data are from the QLFS 1994-2011. The sample contains all employed men and women age between 21 and 60. STEM graduates have Science, Technology, Engineering and Maths single subject degrees.

Figure 4 Changes in the Female/Male Wage Differential, 1994-2011



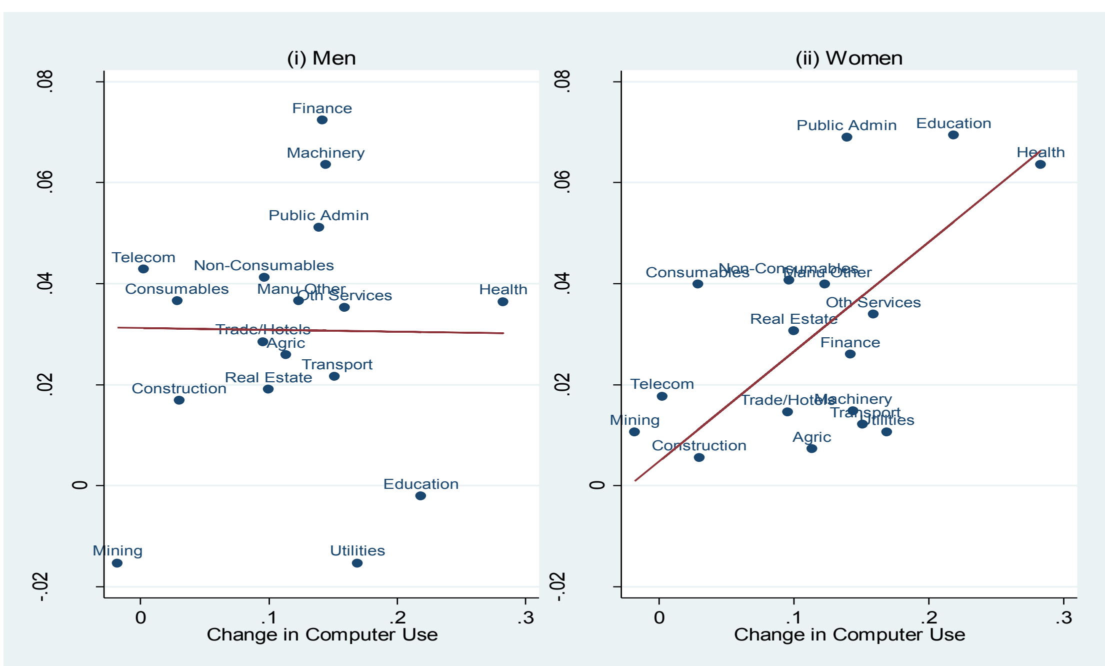
Notes: Data are from the QLFS 1994-2011. The sample contains full time men and women age between 21 and 60. STEM graduates have Science, Technology, Engineering and Maths single subject degrees. Estimates are taken from log weekly wage equations where these contain additional controls for age and age squared, as well as a dummy variable for whether the individual lives in London.

Figure 5 Levels of high education wage bill shares and computer use in 1997, by industry.



Notes: Table A2 in the Appendix provides a full description of the industries and the Standard Industrial Classification (SIC92) codes. All estimates are weighted using industry employment shares.

Figure 6 Changes in high education wage bill shares and computer use, 1997 to 2006.

