Rising Wage Inequality and Postgraduate Education

Joanne Lindley*and Stephen Machin**

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*   *Department of Economics, University of Surrey*

**   *Department of Economics, University College London and Centre for Economic Performance, London School of Economics*

Abstract

This paper documents significant increases in the number of postgraduates working in the United States and Great Britain and reports that their relative wages have significantly risen over time. Postgraduates and college only workers are shown to be imperfect substitutes in production and, amongst graduate workers, relative demand has shifted faster in favour of postgraduates. We study reasons for this and find that postgraduates more highly complement computers and thus have benefited more from their spread than have college only workers. Moreover, the skills sets possessed by postgraduates and the occupations in which they are employed are significantly different to the college only group. Hence, the growing presence of postgraduates in the workplace has been an important factor in explaining rising wage inequality amongst graduates.

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Author Emails: j.lindley@surrey.ac.uk; s.machin@ucl.ac.uk

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1. Introduction

Rising wage differentials between education groups have been identified as a key feature of rising wage inequality in a number of countries (most notably the US and UK, but also elsewhere).[1] Rising relative wages for college educated workers, despite their increased numbers, and the increased relative demand for workers that are more educated (and the drivers of these increases) have featured prominently in discussions of why overall wage inequality has risen.

One feature of the increased supply of college educated workers is that over time more individuals have not stopped their education once graduating with a first degree. Rather, they have gone on to acquire postgraduate qualifications. In fact, in 2010 in both the countries we study in this paper (the United States and Great Britain) over 10 percent of the adult workforce (or 36 percent of all college graduates) have a postgraduate qualification.

Study of the increased importance of postgraduate education in the labour market has not yet received much direct attention from the contributors to the rising wage inequality literature. Postgraduate education does feature as a focus of one US paper (by Eckstein and Nagypal, 2004) which studies trends in overall wage inequality in the US from 1961 to 2002 and, unlike others in the literature, does highlight rising wage differentials for workers with postgraduate degrees. Also, whilst not their main focus, there are also several references to rising postcollege wages in the US in Autor, Katz and Kearney (2008) where they argue this feature of wage trends is difficult to rationalise in the standard two skill CES production approach they favour.[2]

In terms of the potential importance of the issue, it is noteworthy that when Lemieux (2006a) looks at all postsecondary education, rather than just college only graduates, in a decomposition of inequality changes between the mid-1970s and mid-2000s he concludes that

[1] See Acemoglu and Autor (2010) for an up to date review of this literature.

[2] Acemoglu and Autor (2010) also present charts showing faster wage growth amongst the postgraduate group and the 'convexification' of the wage returns to education over time that has resulted from this.

'Understanding why postsecondary education, opposed to other observed or unobserved measures of skills, plays such a dominant role in changes in wage inequality should be an important priority for future research' [Lemieux, 2006a, p.199].

Much of the existing wage differentials literature (at least as its starting point) bases itself on what has become known as the canonical model of relative supply and demand (see, among others, Tinbergen, 1974; Katz and Murphy, 1992; Acemoglu and Autor, 2010; Carneiro and Lee, 2011). In this model, wage differentials between workers with different education levels are empirically related to measures of the relative supply of the different groups and proxies for demand (usually trends assumed to be driven by technical change). The focus is usually placed on studying particular wage differentials (usually the college only/high school or college plus/high school wage gap) and modelling labour supply for just two (aggregated) education groups: 'college equivalent' workers and 'high school equivalent' workers (see, *inter alia*, the influential US papers of Katz and Murphy, 1992, Card and Lemieux, 2001, and Autor, Katz and Kearney, 2008).[3]

In this approach, the only way that postgraduates and college only workers are distinguished is via constant efficiency weights in the college equivalent labour supply group. This (implicitly) presumes postgraduates to be more productive versions of college only workers, but that they do the same jobs and are perfect substitutes in production. In this paper, we present several pieces of evidence showing this is not the case. First, estimates of the canonical model reveal evidence of imperfect substitutability between postgraduate and college only workers. Second, the skills and job tasks done by postgraduates and college only

[3] In their estimation of relative supply-demand models in the US labour market, these authors make assumptions on the labour supply of the following five groups of workers: workers with a high school degree supply one 'high school equivalent', whilst workers with less than a high school degree supply a (constant relative wage weighted) proportion of this; workers with a college degree supply one 'college equivalent', whilst workers with a postgraduate degree supply a (constant relative wage weighted) mark up of this; and, finally, the intermediate group with some college are split between the two groups (Katz and Murphy, 1992, and Autor, Katz and Kearney, 2008, split them 50-50, whilst Card and Lemieux, 2001, assume they supply α high school equivalents and (1-α) college equivalents, where α is a high school weight used to measure the wages of some college workers as a weighted mean of high school and college wages.

workers are shown to be different, as are in the occupations in which the two groups of graduates work. The canonical model estimates also show that, whilst relative demand shifts have favoured all college graduates relative to other workers so that relative wages of all graduates have risen, it turns out that demand has shifted faster for postgraduates so that within the college graduate group this has significantly widened the wage gap between postgraduates and college only workers. Further examination of the relative demand shifts reveals that postgraduates more highly complement computers and thus have benefited more from their spread than have college only workers, in part because of the skills sets they possess. Hence, overall, the growing presence of postgraduates in the workplace has been an important factor behind rising wage inequality amongst graduates.

The rest of the paper is structured as follows. In Section 2, we present initial descriptive evidence on changes in the relative wages of postgraduates and college only workers. In Section 3, we show results from estimating models of the relative demand and supply of workers with different levels of education, placing a specific focus on estimating differential supply and demand effects for postgraduate versus college only workers. We also look ay differences in the skills and job tasks of postgraduate and college only workers, and the occupations of these groups of workers. Section 4 explores the nature of relative demand shifts in more detail by looking at differences in technology complementarities for postgraduates and college only workers. Finally, Section 5 concludes.

2. Changes in Postgraduate Employment and Wages

Rising Wage Inequality and Education

The broad motivation underpinning this paper comes from the observation that wage inequality has risen rapidly in the United States and Great Britain over the last thirty to forty years. To see this, Figure 1 shows the 90-10 ratio of log (weekly wages) for full-time workers (and for the US, full-year workers) from the March Current Population Survey (CPS) for the United States and New Earnings Survey/Annual Survey of Hours and Earnings (NES/ASHE) for Great Britain.[4] The Figure shows the evolution of the 90-10 ratio for men and women in the US between 1963 and 2010 and for GB between 1970 and 2010. In both countries, for both sexes, overall wage inequality measured by the 90-10 stands at a substantially higher level in the final year, and there is a strong trend upwards in both countries starting from somewhere around the late 1960s in the US and the late 1970s in Britain.

As noted in the introduction, a focus in the literature on understanding rising wage inequality has been to study between-group and within-group changes in inequality. By far the most attention in the former category has been on studying wage gaps between workers with different education levels, as rising wage gaps between high and low education workers have been shown to be important determinants of rises in overall wage inequality (see the reviews of Katz and Autor, 1999, and Acemoglu and Autor, 2010, for more details).

In the existing work, however, the emphasis has to date mostly been placed on studying the evolution through time of rather narrowly defined wage differentials. For example, the influential US papers of Katz and Murphy (1992), Card and Lemieux (2001) and Autor, Katz and Kearney (2008) all consider the evolution through time of one specific educational wage differential, the college only/high school graduate wage gap (i.e. the wage gap between workers with exactly 16 and 12 years of education).

The fixed four year gap in schooling between college only and high school graduates has the advantage that it should yield a good, consistently defined, measure of the college wage premium. However, it does select a specific group of graduates, eliminating those with more advanced postgraduate qualifications. Contributors to this literature are certainly aware

[4] The March CPS is used for the US as it has a time series with wage and education data running as far back as 1963. The NES/ASHE data is used for GB as it has wage data back to 1970. However, it does not contain an education variable and so we cannot go as far back in our analysis that requires education data for GB - for this we use a combination of General Household Survey data (from 1977 to 1992) and the much larger sample sizes from the Labour Force Survey (from 1993 onwards when it first recorded earnings information).

of this and sometimes report additional estimates looking at the wage gap between workers with 16 or more years of education (i.e. college only and postgraduates, or college plus) as compared to workers with a high school degree. In Card and Lemieux's (2001) analysis, for example, they state that, based on data running up to 1995, it makes little difference. However, as we have already noted, aggregating college only and postgraduates workers into one composite group presumes them to be perfect substitutes and therefore that their relative wages (net of supply) should have remained constant over time.

We believe there is good reason to revisit this question. First, wage inequality has risen within the college plus group. Consider Figure 2, which shows the 90-10 ratio for all male and female graduates in the US and GB samples, again running from 1963 to 2010 in the US and now (because of requiring a consistent education variable) from 1977 to 2010 in GB using the General Household Survey (1977 to 1992) and Labour Force Survey (1993 to 2010). The Figure shows significant rises in graduate wage inequality. Second, the relative employment and wages of postgraduate versus college only workers have shifted quite substantially through time. This is especially the case in the time periods after the data used in existing work that does consider both college only and college plus measures. We show this in the next sub-section.

Trends in Postgraduate Employment and Wages

Table 1 shows the employment shares of all graduates (college degree or higher), postgraduates and college only employment shares and the postgraduate share amongst graduates for the United States and Great Britain over time. The upper panel of the Table shows that the overall graduate proportion is higher in the US, and has risen from 0.14 in 1963 through to 0.37 by 2010.[5] The decade by decade changes reveal a well known pattern, where

[5] In the early 1990s, the education variable changed definition in the US and after the definition change one can identify whether postgraduates hold a master's degree, a professional qualification or a doctoral degree. Looking at trends in these shows that a large part of the increased number of people holding a postgraduate degree was due to a rise in masters degrees (which are typically two year post-bachelor degrees). Sample sizes and the

the employment share of graduates rose rapidly in the 1970s, and continued to rise at a slower rate in the decades that followed. Considering the postgraduate and college only proportions, they broadly show the same decade by decade pattern of change, although the overall change is faster for postgraduates whose graduate share rises to 36 percent of graduates by 2010 (up from 27 percent in 1963).

The GB numbers are in the lower panel of the Table. These are taken from the Labour Force Survey (LFS) and are reported from 1996 to 2010, since the definition of postgraduate qualifications is only consistent from 1996 onwards. There is a rapid increase in the share of all graduates in employment (from 0.15 in 1996 to 0.30 by 2010). This reflects a longer run rapid increase in the graduate share, which has which speeded up through time.[6]

In the 1996 to 2010 period, there is also a sharper increase in the postgraduate share, from 0.044 in 1996, rising to 0.110 of the workforce in 2010. In terms of changing shares within the graduate group, in 1996 30 percent of graduates had a postgraduate qualification and this rises to 36 percent (interestingly, the same percentage as the US share) by 2010.

