The Rising Post-College Wage Premium in America and Britain

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Abstract

Despite post-college degree holders now making up nearly 15 percent of the adult workforce in America and Britain, studies of their labour market performance remain sparse. This is surprising given they are the most educated group of workers in the labour force and when, as is very clearly shown in this paper, over time they have done significantly better in terms of their economic rewards from work. Their relative supply has increased and at the same their wages relative to college only graduates and to non-college workers have risen. Thus the relative demand for postgraduates has sharply increased, because of their superior skill sets and because they work in more productive jobs, namely the non-routine occupations that have expanded their employment shares in the upper part of the job growth distribution. We show these patterns of change using data from the United States and Great Britain. The increase in the demand for postgraduates is a key factor in understanding why wage inequality has risen within the increasingly heterogeneous college graduate workforce.

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1. Introduction

It is well known that over the last forty years or so wage inequality has risen significantly in a number of countries (most notably the US and UK, but also elsewhere).[1] One key dimension of this has been rising relative wages for college educated workers compared to their lower educated counterparts, despite the relative supply increase resulting from their greater numbers. Indeed, the increased relative demand for more educated workers, coupled with technology and tasks as drivers of change, has featured prominently in discussions of why overall wage inequality has risen.

Whilst the rising wage gap between college educated and non-college educated workers is a significant dimension of the overall rise in wage inequality, just an important focus of study is the rise in wage inequality within the college and non-college education groups. This is often referred to as residual wage inequality, or within-group wage inequality, in existing research.[2] Figure 1 uses March Current Population Survey (CPS) data to show the big rise in the overall 90-10 wage differential that occurred in the US between 1979 and 2012. For all workers, the 90-10 inequality measure (depicted by the solid line) grew by around 30 percent over these years. The Figure also shows the 90-10 differential within the groups of college educated and non-college educated workers (respectively the long dashed and short dashed lines on the Figure). It is very clear that increased wage inequality has occurred within the two education groups. The increase is particularly pronounced for the college group.

This rise in within-college wage inequality offers a broad motivation for what we study in this paper. We have an interest in further uncovering what lies behind rising wage inequality within the college graduate group and, in doing so, we place a particular emphasis on the distinction between those workers who end their education with just a college degree (e.g. a Bachelors degree in the US, or an undergraduate degree in GB) as compared to those who go

[1] See Acemoglu and Autor (2010) for a review of this literature.
[2] See, *inter alia*, Lemieux (2006) or Autor, Katz and Kearney (2008).

further on in university and acquire advanced qualifications higher than a college degree. Our aim is to establish the extent to which rising college graduate inequality is connected to differences in wages between post-college advanced degree and college only degree holders.

Despite there being very marked differences in the labour market performance of post-college and college only workers, this remains relatively unexplored research territory. Whilst there is a huge literature studying the evolution of wages between college and non-college educated workers, study of the increased importance of postgraduate education in the labour market has to date not received much direct attention from economists. Postgraduate education does feature as part of the 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, several references are made to rising post-college wages in charts presented in Autor, Katz and Kearney's (2008) study of US wage inequality trends and in Acemoglu and Autor's (2010) review.[3]

One clear and distinct 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 advanced postgraduate qualifications. In fact, advanced degree holders now comprise a significant (and growing) part of the workforce. In 2012 in both the countries we study in this paper (the United States and Great Britain) over 14 percent of the adult workforce (or 37-38 percent of all college graduates) have a postgraduate qualification.

We show that rising wage inequality within the graduate group strongly reflects different wage trends amongst postgraduates and college only workers. Whilst both groups have done much better on average than non-college workers over the entire forty year time

[3] Acemoglu and Autor (2010) 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.

period we study, there is significant variation in this over time and, in line with other recent work (Beaudry, Green and Sand, 2013), we also see that some college only workers do much less well in the later time period we analyse (specifically those in routine occupations in the 2000s). On the contrary, the postgraduate wage advantage has continued to grow. Jobs involving the tasks that have yielded higher wage returns to college workers over time are shown to have disproportionately generated wage gains for postgraduates.