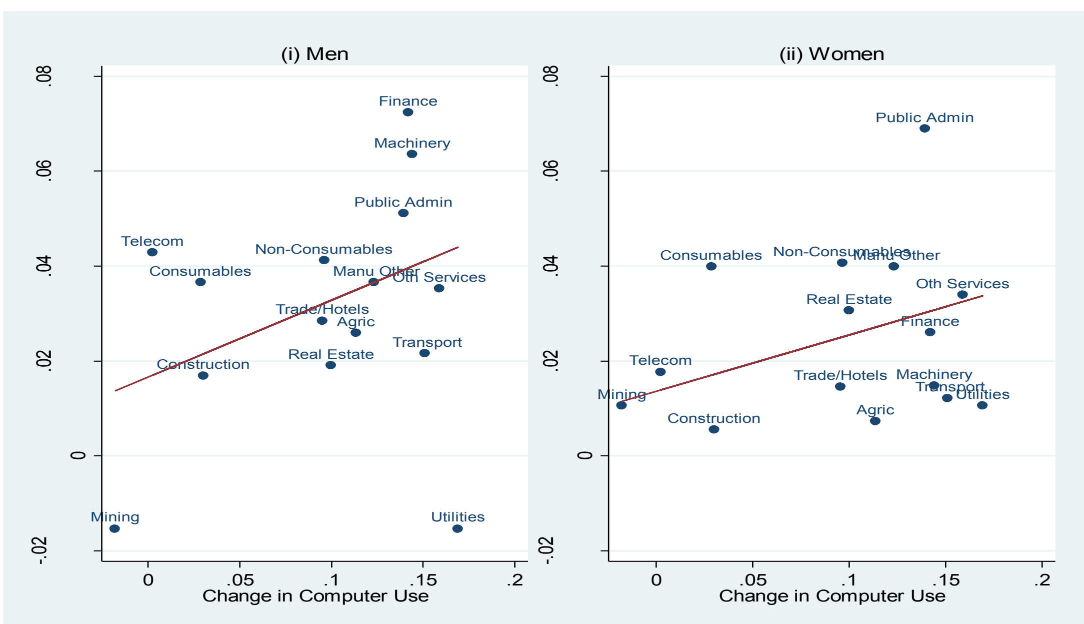


Notes: As per Figure 5.

Figure 7 Changes in medium education wage bill shares and computer use, 1997 to 2006.

Notes: As per Figure 5.

Figure 9 Changes in high education wage bill shares and computer use, 1997 to 2006. (Excluding the Education and Health Sector).



Notes: As per Figure 5.

Table 1: Employment shares of graduates by subject of undergraduate degree and gender, 1994-2011

	1994			2011			
	Men	**Women**	**Δ (SE)**	**Men**	**Women**	**Δ (SE)**	**DiD (SE)**
STEM Subjects							
Medical	0.028	0.022	-0.007* (0.002)	0.022	0.023	0.002 (0.002)	-0.006* (0.002)
Medical Related	0.013	0.029	0.016* (0.002)	0.029	0.115	0.085* (0.003)	0.070* (0.004)
Biology	0.050	0.058	0.008* (0.003)	0.066	0.083	0.017* (0.003)	0.009* (0.005)
Agriculture	0.010	0.013	0.004* (0.001)	0.009	0.006	-0.002* (0.001)	-0.006* (0.002)
Physical Science	0.098	0.046	-0.052* (0.004)	0.079	0.035	-0.044* (0.003)	0.008** (0.004)
Maths/Statistics	0.039	0.025	-0.014* (0.002)	0.029	0.020	-0.009* (0.002)	0.005 (0.003)
Computer Science	0.032	0.013	-0.020* (0.002)	0.080	0.016	-0.064* (0.002)	-0.044* (0.004)
Engineering	0.156	0.010	-0.147* (0.004)	0.123	0.012	-0.110* (0.003)	0.037* (0.005)
Technology	0.172	0.004	-0.013* (0.001)	0.010	0.006	-0.005* (0.001)	0.008* (0.002)
Non-STEM Subjects							
Law	0.035	0.032	-0.002 (0.002)	0.037	0.044	0.007* (0.002)	0.009* (0.004)
Economics	0.040	0.014	-0.026* (0.002)	0.028	0.011	-0.017* (0.001)	0.009* (0.003)
Business/Management	0.086	0.064	-0.022* (0.003)	0.153	0.125	-0.028* (0.004)	-0.005 (0.006)
Other Social Science	0.052	0.087	0.035* (0.003)	0.048	0.082	0.033* (0.003)	-0.002 (0.005)
Arts/Humanities	0.129	0.210	0.081* (0.004)	0.187	0.204	0.017* (0.004)	-0.064* (0.007)
Education	0.044	0.117	0.073* (0.003)	0.048	0.152	0.103* (0.003)	0.030* (0.005)
Combined Studies	0.170	0.256	0.086* (0.005)	0.049	0.064	0.015* (0.003)	-0.070* (0.005)
N	13902	9789		14808	16536		

Notes: Data are from the QLFS 1994 and 2011. The sample contains employed male and female graduates age between 21 and 60. **Δ** represents the gender difference. **DID** denotes the difference in the male and female differentials, **Δ**. **SE** denotes standard errors, whilst * indicates statistically significant at the 5 percent level. All estimates are weighted using LFS person weights.