We next consider the relative wages of these education groups and results are reported in Table 2 for the US in the upper panel and for GB in the lower panel. The first three rows of the Table show wage differentials over time for the different graduate groups (college degree or higher, postgraduates, college only) measured relative to intermediate groups of workers (in the US high school graduates, in GB workers with intermediate qualifications[7]). The fourth row shows estimated differentials between postgraduates and college only workers (i.e. the gap between rows 2 and 3). The differentials are reported for full-time workers aged 26 to 60 with 0 to 39 years of potential experience in both countries.

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shorter time series on this breakdown precluded us undertaking any detailed analysis of these patterns of change although Tables showing descriptive statistics are available from the authors on request.

[6] See Machin (2011) and Walker and Zhu (2008). The graduate share was around 6 percent in 1977 and therefore graduate supply has increased very rapidly through time, in part reflecting the expansion of higher education that occurred in the early 1990s (see Devereux and Fan, 2011, or Machin and Vignoles, 2005).

[7] Intermediate qualifications in GB are A level and O level/GCSE qualifications. See the Data Appendix for more detail.

As is well known in the wage inequality literature, the wage differential between all college graduates and the relevant intermediate groups has risen significantly in both countries through time, ending up at higher levels at the end of the period under consideration. The pattern by decade has, however, been different. In the US, where we can study a longer time series, it is clear that there was a fall in the 1970s followed by sharp rises thereafter. The first row shows that the college degree or higher group had 0.68 higher log weekly wages in 2010 (up from 0.34 in 1963 and 0.38 in 1980) in the US. For the shorter time series in Britain, the comparable gap relative to intermediate qualification workers rose from 0.47 in 1996 to 0.50 by 2010.[8]

Turning to possible differences between postgraduates and college only workers, it is evident that postgraduates have significantly strengthened their relative wage position in both countries. In the US the postgraduate/high school graduate premium reaches 0.86 log points by 2010 (up by 0.52 log points from 0.34 in 1963). The college only/high school premium also rises, but by less (going up by 0.24 log points from 0.34 to 0.58). Hence, considering the evolution of wage gaps within the graduate group, the final row of the upper panel of the Table shows that the postgraduate/college only wage differential rises sharply through time, from zero in 1963, but trending up continuously since, reaching a 0.27 log gap by 2010.[9]

Postgraduates have also done better in Britain. Relative to workers with intermediate qualifications, the postgraduate wage gap increases through time (going from 0.50 to 0.58). The college only gap stays constant, however, at 0.45. Thus, the postgraduate/college only gap increases over time: it was 0.05 in 1996 and reached 0.13 by 2010.

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[8] The longer run evolution of the college plus premium in GB is not our main focus here but, like the US, this also rose sharply in the 1980s (see Machin, 2011).

[9] Looking at data from the 1960 to 2000 US Census and the 2010 American Community Survey very much confirms the US trends. For samples defined the same as the CPS analysis, the postgraduate employment share rises from 0.029 in 1960 to 0.126 by 2010 and the postgraduate/college only wage gap (standard error) increases from -0.014 (0.006) in the 1960 Census (for 1959 wages) to 0.256 (0.002) in the 2010 ACS (for 2009 wages).

Overall, Tables 1 and 2 show that the relative labour market fortunes of postgraduate and college only workers have been different through time. The clear pattern that emerges in the two countries is of an increase in both the employment shares and wage differentials for postgraduates *vis-à-vis* college only workers. The wage inequality literature has noted coincident increases in relative supply and relative wages of the college only group before and has developed empirical supply-demand models to consider their evolution through time. The within college graduates variation we have identified has been discussed less in the context of these models and so we turn to this in the next section of the paper.

3. Relative Supply-Demand Models

In this section we consider how the relative wage and employment patterns documented in the previous section of the paper map into shifts in the relative demand and supply of graduate workers with postgraduate and college only education. Our strategy is to draw upon established methods from the existing literature, so we begin by presenting estimates of what has become known as the canonical model of relative supply and demand, where relative wage differentials by education are empirically related to measures of the relative supply and proxies for demand (usually trends assumed to be driven by technical change). This approach was formalised in a general way by Katz and Murphy (1992) and has been empirically estimated by a number of authors since (see Acemoglu and Autor, 2010).

The starting point in this approach is a Constant Elasticity of Substitution production function where output in period t (Y_t) is produced by two education groups (E_{1t} and E_{2t}) with associated technical efficiency parameters (θ_{1t} and θ_{2t}) as follows:

$$Y_t = (\theta_{1t}E_{1t}^{\rho} + \theta_{2t}E_{2t}^{\rho})^{1/\rho} \qquad (1)$$

where $\rho = 1 - 1/\sigma_E$, where σ_E is the elasticity of substitution between the two education groups.

Equating wages to marginal products for each education group, taking logs and expressing as a ratio leads to the relative wage equation $\log\left(\frac{W_{1t}}{W_{2t}}\right) = \log\left(\frac{\theta_{1t}}{\theta_{2t}}\right) - \frac{1}{\sigma_E}\log\left(\frac{E_{1t}}{E_{2t}}\right)$ that can be transformed by parameterising the demand shifts term as $\log\left(\frac{\theta_{1t}}{\theta_{2t}}\right) = \alpha_0 + \alpha_1 t + e_t$, where t is a time trend and e_t is an error term, to give

$$\log\left(\frac{W_{1t}}{W_{2t}}\right) = \alpha_0 + \alpha_1 t + \alpha_2 \log\left(\frac{E_{1t}}{E_{2t}}\right) + e_t \qquad (2)$$

where $\alpha_2 = -1/\sigma_E$.

Thus, the relative wage is a function of a linear trend and relative supply. The typical approach for estimating (2) focuses on a narrowly defined wage differential (usually the college only/high school gap) and models supply in terms of college equivalent and high school equivalent workers. To define equivalents within the college and high school groups, individuals with different education are assumed to be perfect substitutes, but are given different efficiency weights. So, for example, in terms of defining college equivalents, postgraduates are assumed to be perfect substitutes for college only graduates but they are given a higher relative efficiency (e.g. in some work of around 125% which is assumed constant over time).

This assumption of perfect substitutability, but different efficiency weightings, effectively says postgraduates do the same jobs as college only workers, but are just more productive. It presumes therefore that their relative wages should have been constant through time, a presumption that is at odds with the descriptive wage trends we showed in the previous section of the paper (and as also remarked upon noted by Autor, Katz and Kearney, 2008).

Card and Lemieux (2001) have noted that the above model also imposes the restriction that different age or experience groups with the same education level are perfect substitutes, an assumption that is not consistent with the US data they analyse where the wage differentials between college only and high school graduates do not move in the same way for different age or experience groups through time.[10] One can relax this assumption by decomposing E_{1t} and E_{2t} into CES sub-aggregates as $E_{1t} = \left[\sum_j \beta_{1j} E_{1jt}^{\eta}\right]^{1/\eta}$ and $E_{2t} = \left[\sum_j \beta_{2j} E_{2jt}^{\eta}\right]^{1/\eta}$, where there are j age or experience groups and $\eta = 1 - 1/\sigma_X$, where σ_X is the elasticity of substitution between different experience or age groups within the same education level.[11]

If workers are paid their marginal productivity, we can derive a model for the wage gap between group 1 and 2 workers as:

$$\log\left(\frac{W_{1jt}}{W_{2jt}}\right) = \log\left(\frac{\theta_{1t}}{\theta_{2t}}\right) + \log\left(\frac{\beta_{1j}}{\beta_{2j}}\right) - \left(\frac{1}{\sigma_E}\right)\log\left(\frac{E_{1t}}{E_{2t}}\right) - \left(\frac{1}{\sigma_X}\right)\left[\log\left(\frac{E_{1jt}}{E_{2jt}}\right) - \log\left(\frac{E_{1t}}{E_{2t}}\right)\right] \tag{3}$$

Equation (3) is a generalised version of the canonical model allowing for imperfect substitution between workers of different experience or age within education groups as well as for substitutability across education groups. Card and Lemieux (2001) report estimates of this model based on US data, and Autor, Katz and Kearney (2008) present a variant where imperfect substitution is allowed across potential experience, rather than age, groups.

As with the Katz-Murphy model, we can again make the technological parameters a function of the linear time trend so that the estimating equation becomes the following:

$$\log\left(\frac{W_{1jt}}{W_{2jt}}\right) = \delta_0 + \delta_1 t + \delta_2 \log\left(\frac{E_{1t}}{E_{2t}}\right) + \delta_3\left[\log\left(\frac{E_{1jt}}{E_{2jt}}\right) - \log\left(\frac{E_{1t}}{E_{2t}}\right)\right] + v_{jt} \tag{4}$$

where the coefficient on the trend δ_1 indicates the relative demand shift over and above supply changes, $\delta_2 = -1/\sigma_E$, $\delta_3 = -1/\sigma_X$ and v is an error term.[12]

[10] They show that the college only/high school graduate wage rises faster over time for younger and workers with lower potential experience.

[11] Of course, if $\eta = 1$ (because σ_X is infinity owing to perfect substitution) this collapses back to the standard Katz-Murphy model. Notice we use X denoting experience as notation here as we focus on substitution across experience groups for most of our analysis (much the same emerged if we looked at substitution across age groups as well - these results are available on request from the authors).

[12] In practice, the equation from the two-level nested CES model is estimated as a two step procedure. First, the coefficient δ_3 can be estimated from regressions of the relative wages of different experience/age groups to their relative supplies to derive a first estimate of σ_X and a set of efficiency parameters (the β_1's and β_2's in the CES

Estimates of Supply-Demand Models

We present estimates of the Katz-Murphy (KM) and Card-Lemieux (CL) specifications (respectively equations (2) and (4) above) in Table 3. Our time series is too short to undertake a rigorous analysis for the GB data, so this part of the analysis only considers the US. The dependent variable (as in other papers in the literature) is a composition-adjusted relative wage[13], with the relevant relative wage under consideration in different models defined in the Table. The relative supply variables also follow the literature showing supply in terms of the relative group of equivalents (see the Data Appendix).

We begin by discussing estimates of equation (2) and (4) for the wage differential considered in the vast majority of work - the college only/high school relative wage - and for college equivalent versus high school equivalent supply. The KM model is specification [1] in the upper panel of the Table and the CL model (allowing substitutability across experience groups within the two skills groups, and computing the model based supply measures from estimating efficiency weights) is specification [4] in the lower panel of the Table. For the 1963 to 2010 time period, the estimates we obtain are similar to those in other work.

First, consider the KM specification [1]. The model uncovers a significant negative coefficient of -0.353 on the relative supply variable, suggesting an elasticity of substitution of about 2.8. This is in the same ballpark as Autor, Katz and Kearney's (2008) estimate of 2.4 for the same data running from 1963 to 2005. Similarly, there is a significant positive coefficient on the trend variable of 0.014 showing a trend increase in the college only/high school gap over and above supply changes of 1.4 percentage points a year.

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sub-aggregates) can be obtained for each education group from a regression of wages on supply including experience/age fixed effects and time dummies. Given these, one can then compute E_{1t} and E_{2t} to obtain a model based estimate of aggregate supply. See Card and Lemieux (2001) for more detail.