Thus overall it is the postgraduates, namely the most educated group of workers, who have done best in terms of relative labour market performance over time. They have done significantly better in terms of their economic rewards than other graduates and massively better than non-college educated workers. We show that, amongst all college graduates, their relative supply has increased and so have their relative wages. Thus the relative demand for postgraduates has also sharply increased. We present evidence showing that this is because of their superior skill sets and because they work in more productive jobs, namely non-routine occupations that have expanded their employment shares at the upper end of the job growth distribution. We conclude that the superior relative labour market performance of postgraduates through time has been a key feature of rising wage inequality within the increasingly heterogeneous college graduate workforce.

The rest of the paper is structured as follows. Sections 2 through 5 contain empirical findings from our analyses of the US experience. In Section 2, we present initial evidence on the changing relative employment and wage positions of postgraduates and college only workers. Section 3 reports evidence that postgraduate and college only workers have different skills sets and that over time the way in which technology has interacted with the tasks that are required for different occupations has strongly skewed labour market outcomes in favour of the skills possessed by postgraduate workers. Section 4 focusses on the nature of relative demand shifts in more detail by looking at differences in technology complementarities for postgraduates as compared to college only workers. Section 5 looks at how the growth of postgraduate employment in high skill jobs has been an important feature of labour market polarization. Section 6 widens the analysis to consider what has happened to the labour market fortunes of postgraduate and college only workers in a second country, Great Britain. Section 7 concludes and discusses some possible implications for the future.

2. Rising Within-College Wage Inequality in the United States

A prime emphasis in existing work on wage inequality in the US has been placed on studying the evolution through time of one specific educational wage differential, the college only/high school graduate wage gap. For example, the influential US papers of Katz and Murphy (1992), Card and Lemieux (2001), Autor, Katz and Kearney (2008) and Carneiro and Lee (2011) all consider the evolution through time of 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 of being consistently defined measure of the college wage premium. However, it does select a specific group of graduates, eliminating those with more advanced postgraduate qualifications.

Trends in Within-College Wage Inequality

As time has progressed this has become an increasingly misleading approach to take, owing to increased heterogeneity within the group of college educated workers. The first main reason why is the point already noted that wage inequality has significantly risen within the college plus group. To see this clearly consider Figure 2, the long dashed line on the Figure reproduces the 90-10 differential for college graduates shown in Figure 1, which rises significantly. So does residual wage inequality (shown by the short dashed line on the Figure). The second important reason is that wage gaps between postgraduate and collage only workers have significantly widened, as shown by the solid line in Figure 2.

Thus, as with overall wage inequality trends, the upward trend in graduate wage inequality has reflected a mixture of between-group and within-group increases. In this paper, we mainly focus on the particular between-group comparison of interest, namely relative changes in the labour market fortunes of postgraduate and college only workers. Some other work has considered within-college only wage inequality by looking at changing wage and employment patterns for different college majors in the US (e.g. Altonji, Blom and Meghir, 2012; Altonji, Kahn and Speer, 2014), for different undergraduate degree subjects in Europe (e.g. Lindley and McIntosh, 2014, for the UK and Kirkebøen, Leuven and Mogstad, 2014, for Norway) and for different types of higher education institution attended.[4] We know of no work studying within-group wage inequality trends for postgraduates, apart from quite narrowly focussed research on returns to particular postgraduate qualifications (like the work on wage returns to MBAs by Arcidiacono, Cooley and Hussey, 2008, Bertrand, Goldin and. Katz, 2010, or Graddy and Pistaferri, 2000).[5] Whilst our prime focus is on differences between advanced degree and college only degree holders, we do study some within postgraduate (and college only) differences when we look at the changing task composition of jobs and the wage changes that have been associated with them.

Changes in Relative Employment

The relative labour market fortunes of postgraduate and college only workers have thus diverged through time. 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 over time using three different data sources. The upper panel uses the March CPS, the middle panel the Census and American Community Survey (ACS), whilst the lower panel uses the CPS Merged Outgoing Rotation Groups (MORGS).