Table 2: 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)	0.033* (0.016)	-0.046* (0.008)	-0.036* (0.014)	-0.011 (0.016)	-0.010 (0.015)	-0.021* (0.005)	-0.015** (0.008)	-0.022** (.012)	-0.022* (0.010)
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* (0.096)			-0.234* (0.095)	-0.265* (0.090)			-0.008 (0.068)	0.031 (0.063)
Change in the Female Employment Share				0.135 (0.306)				-0.513** (0.288)				0.378* (0.203)
R Squared	0.57	0.31	0.32	0.33	0.13	0.17	0.39	0.51	0.14	0.18	0.14	0.32

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 3: Change in high, medium and low education wage bill shares separately for men and women, 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 4: 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 Literacy	-0.059 (0.062)	0.179* (0.069)	1.138* (0.495)	0.386 (0.448)
Δ Numeracy	-0.254*(0.115)	-0.141 (0.094)	2.611*(0.46)	1.285* (0.484)
Δ External Com.	-0.711 (0.093)	0.119 (0.082)	0.634 (0.516)	0.065 (0.381)
Δ Influencing Com.	-0.007 (0.064)	0.267*(0.058)	0.787 (0.471)	-0.249 (0.302)
Δ Self-Planning	-0.118 (0.074)	0.386*(0.069)	1.293*(0.510)	-0.841*(0.409)
Δ Problem Solving	-0.089**(0.049)	0.189*(0.066)	1.023*(0.367)	-0.331 (0.189)
Δ Physical	-0.046 (0.094)	-0.078 (0.139)	0.631 (0.732)	0.802 (0.658)
Δ Inspecting	-0.125 (0.096)	0.026 (0.042)	1.454*(0.577)	0.419 (0.254)

Notes: The dependent variable is the change of mean tasks. Estimates are weighted using industry weights. 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 5: Adult Numeracy and Literacy Test Scores and Computer Use, BCS 2004.

	Numeracy				**Literacy**			
	Men	**Women**	**Δ**	**SE**	**Men**	**Women**	**Δ**	**SE**
All	13.62	12.57	1.05*	0.072	15.96	16.12	-0.163**	0.076
Use PC at Work	14.31	13.08	1.22*	0.076	16.75	16.72	0.033	0.073
Computer Mainly Used for:								
Internet Use	14.60	13.34	1.26*	0.089	17.05	17.03	0.019	0.081
Word Processing	14.58	13.22	1.36*	0.083	17.06	16.87	0.187**	0.076
Spread Sheets	15.29	14.24	1.06*	0.196	17.64	17.51	0.128	0.165
Accounts	14.96	13.60	1.36*	0.328	17.28	17.04	0.242	0.283
Data Analysis	15.68	13.22	2.46*	0.694	17.93	17.16	0.771**	0.431
Programming	15.33	14.29	1.03**	0.439	17.39	18.03	-0.639	0.443
Design	14.89	13.26	1.63*	0.375	17.10	17.37	-0.276	0.293
N	4266	3733			4266	3733		

Notes: **Δ** represents the male and female differential. Estimates are weighted using person weights **SE** denotes standard deviations, whilst * and ** implies statistically significant at the 5 and 10 percent level respectively. The sample contains British men and women at age 34.

Appendix

Table A1: The Composition of the specific 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
	TOOLS: use or operate tools, equipment or machinery
Inspecting:	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 the factor analysis conducted in Green (2009).

Table A2: Standard Industrial Classifications for Aggregated Industries.

Industry Label	Description	SIC92 Codes
Agric:	Agriculture, forestry & fishing	1-5
Mining:	Mining & quarrying	10-14
Consumables:	Manufacturing of consumable goods (food, tobacco & textiles)	15-16, 17-19
Non-Consumables:	Manufacturing of non-consumables (wood, paper, chemicals, minerals & metals)	20-22, 23-25, 26-28
Machinery:	Manufacturing of machinery	29, 30-33, 34-35
Manu Other:	Manufacturing of furniture and other manufacturing	36-37
Utilities:	Water, gas and electricity industries	40-41
Construction:	Construction sector	45
Trade/Hotels:	Wholesale & retail trade, hotels and restaurants	50-52, 55
Transport:	Air, sea, rail and other transport	60-63
Telecom:	Postal services and telecommunications	64
Finance:	Financial intermediation	65-67
Real Estate:	Real Estate and other business activities	70, 71-74
Public Admin:	Public administration and defence	75
Education:	Education sector	80
Health	Health and social work sector	85
Oth Services:	Other community, social and personal services (including private households)	90-93, 95

Table A3: Change in high, medium and low education wage bill shares separately for men and women, 1997-2006. (Excluding the Education and Health Sectors)

	Men						**Women**					
N=15	High Education		Medium Education		Low Education		High Education		Medium Education		Low Education	
Constant	0.024* (0.005)	0.005 (0.010)	-0.011* (0.010)	0.025 (0.017)	-0.007** (0.004)	-0.020* (0.009)	0.028* (0.004)	0.017 (0.010)	-0.009 (0.006)	-0.001 (0.015)	-0.025* (0.006)	-0.027** (0.015)
Changes in % Using Computer at Work For Moderate and Complex Tasks[a]		0.166* (0.083		-0.333 (0.190)		0.122 (0.073)		0.095 (0.082)		-0.074 (0.130)		0.025 (0.128)
R Squared	0.02	0.25	0.18	0.35	0.06	0.19	0.36	0.42	0.02	0.04	0.07	0.08

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.