[13] The composition adjustment is described in the Data Appendix. Essentially we take a similar approach to Autor, Katz and Kearney (2008) and estimate predicted fixed weight wage differentials from annual wage regressions disaggregated by gender and the four potential experience groups (i.e. eight separate regressions for each year) controlling for a linear experience variable (and for broad region and race). These wages are then weighted by the hours shares of each group for the whole time period. For further discussion of issues on composition see Carneiro and Lee (2011) and Lemieux (2006b).

Second, consider the CL specification [4]. This specification shows a negative impact of aggregate supply (with an implied elasticity of substitution of 2.3) and a significant trend increase of 1.8 percentage points per year. These are different to the KM model because of the salient feature of the CL model, namely the significant estimate of σ_X of 4.0 showing imperfect substitutability across experience groups.

As noted above, some authors have remarked that if the same exercise is carried out for a wage differential defined between college plus (i.e. postgraduates and college only workers) and high school graduates and the same supply measure that much the same results follow. We consider this in specifications [2] and [5] in the Table where we now consider a relative wage as the postgraduate to high school graduate wage. If the college plus group is homogenous (and the postgraduates and college only workers can be thought of as perfect substitutes) then one should see the same estimates as in specifications [1] and [4].

Whilst qualitatively similar (i.e. supply depresses wage differentials and there is a significant trend increase in relative wages over and above supply) the magnitudes of the estimated effects turn out to be rather different. In the KM model, the implied elasticity of substitution is now 2.2 (as compared to the 2.8 above for college only), not surprisingly showing less substitutability of postgraduates with high school graduates. Moreover, the trend coefficient is around 50 percent higher at 0.020 compared to 0.014. Both these postgraduate/college only gaps are statistically significant. The same pattern emerges for the CL model. In specification [5], the estimated impact of aggregate relative supply on relative wages is more marked than in specification [4], suggesting a slightly lower substitution elasticity of 1.9 (as compared to 2.3). In addition, the trend coefficient is larger (at 0.024 *vis-à-vis* 0.018).

We have also considered what happens when looking at the extent of substitutability within the graduate group E_{1t}. This amounts to generalising the original production function in equation (1) to three worker types as follows:

$$Y_t = (\theta_{1t} E_{1t}^{\rho} + \theta_{2t} E_{2t}^{\rho})^{1/\rho} \qquad (5)$$

$$E_{1t} = (\theta_{11t} P_t^{\eta} + \theta_{12t} O_{2t}^{\eta})^{1/\eta}$$

where P denotes postgraduates and O denotes college only workers and $\eta = 1 - 1/\sigma_{PO}$, where σ_{PO} is the elasticity of substitution between the two graduate groups.[14]

As in the spirit of the tests introduced by Ottaviano and Peri (2012) on whether more narrowly defined education groups can be grouped together or not (as they can if there is an infinite supply elasticity with perfect substitution), we can consider the KM and CL specifications when E_{1t} is specified as in equation (5).[15] In this case, the estimating equations within the graduate group now become:

$$\log\left(\frac{W_{Pt}}{W_{Ot}}\right) = \lambda_0 + \lambda_1 t + \lambda_2 \log\left(\frac{P_t}{O_t}\right) + \upsilon_t \qquad (6)$$

$$\log\left(\frac{W_{Pjt}}{W_{Ojt}}\right) = \psi_0 + \psi_1 t + \psi_2 \log\left(\frac{P_t}{O_t}\right) + \psi_3 \left[\log\left(\frac{P_{jt}}{O_{jt}}\right) - \log\left(\frac{P_t}{O_t}\right)\right] + \omega_{jt}$$

where in the KM model $\lambda_2 = -1/\sigma_{PO}$ and in the CL model $\psi_2 = -1/\sigma_{PO}$ and $\psi 3 = -1/\sigma_{XPO}$ (with σ_{XPO} being the elasticity of substitution between different experience groups within the more narrowly defined education groups). As before in the CL model we compute the efficiency weights to form the model based relative supply measures. [16]

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[14] It should be noted at this juncture that the same arguments could potentially be made about high school graduates and dropouts in E_{2t}. However, and in common with other work in this area (Card, 2009; Goldin and Katz, 2008; Ottaviano and Peri, 2012), it turns out there is no need to as we were unable to reject the null hypothesis of perfect substitutability within the high school equivalent group when we specified a lower nest for E_{2t}.

[15] Other papers in the immigration literature take a similar approach of testing for substitution of different worker types in relative wage equations derived from nested CES production functions. For the US, see Aydemir and Borjas (2007) and for Britain see Manacorda, Manning and Wadsworth (2012).

[16] In practice, this is done by obtaining estimates of σ_{PO} as a first step and then the relative efficiency parameters θ_{11t} and θ_{12t} from wage equations for postgraduate and college only workers, and then constructing the aggregate

This graduate only model thus looks for further substitution between postgraduate and college only workers within the graduate group. The estimates are shown in specifications [3] and [6] of Table 3. The specifications here define relative wages as the postgraduate/college only wage and split the college equivalent supply into postgraduates and college only equivalents. In both the KM and CL models, we reject the hypothesis of a zero supply effect and therefore perfect substitutability. The estimated coefficient on the aggregate supply variable is negative and significant in both cases, and produces the same point estimate of -0.13, implying an elasticity of substitution of 7.7. Interestingly, in CL model there is no evidence at all of substitution across experience groups (i.e. we cannot reject the hypothesis that $1/\sigma_{XPO} = 0$), hence the reason why the KM and CL models yield the same substitution elasticities. Another way to note the similarity of the KM and CL estimates in the postgraduate/college only comparison is to note that relative wages do not show strongly different patterns over time for low versus high experience (or younger versus older) workers. This is made clear by looking at Figure 3, which shows trends in the composition adjusted postgraduate/college only relative wage across higher and lower experience groups.

The models also show the importance of relative demand shifts in favour of postgraduates as compared to college only workers. The significant coefficient on the trend variable shows an annual increase in relative wages, over and above supply changes, of 0.5 percentage points per year or cumulatively a very sizable 24 percentage points increase over the full 48 years. Demand driven increase in postgraduate/college only wage gaps have therefore been an important aspect of rising within-group inequality amongst graduates.[17]

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supply index E_{1t}. This estimated model-based supply index that allows for imperfect substitutability within the college plus group is then used in estimating models whose results are reported in the Tables.

[17] In an earlier version of this paper, we explored different ways of modelling the demand shift in the KM and CL models. Some authors (Autor, Katz and Kearney, 2008; Goldin and Katz, 2008) have addressed this issue by looking at trend non-linearities or trend breaks. We took a different approach, replacing the linear trend with a technology proxy, the log of the real ICT capital stock. For our interest in postgraduates, both the KM and CL models incorporating the real ICT capital variable corroborate the findings from before and, if anything, turned out to be stronger. The Ottaviano-Peri (2012) type test in specifications [3] and [6] more strongly rejects the hypothesis of constant wage evolutions for postgraduates and college only graduates. For the KM and CL models

What Are The Skills That Make Postgraduates More in Demand Than College Only Graduates?

An obvious question that emerges is to ask what are the skills possessed by postgraduates that make them imperfect substitutes for college only workers? Data is sparse on this, but we can shed light on the question by looking at the British 2006 Skills Survey that contains information on education levels of workers, but also on their specific skills in terms of the job tasks done by workers.

Table 4 shows postgraduate/college only differences in cognitive skills, problem solving skills, people skills, firm-specific skills, the tasks they use computers for and the routineness of their job. Most of the numbers in the Table (with the exception of the proportions using computers) are based on a scale of 1-5 (5 being highest) from questions on task performance asking 'How important is this task in your current job?', with 1 denoting 'not at all important', 2 'not very important', 3 'fairly important', 4 'very important' and 5 'essential'.

It is clear that both sets of graduates do jobs with high skill and job task requirements. However, in almost all cases the levels are higher (and significantly so) for postgraduates. For example, postgraduates have higher numeracy levels (especially advanced numeracy), higher levels of analysing complex problems and specialist knowledge or understanding.[18] The computer usage breakdowns are also interesting, showing clearly that postgraduates and college only workers have high levels of computer usage, but that using computers to perform complex tasks is markedly higher amongst the postgraduate group.

We view the Table 4 material as confirming that postgraduates do possess different skills and do jobs involving different (usually more complex) tasks than college only workers. This is further evidence of them being imperfect substitutes and, as they seem to possess

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the estimated coefficients (standard errors) on the supply variable were -0.155 (0.071) and -0.158 (0.057). Moreover, the strong and significant coefficient on the real ICT measure suggested that, over time, technology driven demand has been shifting strongly in favour of postgraduate relative to college only workers.

[18] These are all skills that are becoming more highly valued in the labour market through time (see Green, 2012).

higher skill levels, is in line with the fact that relative demand has shifted faster in favour of the postgraduate group within the group of all college graduates.[19] As such, this is an important aspect of rising wage inequality amongst college graduates.

Which Occupations do Postgraduates and College Only Graduates Work in?

We have also looked at another dimension by which postgraduate and college only workers differ and that relates to their imperfect substitutability by looking in which occupations they are employed. Table 5 shows the top ten occupations in terms of their share in employment for college only and postgraduate workers in 2010 for the US (in the upper panel) and for GB (in the lower panel).

There are several interesting features of the top ten occupations of these three groups of workers. First, other than in the education sector, the top ten tend to be different occupations in both countries. Second, whilst the occupational categories are not quite the same across countries, there are some clear similarities. Third, the postgraduate occupations are more segregated than the college only. For postgraduates, in both countries the top ten (in the US out of 497 occupations, and for GB out of 353 occupations) account for just over 40 percent. The college only distribution is more dispersed, with the top ten for more like a quarter.[20] It is evident that college only workers are spread more widely across the occupational structure and the occupational distribution of postgraduates is more segregated.

The differences in the occupational structure of employment for the postgraduate group *vis-à-vis* college only graduates offers additional corroborative evidence relevant to our

[19] They are also in line with the task continuum model that Acemoglu and Autor (2010) introduce in the context of their discussion of the shortcomings of the canonical model. They state that the canonical model is a useful and powerful way to model how the supply and demand for skills have affected wage differentials through time, but argue for generalising it in terms of a task-based model with an allocation of skills to tasks and in which new technology substitutes for workers doing certain (more routine) tasks. In terms of the task continuum in their model, we view our evidence as illustrating that postgraduates do tasks at the top end of the task continuum and thus are not substitutable by computers or other new technologies. This seems very consistent with our results showing postgraduates doing tasks that are more advanced and performing better in the labour market than college only workers and with their higher complementarity with computers.

[20] Benson (2011) considers the spatial distribution of occupations in the US by education group. Whilst not the main focus of his analysis, he shows the occupational structure of postgraduates to be more segregated than for college only workers (and indeed for the rest of the labour force).

earlier findings of less than perfect substitution and in the trend differences in relative wages net of relative supply between the postgraduate and college only group.