[4] In the US, for example, there is work on earnings differences for individuals who attend elite colleges (Dale and Krueger, 2002) or see Chevalier and Conlon (2003) for a study of differential returns to attending UK universities.
[5] Bedard and Herman (2008) also study the determinants of enrolment in advanced degrees in US graduate schools.

Depending on data source, the overall graduate proportion rose from around 0.23-0.25 in 1980 through to 0.37-0.39 by 2012, or a 57-63 percent increase.[6] The decade by decade changes reveal a well known pattern, where the employment share of graduates rose steadily during the 1980s and 1990s.

Considering the postgraduate and college only proportions, they broadly show the same decade by decade pattern of change, although the overall change is quite a lot bigger for postgraduates than for college only workers. There are some discrepancies between the CPS and Census trends, but all show a faster increase in the number of postgraduates and by 2012 around 37-39 percent of college graduates were advanced degree holders, thus comprising a large number of US workers.

Changes in Relative Wages

Table 2 considers the relative wages of these education groups using the three different data sources. The first three rows in each panel show composition adjusted wage differentials over time for the different graduate groups (college degree or higher, postgraduates, college only) measured relative to high school graduates.[7] The fourth row shows estimated differentials between postgraduates and college only workers (i.e. the gap between rows 2 and 3 within each panel). The differentials are reported for full-time workers aged 26 to 64 with 0 to 39 years of potential experience in both countries.

As is well known, the wage differential between all college graduates and high school graduates has risen significantly through time, culminating at higher levels at the end of the

[6] In the early 1990s, the education variable changed definition 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 master's degrees (which are typically two year post-bachelor degrees). Sample sizes and the 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.

[7] The composition adjustment is described in the Data Appendix. Essentially we take a similar approach to Autor, Katz and Kearney (2008) and estimate 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). For further discussion of issues on composition see Carneiro and Lee (2011) and Lemieux (2006).

period under consideration. It is clear that there has been a sharp rise. The first row of panel A shows that in the March CPS data, the college degree or higher group had 0.70 higher log weekly wages in 2012 (up from around 0.37 in 1980) in the US. The rise of 0.33 log points in panel A is matched by increases of 0.30 for the Census in panel B and for 0.29 from the CPS MORGs in panel C.

Turning to the divergent trends between postgraduates and college only workers, it is evident that postgraduates have significantly strengthened their relative wage position. The first panel shows that the postgraduate/high school graduate premium reaches 0.86 log points by 2012 (up by 0.41 log points from 0.45 in 1980). The college only/high school premium also rises, but by quite a lot less (going up by 0.27 log points from 0.33 to 0.60).

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 0.13 in 1980, but trending up continuously since, reaching a 0.26 log gap by 2012. Panels B and C based upon the other two data sources very much confirm these trends. In panel B the postgraduate/college only wage gap increases by 0.15 log points (from 0.109 in the 1980 Census to 0.259 in the 2012 ACS), whilst panel C shows that for the CPS MORGs the postgraduate/college only wage gap increases by 0.10 log points (from 0.125 in 1980 to 0.220 in 2012).

These are sizable increases in wage differentials within the graduate group. One notable feature of their evolution is the consistent widening out across decades. The 2000s are particularly interesting in the light of what Beaudry, Green and Sand (2013) have referred to as the great reversal, by which they mean the stalling of the labour market advantages experienced by college graduates as compared to high school graduates in earlier decades. Much of what they consider is on the employment side of things, with in particular college workers doing routine jobs faring badly in the 2000s (we return to this later in the paper). Our numbers do, however, confirm a slowdown the college only/high school wage gap in the 2000s (e.g. it rises by only 0.050 log points in panel A compared to rises of 0.139 in the 1980s and 0.083 in the 1990s). But the postgraduate wages continue to rise, despite this stalling and slowing down for the college only group.

3. Occupation and Task Differences

The previous section revealed differences in the wage and employment performance amongst different groups of workers within the college graduate group, with our focus on postgraduate and college only workers showing superior outcomes over time for the former group. In this section, we begin to explore heterogeneity of the college group in more detail, first looking at differences in the jobs done and tasks performed by postgraduate and college only workers, and then looking at wage and employment differences connected to these.