1 See Acemoglu and Autor (2010) for a review of this literature.

2 See Katz and Murphy (1992), Autor, Katz and Kearney (2008) for the US and also Machin (2010) and Lindley and Machin (2011) for Britain.

3 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).

4 There seems to be some ambiguities in the definitions of `routine tasks' in the literature. As pointed out by Green (2009) the measure of routine cognitive tasks used in Spitz-Oener (2006) contains `calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature'. In Autor, Levy, and Murnane (2003) the GED Math score which is intended to capture non-routine analytical tasks contains `adds and subtracts 2-digit numbers'. Consequently, this paper is not intended to be a test of the by Autor, Levy, and Murnane (2003) hypothesis. Instead it looks for the correlations between specific tasks and changes in computer use, where the latter is thought to capture some element of technical change.

5 See Katz and Murphy (1992), Autor, Katz and Kearney (2008) for the US and also Machin (2010) and Lindley and Machin (2011) for Britain.

6 Wage differentials are relative to workers who have 2+ A-Levels as their highest qualification. We are restricted to use data from 1994 because this is the first year that provides information on the number of A-levels across all four quarters.

7 Card and Lemieux (2001) find very similar elasticities of substitution between US college graduates and high school graduates on a sample of men compared to a pooled sample of men and women which they suggest implies similarities across men and women.

8 See Autor, Levy, and Murnane (2003) and Autor and Dorn (2009).

9 Following Walker and Zhu (2010) the definition of STEM graduates consists of graduates with Science (including Medicine), Technology, Engineering, Maths and Computing single subject degrees.

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

11 See http://www.euklems.net/ for further information.

12 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).

13 The task questions are based on the question `how important is each task in performing your job?' The potential answers are 1 "Not at all important" 2 "Not very important" 3 "Fairly important" 4 "Very important" 5 "Essential". The task measures used in the paper take the average of this score by gender and year etc. Following Green (2009) 32 job tasks are used to generate 8 specific measures of tasks by averaging the scores of the component tasks. The questions used are identical across the 1997 and 2006 waves. Table A1 in the Appendix provides detailed descriptions of these task measures and their composition.

14 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 and Van Reenen (1998). However, labour demand equations using relative employment shares are also estimated.

15 Since equation (1) 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.

16 This assumption is supported by the data. This paper uses data for 17 industries. All equations estimated are also 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.

17 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.

18 This is typically measured using the change in industry level computer use but can also be measured using information on computing and technology (ICT) investment. Lindley and Machin (2011) use both measures for the US and GB to arrive at similar conclusions.

[19] See Goos and Manning (2007) for a discussion of job polarisation and task bias technical change in Britain.

[20] 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).

[21] The results presented here are consistent to Michaels, Natraj and Van Reenen (2010) since measuring technical change using ICT capital compensation provides consistent results. 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 data in this paper.

[22] Significant gender differences also exist when changes in labour demand are measured using relative employment shares rather than wage bill shares. These show skill-biased technical change patterns for women since the coefficient (standard error) on technical change for changes in the labour demand of highly educated women is 0.146 (0.040), whilst this is -0.082 (0.065) for medium educated women and -0.122 (0.065) for low education women. For men the corresponding coefficients (standard errors) are 0.011 (0.051), -0.010 (0.102) and 0.056 (0.036). Tables are available from the author on request.

[23] Computer use is here confined to moderate and complex use.

[24] Equation (2) 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).

[25] The British Cohort Study follows a cohort of 17,200 babies born in 1970. Follow up surveys took place at age 5, 10, 16, 26, 29 and most recently at age 34 where adult tests for numeracy and literacy were also undertaken. The skills assessment consisted of 20 questions for literacy and 17 questions assessing numeracy skills for 4266 men and 3733 women. These adults were also asked questions about computer use at work as well as questions on the nature of computer use.

[26] Note that these are graduates and therefore exclude teaching and nursing qualifications that are not at the degree level. A Post Graduate Certificate in Education is a higher degree and therefore this is not captured here since the LFS only provides information on first degree subjects.