Thus, overall, we have found evidence of imperfect substitutability of the two different groups of graduates. As a consequence, the (implicit) view that postgraduates are just more productive versions of college only workers does not seem to be tenable. The other key result from the supply and demand modes is that demand has shifted significantly in favour of postgraduates within the graduate group and that this has played an important role in raising wage inequality amongst college graduates. In the next section of the paper, we probe this further, looking at what has driven this increased relative demand for postgraduates by studying differences in technology-skill complementarities for postgraduate as compared to college only workers.

4. Differences in Technology-Skill Complementarities

We now shift the focus to ask why the demand for postgraduate and college only workers has been different. Again utilising the approaches used in existing work that does not distinguish between the two different groups of graduates, we study correlations between temporal shifts in relative demand and observable technology measure and look at whether one can identify cross-country similarities in the observed patterns of change.

Industry Computerization and Skill Demand

A large body of research connects relative demand shifts underpinning increased wage inequality to observable measures of technology, usually relating the two through industry-level regressions.[21] This work reveals that technology measures like R&D, innovation and

[21] The seminal article is Berman, Bound and Griliches (1994) which related changes in the demand for skilled labour in US manufacturing industries to measures of R&D and computer investment. Autor, Katz and Krueger (1998) study connections with industry computerization, and Berman, Bound and Machin (1998) and Machin and Van Reenen (1998) offer cross-country comparisons based on the same industries across countries. This by now sizable literature is reviewed in Katz and Autor (1999).

computerization are positively correlated with long run secular increases in the demand for more educated workers, thus showing important technology-skill complementarities.

For our purposes, it is interesting to ask whether technology-skill complementarities are different for postgraduate and college only workers. We explore this question by estimating the following long run within-industry relationship between changes in relative labour demand of different education groups, S, and changes in computer use, C, as:

$$\Delta S_{ejt} = \lambda_{1e} + \gamma_{1e}\Delta C_j + \omega_{1ejt} \qquad (7)$$

where $\Delta S_{ejt} = S_{ejt} - S_{ej\tau}$ is change in the employment share for education group e in industry j between years τ and t (in the US between 1989 and 2008, and for GB between 1996 and 2008) and ΔC_j is the change in the proportion of workers in industry j using a computer at work between 1984 and 2003 for the US (from the October Current Population Survey Supplements) and between 1992 and 2006 for GB (from the 1992 Employment in Britain and the 2006 Skills Survey).

To evaluate the longer run impact of computer use (since the initial introduction of computers in the PC era) we also augment equation (7) by the initial level of computer usage (in 1984 for the US and 1992 for GB) as follows:

$$\Delta S_{ejt} = \lambda_{2e} + \gamma_{2e}\Delta C_j + \varphi_{2e} C_j^{initial} + \omega_{2ejt} \qquad (8)$$

where $C_j^{initial}$ is the initial computer use proportion (measured in 1984 for the US and 1992 for GB). The inclusion of this variable can be thought one in one of two (related) ways. First, by holding constant the initial stock of computers, its inclusion implies the estimated coefficient on ΔC_j picks up effects of the change in computer use from then. Second, under the assumption that in earlier periods (say back in the 1960s or 1970s) the computer use proportion was essentially zero, the variable itself can be viewed as picking up growth in computer use effects up to the time period in which the variable is measured.

US Results

Estimates of equation (7) and (8) are reported for five education shares in Table 6. As per the main focus of this paper, the five education groups generalise on the four used in earlier work by breaking down the college plus group into postgraduates and college only workers.[22] The upper panel of the Table focuses on the US, the lower panel on GB and in each case the two specifications showing the estimates of γ_{1e} from equation (7) and γ_{2e} and φ_{2e} from equation (8) are shown.

Considering first the US results, specification [1] in Table 6 uncovers different connections between the postgraduate and college only changes in employment shares and changes in computer use. Indeed, the positive connection reported in earlier work (e.g. Autor, Katz and Krueger, 1998) is only present for the postgraduate group. It seems that the connections between industry changes in skill demand and changes in computerization are not neutral across the two groups of college graduates.

Results for the three other education groups (some college, high school graduates and high school dropouts), show much the same pattern as seen in earlier work, where the main losers from increased computerization are the high school graduates (not the dropouts).[23] This, of course, is consistent with computerization playing a significant role in the polarization of skill demand (where jobs were hollowed out and/or relative wages deteriorated in the middle part of the education distribution).[24]

[22] In their US study, Autor, Katz and Krueger (1998) look at four education groups: college, some college, high school graduates and less than high school. Given our focus on heterogeneity in the college group, we split that into postgraduates and college only, so as to look at five groups. We also study five (broadly comparable groups) in the GB data: postgraduates, college only, intermediate 1, intermediate 2 and no qualifications. (See the Appendix for more detail on the precise definitions used.)

[23] Like Autor, Katz and Kreuger (1998), we obtain a positive significant coefficient on computerization in the high school dropouts share equation. Like them, controlling for the initial (lagged) education share does ameliorate this, although our interpretation of the computer effects as reflecting polarization with the bigger negative effects for the intermediate education groups remains robust to this.

[24] For evidence on labour market polarization in the US see Autor, Katz and Kearney (2008), in the UK Goos and Manning (2008) and for Germany Spitz-Oener (2006) or Dustmann, Ludsteck and Schoenberg (2009). Goos, Manning and Solomons (2009) and Michaels, Natraj and Van Reenen (2010) present evidence that polarization connected to computerization is pervasive across a number of countries.

The second US specification [2] in Table 6 shows estimates of equation (6) which additionally include the 1984 computer use proportion. This sheds more light on what has been going on within the graduate group. The change in the postgraduate employment share is significantly related to both the 1984 to 2003 increases in industry computerization and to the 1984 level. On the other hand, the change in the college only wage bill share is insignificantly related to the 1984 to 2003 change and positively and significantly only to the initial 1984 level.

Thus, the initial influx of computers to industries benefited both groups, but thereafter the group of graduates who benefited was confined to those with a postgraduate qualification. This paints a rather different picture as to who benefited most from the computer revolution. It seems initially that labour demand shifted in favour of all graduates, but as time progressed labour demand tilted more in favour of postgraduates. This suggests that more recently postgraduates possess skills that make them more complementary to computers, a point we return to towards the end of this section where we look directly at differences in the skills of postgraduate and college only workers.

It is worth benchmarking the within-college group differences for postgraduates and college only with the earlier work where the overall college share (i.e. the sum of the two shares) was used as dependent variable. If we put them together in one college plus group as in the earlier work, we obtain a coefficient (and associated standard error) of 0.131 (0.031) on the 1984 to 2003 ΔC_j variable and of 0.010 (0.001) on the 1984 $C_j^{initial}$ variable. Therefore, like the earlier work, there is indeed a strong connection between changes in college plus employment shares and computers, but our findings highlight that it is one characterised by non-neutrality of technology-skill complementarity across the postgraduate and college only groups. Put differently, postgraduates more highly complement computers as compared to college only workers and thus have benefited more from their spread.

GB Results

The lower panel of Table 6 gives the GB results. Consider specification [3] first. As with the US findings, we find non-neutrality amongst the two groups of graduates. We obtain a significant positive coefficient on the postgraduate variable and an insignificant (positive) one on the college only variable. The same is true in specification [4] when the initial computer usage variable (measured in 1992) is included. Here though, it is evident that there are strong and significant connections between changes in the postgraduate employment share and both changes in industry computerization and the 1992 level of computer usage. On the other hand, connections with the college only share are not statistically significant.

For the other three education groups, the results also confirm that the British labour market was also characterised by polarization connected to industry computerization and its associations with changes in the relative wages and employment of workers with different education levels. The hollowing out of the middle is seen in the results reported in the Table where the intermediate qualification groups fare worst, whilst those at each end of the education spectrum (the postgraduates at the top and the no qualifications group at the bottom) have the best outcomes in relative terms.

Sub-Period Analysis and Complex/Basic Computer Use

The notion that increased computer usage acts as a measure of new technology over the whole time period we consider also requires some discussion (see Beaudry, Doms and Lewis, 2010, who critically appraise the extent to which the widespread use of personal computers reflects a technological revolution). This is a potentially important aspect of our analysis in that we look at changes in computer usage between 1984 and 2003 as, by 2003, in some industries the percentage of workers using a computer is high. This possible near reaching of a ceiling, of course, shows the need to control for initial levels of computer usage in the regressions. It also raises the question of whether changes in a simple headcount measure of any computer use at work adequately reflect technological change.

We consider this question in two ways for the US analysis (sample size issues precluded a similar analysis being undertaken for GB). First, we break down the analysis into two sub-periods. These are dictated by the availability of computer usage data in the CPS in the October supplements of 1984, 1993 and 2003. We thus look at changes in employment shares between 1998 and 2008 and how they relate to changes in computer usage between 1993 and 2003, and perform the same sub-period split for changes in employment shares between 1989 and 1998 with computer use changes measured from 1984 to 1993.[25]

Estimates of equation (6) are reported in specifications [1] and [2] of Table 7 for these two sub-periods. The analysis corroborates the earlier findings where there is a stronger computerization effect for postgraduates than for college only workers. A closer inspection of the results does, however, reveal that this more true of the first sub-period (in specification [1]). In the second sub-period (specification [2]) the postgraduate and college only computerization effects are more similar.

To further probe this, the second way we consider the usefulness of the computer usage data to measure technological change is by breaking down the computerization measure into whether the computer is used for complex or basic tasks. For the second period of data we can do this since the 1993 and 2003 computer use supplements in the CPS report whether computers are used for more complex tasks like programming as well as for a variety of other

[25] The second period closely approximates the time period studied by Autor, Katz and Krueger (1998). Autor, Katz and Krueger report an estimated coefficient (standard error) of 0.152 (0.025) on the computer use variable in a regression of changes in college plus employment shares between 1979 and 1993 on the 1984 to 1993 change in computer usage for 191 US industries. Running the same regression (i.e. not including the initial level of computer usage) on our 215 industries for the change in college plus employment shares between 1989 and 1998 we obtain a very similar estimate of 0.144 (0.026) on the 1984 to 1993 change in computer use variable. For this specification, considering postgraduate and college only shares separately produces a coefficient (standard error) of 0.087 (0.015) on the change in computer use variable in a change in postgraduate share equation and of 0.057 (0.023) in a change in college only share equation.

more basic purposes (see the Data Appendix for more detail). We therefore define complex use as computer programming and basic use as all other computer use.

Specification [3] of Table 7 reports the results. Changes in complex computer usage are strongly associated with the increased demand for postgraduates. Both the change and the initial level of complex computer usage have a positive and significant impact on the change in the postgraduate share of employment. The same is not true of the college only group, where it is changes in basic computer usage that are significantly related to increased employment of this group of workers.

Thus it seems that whilst increased computer usage over time could in part reflect the widespread use of computers as becoming a general purpose technology, once the complexity of tasks used for by computers is considered, this has been an important factor in explaining the differential demand for postgraduate vis-à-vis college only workers. Therefore in more technologically advanced industries, a higher complementarity of postgraduates with computers used for complex tasks has meant the demand for postgraduates has increased at a faster rate than demand for college only workers over the last twenty five years.