Occupation Differences

When considering potential differences between postgraduates and college only graduates, a good starting point is to consider whether they are employed in different occupations. So we start by comparing the occupations in which postgraduates work as compared to college graduates.

To do so, Table 3 shows the ten occupations with the biggest shares in employment of college only and postgraduate workers in the 2012 March CPS. There are several interesting features of this. First, other than for elementary school teachers, managers (all other) and software developers, the top ten are different occupations. Second, the postgraduate occupations are more segregated than the college only. For postgraduates, the top ten (out of 454 occupations) account for just over 42 percent. The college only distribution is more dispersed, with the top ten at 28 percent.[8] It is evident that college only workers are spread more widely across the occupational structure and the occupational distribution of postgraduates is more segregated.

Task Content Differences

A second question is to ask whether the tasks done in jobs differ between postgraduates and college graduates. We can shed light on the question by looking at the tasks performed by graduates and postgraduates using the 1980 Dictionary of Titles (DoT) occupational task data[9] matched to the occupations of workers in the 1980 Census and 2010 ACS where we have large enough samples to observe how the tasks have grown over time, separately for postgraduates and college only workers.[10]

We start the analysis using the same occupational task measures as Autor, Levy and Murnane (2003). Each occupation is evaluated by the DoT team to determine the extent of involvement for each task and these are: analytical non-routine task content (based on the General Educational Development of worker's mathematics skills); interactive non-routine tasks (based on the extent to which worker's direct, control and plan for others); cognitive non-routine tasks (based on how often worker's set limits, tolerances and standards); and manual non-routine tasks (based on the finger dexterity of workers).

The first four rows of Table 4 display the mean task content for these four tasks when mapped to the occupational structure of employment of postgraduate and college only workers in US Census and ACS data. For the two non-routine task inputs there is a significantly

[8] Benson (2014) 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).

[9] These data are used in Autor and Dorn (2013). We are grateful to David Dorn for making these data available to us.

[10] It should be noted that the task content of occupations remains fixed at the 1980 level and what we actually observe is how the occupations have grown over time based on their 1980 task content. We hold the task content fixed at the 1980 level because task content is likely to change as a consequence of computerization and technical change more generally.

positive gap in favour of postgraduates that has widened out over time, whilst routine tasks show a negative gap which has remained fairly stable over time.

The remaining rows in Table 4 show postgraduate/college gaps for other task measures, also taken from the DoT. These are based on a selection of relevant aptitudes of workers which are taken from the United States Employment Services General Aptitude Test Battery (GATB) and the temperaments required by workers who are employed in a given occupation. These show a similar pattern. Postgraduates demonstrate higher average levels of non-routine task inputs and aptitudes relative to college only graduates that has widened over time.

Relative Wages and Employment by Task Structure

Thus, postgraduates are employed in different jobs and their jobs involve performing more non-routine tasks than college graduates. Arguments put forward by, *inter alia*, Autor, Levy and Murnane (2003), Autor, Katz and Kearney (2008), and others, postulate that the way in which technological change (in particular, computerization, but also other forms of automation) has interacted with the task content of jobs has been to deliver wage and employment gains to workers in jobs involving non-routine tasks because of productivity improvements resulting from task complementarities. At the same time, jobs involving routine tasks have been substituted for (and wage downgraded) by technological change.

It is natural to ask if rising postgraduate wages and employment compared to college only workers have emerged as postgraduates are more concentrated in jobs involving non-routine tasks.[11] We first look at this by splitting the employment shares presented in Table 1 by the routineness of occupations. We class each three digit occupation as routine intensive or non-routine intensive using the same broad definitions as Cortes et al. (2014).[12] We now focus

[11] Beaudry and Lewis (2014) use a similar logic to study the gender wage gap arguing that women are more likely to be in jobs which feature cognitive and people skills (as compared to manual skills) and the driving up of wages through technology complementarities with cognitive and people skills has been a driver of the narrowing of the gender wage gap through time.