Cross-Country Correlations

The fact that we have comparable data in two countries means we can further investigate the relative demand shifts in favour of postgraduates by asking the question whether one sees bigger shifts occurring in the same industries in the two countries. Earlier work on shifts in relative demand by Berman, Bound and Machin (1998) took this very approach to show that there were cross-country commonalities in shifts in industry skill demand in advanced countries in the 1970s and 1980s, as would be predicted by the skill-biased technological change hypothesis.

Table 8 shows US-GB cross-country correlations of industry levels and changes in employment shares and computerization. These are computed for the same 49 (roughly 2-

digit) industries for the two countries. The levels are all strongly correlated as shown in the first column. However, our main interest is in the correlations in the within-industry changes as reported in the second column. These are also strongly correlated for employment shares and for computerization. It seems that it is the same industries in the two countries that had faster increases in computer usage and, at the same time, shifts in relative demand towards postgraduates. The correlations are strong (with p-values showing statistical significance levels of better than 1 percent in all cases). Figure 4 plots US versus GB changes in postgraduate employment shares and changes in computer usage and fits a regression line through them, showing these strong cross-country correlations.

Cost Share Equations

So far, we have considered shifts in relative labour demand by education group and their relation to changes in computerization across industries over time. The advantage of our analysis so far was that we were able to do this for around 215 US industries and 51 GB industries covering the whole economy. Some research in this area estimates more detailed cost share equations derived directly from a translog cost function. These relate changes in cost shares by education group to technology indicators and also to industry capital and output. Thus, one can look at capital-skill and technology-skill complementarity/substitution. We have also considered this approach, albeit implementing for a reduced number and more highly aggregated set of US industries owing to the need for capital and output data.[26]

The cost share equation is of the form

$$\Delta WB_{ejt} = \lambda_{3e} + \gamma_{3e}(CI/Y)_j + \varphi_e \Delta \log K_{jt} + \pi_e \Delta \log Y_{jt} + \omega_{3ejt} \quad (9)$$

where ΔWB_{ejt} is the within-industry change in the wage bill share of education group e, CI/Y is the share of ICT investment in value added, K is the net capital stock and Y is value added.

[26] The reduced number of industries comes about because of the need for capital stock data in service sector industries (which we obtain from the US National Income and Product Accounts, NIPA) which means we have to lose some public sector industries from our analysis where capital is not well measured (as in Autor, Katz and Krueger, 1998, we are forced to omit education and health from this analysis).

Variants of equation (9) have been estimated in the literature exploring capital-skill complementarities (dating back to Griliches, 1969) and more recently in the wage inequality work exploring technology-skill complementarities.

Estimates of equation (9) are given in Table 9 for 52 US industries. Differences in the postgraduate/college only coefficients on the technology variable are a little muted, but they are strongly supportive of the pattern seen earlier in the relative labour demand equations. Industries with more ICT investment saw faster increases in wage bill shares for postgraduates than for college only workers, which is indicative of non-neutrality between the two groups of college graduates. There is also significant hollowing out in the middle part of the distribution with some college and high school graduates faring worst.

5. Conclusions

In this paper, we present new evidence on how the changing education structure of the workforce has contributed to rising wage inequality in the United States and Great Britain. Our main focus is on increasing divergences within the group of workers who have been to university. We document that there have been increases through time in the number of workers with a postgraduate qualification. We show that, at the same time as this increase in their relative supply, their relative wages have strongly risen as compared to workers with only a college degree.

Consideration of shifts in their demand and supply uncovers trend increases in relative demand for postgraduates that are a key driver of increasing within-graduate inequality. In line with these shifts in relative demand, we report various pieces of evidence in line with the notion that postgraduate workers and college only workers are different, in that they are not perfect substitutes, they possess skills that have a higher value in the labour market and that they work in different occupations.

The relative demand shifts in favour of workers with postgraduate qualifications are strongly correlated with technical change as measured by computer usage and investment. It turns out that, in the period when computers have massively diffused into workplaces, postgraduates more highly complement computers as compared to college only workers and thus have benefited more from their spread. This has been an important driver of rising wage inequality amongst graduates over time as the presence of postgraduates in the workplace has grown in importance.

Before concluding, it is worth noting that in this paper we choose to focus on well established empirical approaches that have been used in prior work in the area to show that there have different patterns of change in labour market outcomes for postgraduates and college only workers. We do this deliberately so as not to confuse differences in modelling approach with our findings that postgraduate and college only workers need to be separated out in relative supply-demand models and in studies of the impact of computerization as skill-biased demand shocks. Of course, the findings of this paper do then naturally open up other channels for future research. One important question is to better understand why graduates are increasingly feeling the need to distinguish themselves from college only workers by acquiring postgraduate qualifications. A second is to consider gender differences since women's relative supply has increased faster than men's as more women have gone to college. A third is to study the implications for universities of the changing balance between undergraduate and postgraduate education. Finally, looking at whether evidence of rising graduate wage inequality driven by higher labour market rewards for postgraduates is a feature of changing wage structures in other countries is an important avenue for future research.

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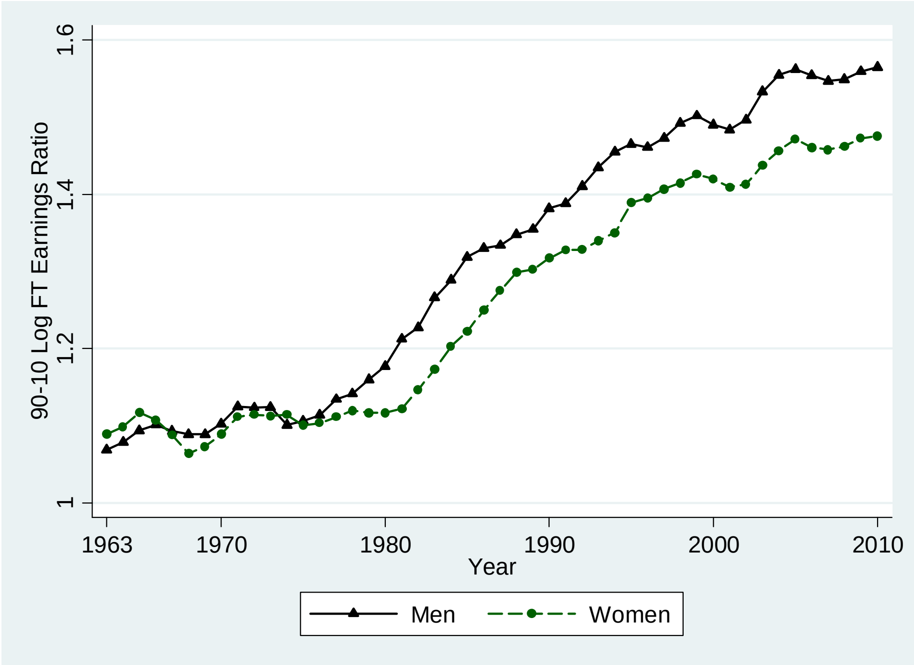
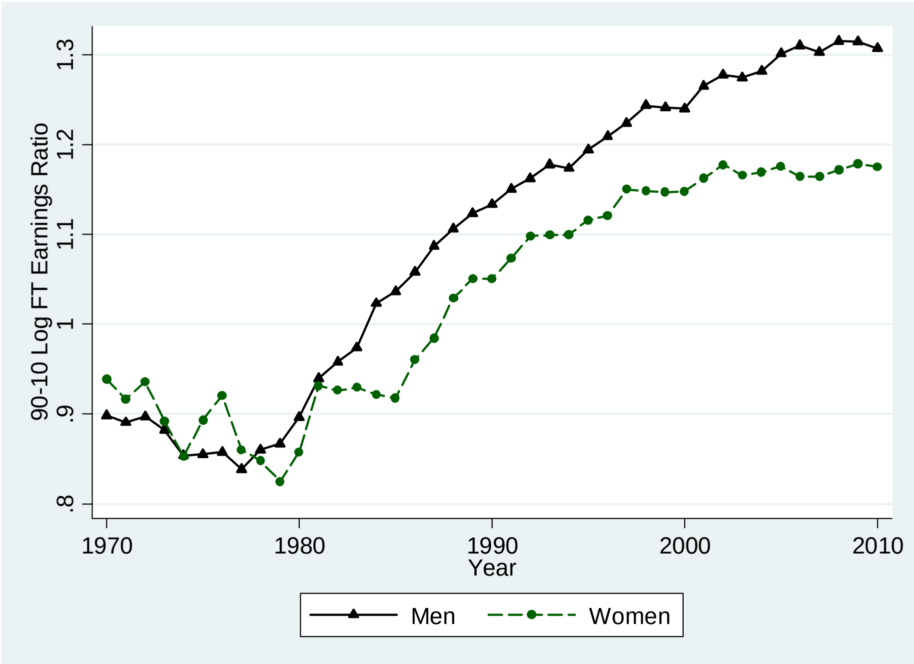
Figure 1: Trends in Overall 90-10 Wage Ratio

United States, 1963 to 2010



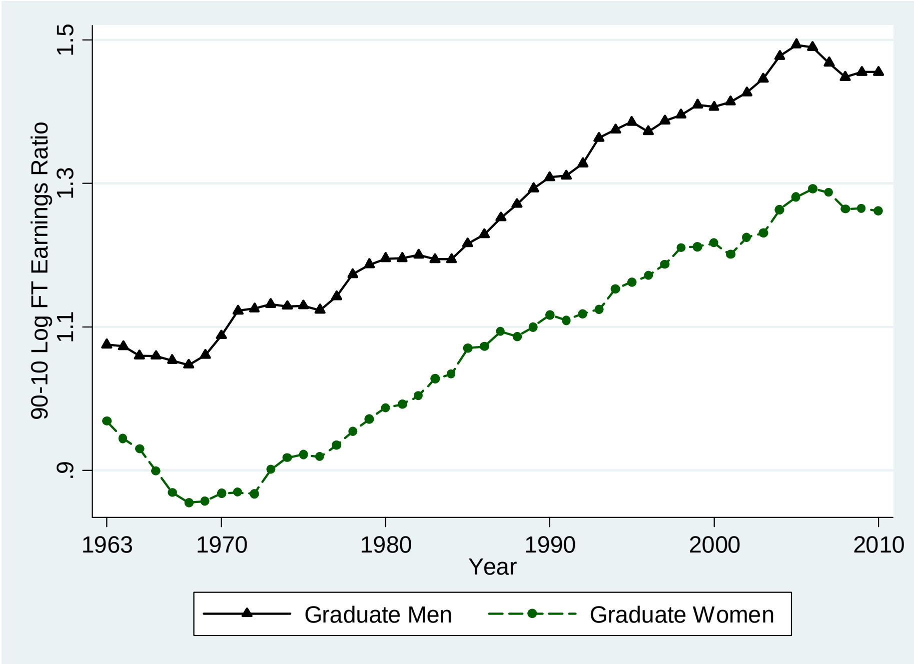
Great Britain, 1970 to 2010



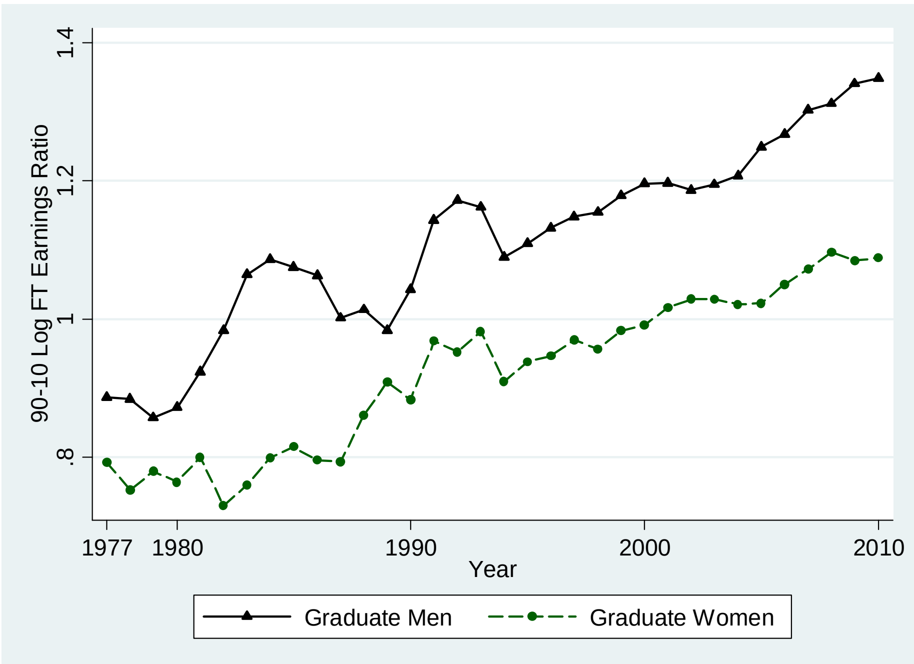
Notes: US 90-10 Log(Earnings) ratios from March Current Population Surveys for income years 1963 to 2010. Weekly earnings for full-time full-year workers. GB 90-10 Log(Earnings) ratios from 1970 to 2010 from the New Earnings Survey/Annual Survey of Hours and Earnings. Weekly earnings for full-time workers.

Figure 2: Trends in 90-10 Wage Ratio For Graduates

United States, 1963 to 2010

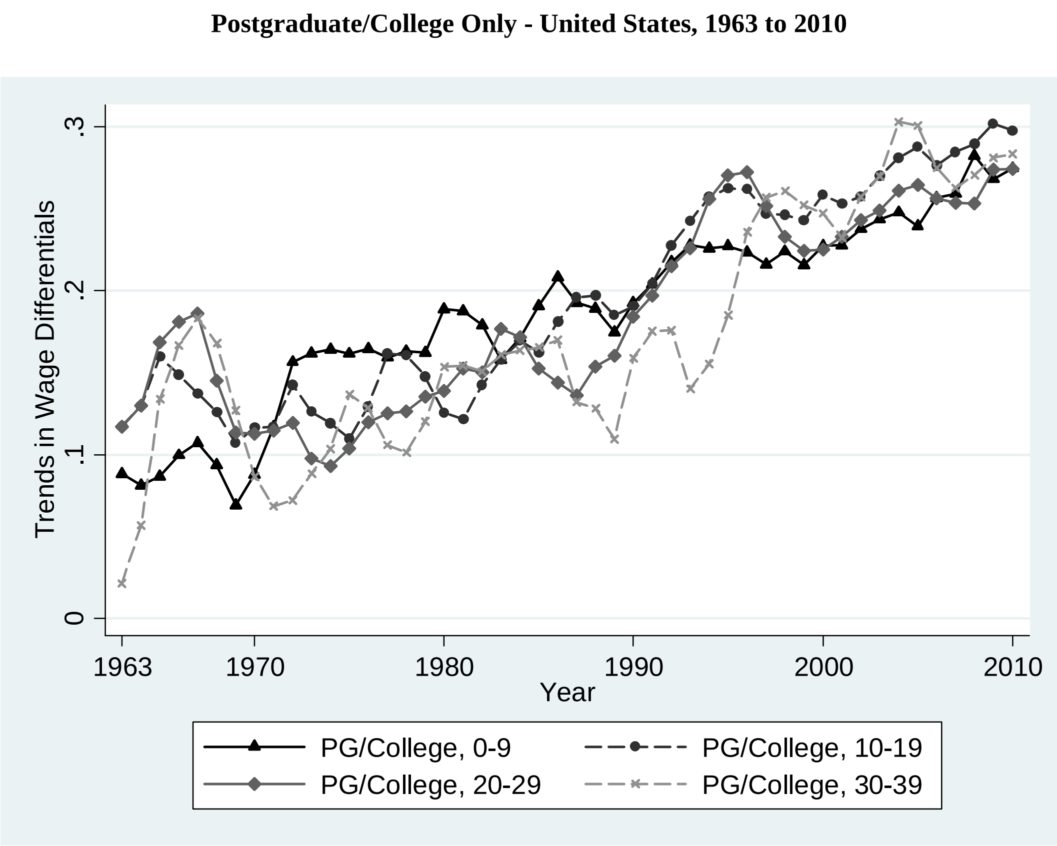


Great Britain, 1977 to 2010



Notes: US 90-10 Log(Earnings) ratios from March Current Population Surveys for income years 1963 to 2010. Weekly earnings for full-time full-year workers. GB 90-10 Log(Earnings) ratios from 1977 to 2010 from splicing together the General Household Survey (1977-1992) to the Labour Force Survey (1993 to 2010). Weekly earnings for full-time workers (those working 30 or more hours).

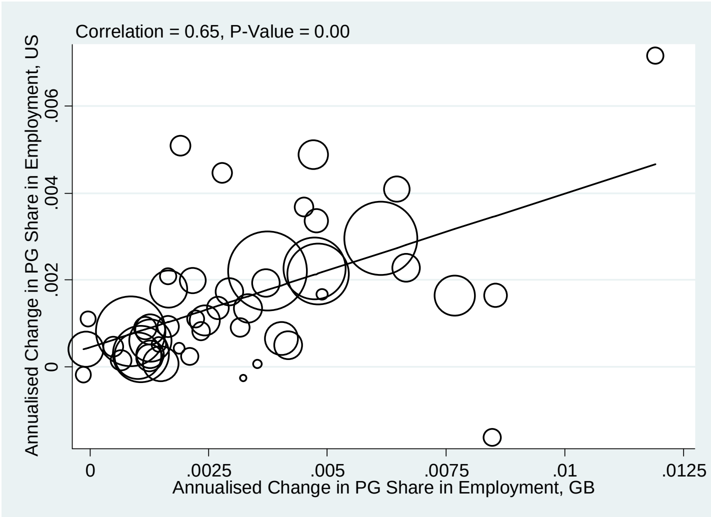
Figure 3: Trends in Composition Adjusted Postgraduate Wage Differentials by Experience Group



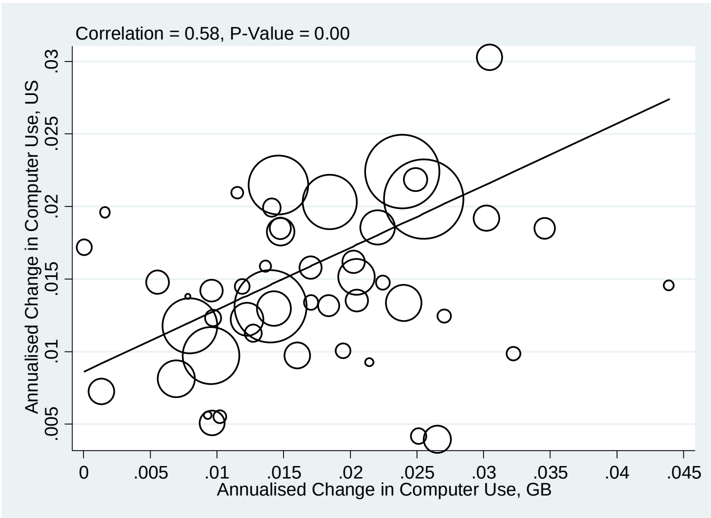
Notes: Composition adjusted log relative wage differentials by experience group computed from March CPS data for full-time full-year workers aged 26-60.

Figure 4: Cross-Country Correlations in Within-Industry Changes in Postgraduate Shares and Computer Usage (49 Industries)

Postgraduate Employment Shares



Computer Usage



Notes: Based on the same 49 industries across the two countries.

Table 1: Employment Shares by Education

	United States					
	1963	1970	1980	1990	2000	2010
College Degree or Higher	0.137	0.158	0.238	0.277	0.316	0.370
Postgraduate Degree	0.037	0.046	0.075	0.089	0.106	0.132
College Degree Only	0.100	0.112	0.164	0.189	0.209	0.238
Postgraduate Share	0.268	0.290	0.313	0.320	0.337	0.357

	Great Britain		
	1996	2000	2010
College Degree or Higher	0.145	0.180	0.304
Postgraduate Degree	0.044	0.057	0.110
College Degree Only	0.101	0.123	0.194
Postgraduate Share	0.301	0.315	0.362

Notes: Source for United States is March Current Population Surveys. Source for Great Britain is Labour Force Surveys. Employment shares are defined for people in work with 0 to 39 years of potential experience and aged 26 to 60.

Table 2: Wage Differentials by Education

	United States					
	1963	1970	1980	1990	2000	2010
College Degree or Higher	0.337	0.416	0.384	0.529	0.628	0.682
	(0.011)	(0.008)	(0.007)	(0.006)	(0.008)	(0.007)
Postgraduate Degree	0.338	0.455	0.470	0.641	0.768	0.856
	(0.020)	(0.013)	(0.010)	(0.009)	(0.010)	(0.008)
College Degree Only	0.337	0.402	0.344	0.476	0.555	0.583
	(0.012)	(0.009)	(0.007)	(0.007)	(0.008)	(0.007)
Postgraduate Degree Versus College Degree Only	0.001	0.053	0.125	0.165	0.214	0.273
	(0.021)	(0.014)	(0.010)	(0.010)	(0.011)	(0.008)
Sample Size	12100	23217	29546	34944	29436	41961

	Great Britain		
	1996	2000	2010
College Degree or Higher	0.468	0.470	0.497
	(0.007)	(0.007)	(0.007)
Postgraduate Degree	0.504	0.540	0.579
	(0.015)	(0.010)	(0.010)
College Degree Only	0.451	0.435	0.449
	(0.011)	(0.008)	(0.009)
Postgraduate Degree Versus College Degree Only	0.052	0.104	0.130
	(0.017)	(0.011)	(0.011)
Sample Size	20072	36590	23964

Notes: Source for United States is March Current Population Survey. Source for Great Britain is 1996, 2000 and 2010 Labour Force Surveys. Full-time full-year workers with 0 to 39 years of potential experience and aged 26 to 60 in the US; full-time workers with 0 to 39 years of potential experience and aged 26 to 60 in GB. Wage differentials relative to high school graduates in the US and intermediate qualifications in GB. Control variables included are: gender, experience, experience squared, broad region and race (US); gender, experience, experience squared, London and white. Standard errors in parentheses.

Table 3: Estimates of Supply-Demand Models of Educational Wage Differentials, US

	United States, 1963-2010		
Wage Differential	College Only/High School	Postgraduate/High School	Postgraduate/College Only
Relative Supply	College/High School	College/High School	Postgraduate/College Only
A. KM Aggregate Model	[1]	[2]	[3]
Log(Aggregate Relative Supply)	-0.353 (0.034)	-0.450 (0.040)	-0.130 (0.061)
Trend	0.014 (0.001)	0.020 (0.001)	0.005 (0.001)
Sample Size	48	48	48
R-Squared	0.92	0.96	0.88
B. CL Experience Groups Model	[4]	[5]	[6]
Log(Aggregate Relative Supply)	-0.440 (0.030)	-0.528 (0.041)	-0.130 (0.052)
Log(Experience Specific Relative Supply) - Log(Aggregate Relative Supply)	-0.250 (0.019)	-0.228 (0.026)	0.005 (0.032)
Trend	0.018 (0.001)	0.024 (0.001)	0.005 (0.001)
Sample Size	192	192	192
R-Squared	0.86	0.90	0.71

Notes: The dependent variable is the log of the relevant fixed weighted (composition adjusted) wage differentials. Standard errors in parentheses. Four experience specific groups (0-9, 10-19, 20-29, 30-39). The CL models include dummies for experience groups and are estimated using the two step process to generate model based relative supply measures discussed in footnote 12 and 16 of the paper and in Card and Lemieux (2001).

Table 4:
What Are The Skills and Job Tasks Implying Postgraduates Are More in Demand Than College Only Graduates?

Skill/Job Task	Postgraduates	College Only	Gap (Standard Error)	Regression Corrected Gap (Standard Error)
Cognitive Skills				
Literacy	4.067	3.763	0.304 (0.079)	0.299 (0.079)
Simple Numeracy (Basic Arithmetic)	3.606	3.583	0.026 (0.094)	0.023 (0.093)
Advanced Numeracy (Maths and Statistics)	3.004	2.715	0.289 (0.104)	0.285 (0.103)
Problem Solving Skills				
Thinking of Solutions to Problems	4.311	4.277	0.035 (0.064)	0.037 (0.064)
Analysing Complex Problems	4.179	3.880	0.299 (0.083)	0.291 (0.083)
People Skills				
Making Speeches/Presentations	3.658	3.148	0.510 (0.095)	0.496 (0.095)
Teaching People	4.023	3.843	0.180 (0.086)	0.187 (0.085)
Dealing With People	4.658	4.684	-0.026 (0.047)	-0.017 (0.047)
Firm Specific Skills				
Knowledge of Products/Services	3.817	3.831	0.014 (0.091)	-0.002 (0.091)
Specialist Knowledge or Understanding	4.704	4.548	0.156 (0.055)	0.158 (0.055)
Computer Usage				
Using a Computer or Computerised Equipment	4.607	4.384	0.223 (0.068)	0.234 (0.068)
Proportion That Do Not Use a Computer	0.019	0.045	-0.025 (0.014)	-0.027 (0.014)
Simple (General Purpose) Computer Users	0.074	0.109	-0.035 (0.021)	-0.044 (0.021)
Moderate Computer Users	0.428	0.486	-0.058 (0.035)	-0.047 (0.034)
Complex Computer Users	0.479	0.361	0.118 (0.034)	0.118 (0.033)
Routineness of Job				
Performing Short Repetitive Tasks	2.689	2.890	-0.202 (0.073)	-0.204 (0.073)
Variety in Job	4.315	4.195	0.119 (0.061)	0.129 (0.061)
Sample Size	257	1095		

Notes: From 2006 Skills Survey. The questions on task performance is `How important is this task in performing your current job' which are 1 `not at all important', 2 `not very important', 3 `fairly important', 4 `very important', 5 `essential'. The regression corrected gap standardises for age, age squared, gender, region and ethnicity.

Table 5: Top Ten Occupations - College Only and Postgraduates

US, March 2010, 497 Detailed Occupations			
College Only		Postgraduates	
Top 10 Occupations	Share (%)	Top 10 Occupations	Share (%)
1. Elementary and middle school teachers	4.6	1. Elementary and middle school teachers	8.2
2. Managers, all other	3.6	2. Lawyers, judges, magistrates and other judicial	6.7
3. Accountants and auditors	3.3	3. Postsecondary teachers	6.1
4. Chief executives	2.3	4. Physicians and surgeons	4.7
5. First-line supervisors/managers of retail sales workers	2.2	5. Secondary school teachers	3.6
6. Secondary school teachers	1.9	6. Managers, all other	3.5
7. Computer software engineers	1.9	7. Education administrators	2.9
8. Retail salespersons	1.8	8. Chief executives	2.5
9. Secretaries and administrative assistants	1.8	9. Computer software engineers	2.3
10. Financial managers	1.7	10. Accountants and auditors	2.1
Share of top 10	25.1		42.6

GB, 2010, 353 Detailed Occupations			
College Only		Postgraduates	
Top 10 Occupations	Share (%)	Top 10 Occupations	Share (%)
1. Primary and nursery education teaching professionals	5.1	1. Secondary education teaching professionals	12.5
2. Marketing and sales managers	4.5	2. Primary and nursery education teaching professionals	7.1
3. Nurses	3.6	3. Higher education teaching professionals	4.7
4. Software professionals	3.2	4. Medical practitioners	4.0
5. Information and communications technology managers	3.1	5. Software professionals	2.8
6. Secondary education teaching professionals	3.0	6. Marketing and sales managers	2.6
7. Financial managers	2.4	7. Information and communications technology managers	2.3
8. Production works and maintenance managers	2.3	8. Management consultants, actuaries, economists and statisticians	2.1
9. Solicitors and lawyers, judges and coroners	1.7	9. Bioscientists and biochemists	2.0
10. Educational assistants	1.6	10. Solicitors and lawyers, judges and coroners	1.6
Share of top 10	30.5	Share of top 10	41.7

Notes: US source March 2010 Current Population Survey; GB source 2010 Labour Force Survey. For workers aged 26-60 with 0-39 years of potential experience.

Table 6: Estimates of the Relationship Between Changes in Employment Shares and Changes in Computer Usage Across Industries

	United States, 215 Industries									
	[1]					[2]				
Change in Employment Shares, 1989-2008	Post-Graduates	College Only	Some College	High School Graduates	High School Dropouts	Post-Graduates	College Only	Some College	High School Graduates	High School Dropouts
Change in Computer Use, 1984-2003	0.080	0.005	-0.046	-0.096	0.057	0.105	0.026	-0.080	-0.142	0.090
	(0.022)	(0.026)	(0.028)	(0.036)	(0.025)	(0.019)	(0.025)	(0.024)	(0.029)	(0.020)
Computer Use, 1984						0.005	0.004	-0.007	-0.009	0.007
						(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-Squared	0.06	0.06	0.01	0.02	0.02	0.30	0.12	0.29	0.34	0.36
	Great Britain, 51 Industries									
	[3]					[4]				
Change in Employment Shares, 1996-2008	Post-Graduates	College Only	Interm-ediate 1	Interm-ediate 2	No Qualifications	Post-Graduates	College Only	Interm-ediate 1	Interm-ediate 2	No Qualifications
Change in Computer Use, 1992-2006	0.094	0.037	-0.234	0.181	-0.078	0.133	0.055	-0.238	0.088	-0.037
	(0.039)	(0.052)	(0.057)	(0.093)	(0.043)	(0.033)	(0.053)	(0.058)	(0.079)	(0.038)
Computer Use, 1992						0.009	0.004	-0.001	-0.021	0.009
						(0.002)	(0.003)	(0.003)	(0.004)	(0.002)
R-Squared	0.11	0.01	0.26	0.07	0.06	0.39	0.05	0.26	0.37	0.33

Notes: Standard errors in parentheses. All changes are annualised. US employment shares are from the 1989 and 2008 Merged Outgoing Rotation Groups of the CPS; US computer usage from the 1984 and 2003 October CPS. GB employment shares from the 1986 and 2008 LFS; GB computer usage is from the 2006 Skills Survey and the 1992 Employment in Britain.. All regressions weighted by the average employment share in total industry averaged across the two years.

Table 7: Sub-Period Analysis and Complex/Basic Computer Use in US Industries

	United States, 215 Industries				
	[1]				
Change in Employment Shares, 1989-1998	Post-Graduates	College Only	Some College	High School Graduates	High School Dropouts
Change in Computer Use, 1984-1993	0.073	0.029	-0.011	-0.144	0.048
	(0.016)	(0.023)	(0.025)	(0.028)	(0.018)
Computer Use, 1984	0.003	0.006	-0.005	-0.012	0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
R-Squared	0.17	0.11	0.07	0.34	0.26
	[2]				
Change in Employment Shares, 1998-2008	Post-Graduates	College Only	Some College	High School Graduates	High School Dropouts
Change in Computer Use, 1993-2003	0.062	0.053	-0.050	-0.084	0.019
	(0.019)	(0.026)	(0.028)	(0.030)	(0.021)
Computer Use, 1993	0.005	0.003	-0.007	-0.005	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-Squared	0.20	0.04	0.20	0.09	0.09
	[3]				
Change in Employment Shares, 1998-2008	Post-Graduates	College Only	Some College	High School Graduates	High School Dropouts
Change in Complex Computer Use, 1993-2003	0.100	0.040	-0.087	-0.083	0.030
	(0.044)	(0.062)	(0.065)	(0.071)	(0.050)
Change in Basic Computer Use, 1993-2003	0.065	0.055	-0.052	-0.082	0.014
	(0.020)	(0.028)	(0.029)	(0.032)	(0.022)
Complex Computer Use, 1993	0.012	0.004	-0.014	-0.003	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Basic Computer Use, 1993	0.003	0.003	-0.005	-0.005	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-Squared	0.25	0.05	0.22	0.09	0.13

Notes: Standard errors in parentheses. All changes are annualised. US employment shares are from the 1999 and 2008 Merged Outgoing Rotation Groups of the CPS; US computer usage from the 1993 and 2003 October CPS. Complex computer usage is for programming. Basic computer usage is all other computer use. All regressions weighted by the average employment share in total industry averaged across the two years.

Table 8:
US-GB Cross-Country Industry Correlations

	Levels	Within-Industry Changes
Employment Shares		
Postgraduates	0.93 (p = 0.00)	0.65 (p = 0.00)
College Only	0.87 (p = 0.00)	0.64 (p = 0.00)
Less Than College	0.92 (p = 0.00)	0.59 (p = 0.00)
Computerization		
Computer Use	0.86 (p = 0.00)	0.58 (p = 0.00)

Notes: Pearson correlation coefficients with p-values in parentheses. Based on the same 49 industries across the two countries. Less than college is some college, high school graduates and high school drop outs in the US and intermediate 1, intermediate 2 and no qualifications in GB.

Table 9: Estimates of US Cost Share Equations, NIPA ICT Investment, 52 Industries

Change in Wage Bill Shares, 1989-2008	Post-Graduates	College Only	Some College	High School Graduates	High School Dropouts
CI/Y	0.038	0.023	-0.038	-0.049	0.026
	(0.010)	(0.010)	(0.009)	(0.013)	(0.010)
Change in log(K), 1989-2008	0.009	0.030	-0.006	-0.036	0.003
	(0.017)	(0.018)	(0.017)	(0.024)	(0.018)
Change in log(Y), 1989-2008	-0.010	0.000	-0.024	0.023	0.011
	(0.009)	(0.009)	(0.008)	(0.012)	(0.009)
R-Squared	0.26	0.22	0.52	0.26	0.24

Notes: Standard errors in parentheses. All regressions weighted by the average wage bill share in total industry averaged across the two years. All changes are annualised. US wage bill shares are from the 1989 and 2008 Merged Outgoing Rotation Groups of the CPS; US computer usage from the 1984 and 2003 October CPS. CI/Y is the share of IT investment in value added. NIPA real IT investment (CI), real non-ICT capital stock (K) and real gross value added (Y) data are for non-residential private fixed assets measured in millions of US dollars in 2005 prices. Real IT investment, real non-ICT capital stock and real gross value added data measured as 5 year averages. The NIPA data are for the private sector only so industries with high government employment (education and health services) are excluded.

Data Appendix

1. Basic Processing of the March CPS Data

We use the March Current Population Survey from 1964 to 2011 (corresponding to earnings years 1963 to 2010 as earnings data refer to the previous year). Our basic sample consists of workers with 0 to 39 years of potential experience. Hours are measured using usual hours worked in the previous year. Full-time weekly earnings are calculated as the logarithm of annual earnings over weeks worked for full-time, full-year workers. Allocated earnings observations are excluded after (sample year) 1966 using family earnings allocation flags (1964 to 1975) or individual earnings allocation flags (1976 onwards).Weights are used in all calculations. Full-time earnings are weighted by the product of the CPS sampling weight and weeks worked. All wage and salary income before March 1988 was reported in a single variable, which was top-coded at values between $50,000 and $99,999 in years 1964 to 1987. Following Katz and Murphy (1992), we multiply the top-coded earnings value by 1.5. From 1989 onwards, wage and salary incomes were collected in two separate earnings variables, corresponding to primary and secondary labour earnings. After adjusting for top-coding, we sum these values to calculate total wage and salary earnings. Following Autor, Katz and Kearney (2008), top-codes are handled as follows. For the primary earnings variable, top-coded values are reported at the top-code maximum up to 1995. We multiply these values by 1.5. Starting in 1996, top-coded primary earnings values are assigned the mean of all top-coded earners. In these cases, we reassign the top-coded value and multiply by 1.5. For the secondary earnings value, the top-coded maximum is set at 99,999 from 1988 to 1995, falls to 25,000 for 1996 through 2002, and rises to 35,000 in 2003 through 2006. Again, we use the top-coded value multiplied by 1.5. Earnings numbers are deflated using the PCE deflator.

2. Basic Processing of the LFS Data

We mainly use the 1996 to 2010 Quarterly Labour Force Surveys (although earlier data back to 1993 is used in Figure 2 and combined with General Household Survey data back to 1977). The reason for starting in 1996 is that prior to that the LFS does not include Post-Graduate Certificates in Education (PGCEs) in the higher degree qualification category (see the education variable definitions below). Our main sample consists of workers with 0 to 39 years of potential experience. We exclude all respondents from Northern Ireland. Full-time weekly earnings are calculated as the logarithm of weekly earnings for all full-time workers. Hours are measured using total hours worked in main job plus usual hours of paid overtime. Weights are used in all calculations. Full-time earnings are weighted by LFS person weights. Earnings numbers are deflated using the RPI deflator.

3. Coding of Education and Potential Experience in the CPS and LFS Data

For the CPS data, we construct consistent educational categories using the method proposed by Jaeger (1997). For the pre 1992 education question, we defined high school dropouts as those with fewer than twelve years of completed schooling; high school graduates as those having twelve years of completed schooling; some college attendees as those with any schooling beyond twelve years (completed or not) and less than sixteen completed years; college-only graduates as those with sixteen or seventeen years of completed schooling and postgraduates with eighteen or more years of completed schooling. In samples coded with the post Census 1992 revised education question, we define high school dropouts as those with fewer than twelve years of completed schooling; high school graduates as those with either twelve completed years of schooling and/or a high school diploma or G.E.D.; some college as those attending some college or holding an associate's degree; college only as those with a bachelor degree; and postgraduate as a masters, professional or doctorate degree.

For the LFS, we use the highest qualification variable to construct consistent education categories over time. For postgraduates this consists of those with a higher degree; for college only it is those with an NVQ level 5 or a first degree; for intermediate 1 this consists of those with other degree, an NVQ level 4, a diploma in higher education or a teaching qualification; for intermediate 2 it is everything else except those with no qualifications.

To ensure we have enough postgraduates in the analysis, we further restrict our analysis to cover individuals aged 26 and higher. For the wage regressions, we consider ages 26 to 60 and for our relative supply measures, we consider ages 26 to 65.

To calculate potential experience in the CPS data for the years coded with the 1992 revised education question, we use figures from Park (1994) to assign years of completed education to each worker based upon race, gender, and highest degree held. For the other CPS years, years of potential experience were calculated as age minus assigned years of education minus 6, rounded down to the nearest integer value. For GB years of potential experience were calculated as age minus age left full time education.

4. Construction of the Relative Wage Series

We calculate composition-adjusted relative wages overall and by age and experience using the CPS and LFS samples described above, excluding the self-employed. The data are sorted into gender-education-experience groups based on a breakdown of the data by gender, the five education categories described above, and four potential experience categories (0–9, 10–19, 20–29, and 30 plus). We predict wages separately by sex and experience groups. Hence, we estimate eight separate regressions for each year including education and a linear experience variable (as well as for broad region and race). The (composition-adjusted) mean log wage for each of the forty groups in a given year is the predicted log wage from these regressions for each relevant education group. These wages are then weighted by the hours shares of each group for the whole time period.

5. Construction of the Relative Supply Measures

We calculate relative supply measures using the CPS sample above. We form a labour quantity sample equal to total hours worked by all employed workers (including those in self-employment) age 26 to 65 with 0 to 39 years of potential experience in 400 gender, education and potential experience cells: experience groups are single-year categories of 0 to 39 years; education groups are high school dropout, high school graduate, some college, college graduate, and postgraduate. The quantity data are merged to a corresponding price sample containing real mean full-time weekly wages by year, gender, potential experience, and education. (Wage data used for the price sample correspond to the earnings samples described above.) Following Autor, Katz and Kearny (2008), wages in each of the 400 earnings cells in each year are normalized to a relative wage measure by dividing each by the wage of high school graduate males with ten years of potential experience in the contemporaneous year. We compute an "efficiency unit" measure for each gender experience-education cell as the arithmetic mean of the relative wage measure in that cell over 1963 through 2010. The quantity and price samples are combined to calculate relative log education supplies. We define the efficiency units of labour supply of a gender by education by potential experience group in year *t* as the efficiency unit wage measure multiplied by the group's quantity of labour supply in year *t*.

We calculate aggregate postgraduate equivalent labour supply as the total efficiency units of labour supplied by postgraduate workers. We calculate the college-only equivalent labour supply as the total efficiency units of labour supplied by college only workers plus 30 percent of the efficiency units of labour supplied by workers with some college. Similarly, aggregate high school equivalent labour supply is the sum of efficiency units supplied by high school or lower workers, plus 70 percentf of the efficiency units supplied by workers with some college. Hence, the college-only/high school log relative supply index is the natural logarithm of the ratio of college-only equivalent to non-college equivalent labour supply (in efficiency units) in each year. This measure is calculated overall for each year and by ten-year potential experience groupings.

6. The Industry Level MORG CPS Data and the LFS Data

For the US industry level analysis, we use the Merged Outgoing Rotation Groups for 1989 and 2008 for all employed workers. An industry level crosswalk was generated between the 1980 Census and the 2002 NAICS industry codes to generate 215 common industrial categories. This is available from the authors on request. Education groups are coded based on the method described above and wage bill shares are measured by summing worker gross weekly wages by education group, industry and year. Top coded weekly wage observations are multiplied by 1.5. Similarly, employment shares are constructed by summing all workers by education group, industry and year.

For GB we use the Quarterly Labour Force Survey for 1996 and 2008 for all employed workers. The Labour Force Survey data uses the two-digit 1992 Standard Industrial Classification throughout the period but changes to the 2007 Standard Industrial Classification in 2009. Education categories are coded based on the method described above. Wage bill shares are measured by summing worker gross weekly wages in the main job by group, industry and year. Again, employment shares are constructed in an analogous way to the wage bill shares.

7. The Computer Use Data

The US computer use data are taken from the October 1984 and 2003 CPS supplements, whilst the GB computer use data are taken from the 1992 Employment in Britain Survey and the 2006 Skills Survey. All samples consist of all employees. CPS computer use is derived from the question `Do you use a computer at work?' whilst in the EIB and the SS this question is `Does your job involve the use of computerised or automated equipment?'. The GB data here require the generation of a 1980 SIC to 1996 SIC industry crosswalk to generate 51 consistent industries. This is available from the authors on request. The CPS complex computer use variable is derived from the 1993 and 2003 CPS computer use supplements from the question `Is the computer at work used for computer programming?' The basic computer use variable is for all other computer use other than programming. Other questions for work computer use that are comparable across the 1993 and 2003 CPS are for word processing/desktop publishing, internet/email, calendar/scheduling, graphics/design spread sheets/databases and other computer use.

8. The Investment, Capital Stock and Value Added Data

The US data for investment, capital stock and value added are taken from the National Income and Product Accounts made available through the Bureau of Economic Analysis. NIPA real investment, capital stock and gross value added data are for non-residential private fixed assets measured in millions of US dollars in 2005 prices. The investment and capital stock data are taken from the fixed assets accounts. IT investment is investment in mainframe computers, personal computers, direct access storages devices, printers, terminals, tape drives, storage devices, system integrators and software. Total investment is investment in all total equipment (excluding structures). Non-ICT capital stock is the capital stock of structures. Real value added is taken from the gross-domestic-product by industry accounts. Real investment, real non-ICT capital stock and real gross value added data are measured as 5 year averages.

9. The Skills Survey Job Tasks Data

The 2006 Skills Survey contains questions on task performance and educational qualifications for over 2,467 working men and women. Respondents are asked the question `How important is this task in performing your current job' which are 1 `not at all important', 2 `not very important', 3 `fairly important', 4 `very important', 5 `essential'. We define postgraduate workers as having a Masters or PhD and college only workers as having a university or CNAA degree.