[12] The precise occupational breakdowns are given in detail in their Appendix A.

just on graduates and omit all farming and military workers from the sample. Again we have three panels drawing on the March CPS, the Census and ACS and finally the CPS MORGs.

Table 5 shows that, not surprisingly, the majority of postgraduates (around 90 percent) were employed in non-routine jobs in 2012. Only a small number were in routine jobs (around 10 percent) in 2012. However, both the share of both non-routine and routine postgraduate employment has grown over time. More college only graduates were also employed in non-routine jobs (around 72 percent) than in routine jobs (around 28 percent) in 2012, but their shares amongst graduates have fallen over time. This is more so in non-routine than in routine jobs over the whole time period considered in the Table, although the 2000s sees declines in the college only routine group (as per the work of Beaudry, Green and Sand, 2013).

For wages, Table 6 presents composition adjusted wage differentials over time for three graduate groups (postgraduate non-routine, postgraduate routine and college only non-routine) measured relative to college only routine graduates. All of these are positive in the individual yearly cross-sections, with the largest being for postgraduate non-routine workers who earned on average around 43 percent more than college only graduates employed in routine intensive jobs in 2012. Postgraduates employed in routine jobs still earn significantly more (by around 18 percent) than their college only counterparts also employed in routine jobs, but less than college only graduates in non-routine jobs (who earned around 21 percent more).

In terms of changes over time, the final column in Table 6 shows that the wage growth has mainly been for postgraduates, with the largest being for those employed in non-routine jobs. Figure 3 plots the differentials from the first panel in Table 6 separately by year and these clearly show that it is the postgraduates in non-routine jobs that have experienced the highest wage growth. Postgraduate routine workers and college only non-routine earnings are much more similar and growth has been much more modest.

Thus, overall, we have found evidence that postgraduate workers are employed in different occupations and they perform more non-routine intensive tasks on average than college graduates. One might conclude from thus that postgraduates and college only graduates might not be perfect substitutes in production, although we present formal statistical tests that this is so in the next section of the paper.

We have also seen that postgraduates have experienced much higher wage growth vis-à-vis college only workers, and this is especially large for those employed in non-routine intensive jobs. This suggests that demand has shifted in favour of postgraduates and away from college graduates. The wage inequality literature has noted coincident increases in relative supply and relative wages of the college only group before and developed empirical supply-demand models to consider this. The within college graduate variation we have identified has been discussed less and so we turn to this in the next section of the paper.

4. Relative Demand Shifts Within the Graduate Group

Relative wage and employment improvements in favour of postgraduates compared to college only workers imply relative demand has moved in their favour. In this section, we first quantify this in terms of the commonly used demand-supply model of the labour market, initially introduced by Katz and Murphy (1992) and which has been developed and estimated by many authors since (see Acemoglu and Autor, 2010). We use this to first show that within the graduate group, there has been a trend shift in demand for postgraduates, then move on to consider the extent to which technology-skill complementarities underpin this shift.

Relative Demand Shifts Between Graduates

For a Constant Elasticity of Substitution (CES) 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}), $Y_t = (\theta_{1t}E_{1t}^{\rho} + \theta_{2t}E_{2t}^{\rho})^{1/\rho}$, where $\rho = 1 - 1/\sigma_E$, and σ_E is the elasticity of substitution between E_{1t} and E_{2t}, one can equate wages to marginal products for each education group to derive the following relative wage equation:

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

where the trend variable, t, appears from parameterising the ratio of the technical efficiency parameters as $\log\left(\frac{\theta_{1t}}{\theta_{2t}}\right) = \alpha_0 + \alpha_1 t + v_t$, where v is an error term. In (1) α_2, the coefficient on the relative supply variable, equals $1/\sigma_E$ and α_1 shows trend shifts in relative wages over and above relative supply (i.e. the extent of relative demand shifts).

Much of the existing literature has focussed on a narrowly defined wage differential (usually the college only/high school gap – or 16/12 years of completed education) and models supply in terms of college equivalent and high school equivalent workers. In defining equivalents within the college and high school groups, individuals with different education are assumed to be perfect substitutes, but are given different (constant over time) 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 percent which is an assumed constant postgraduate/college only wage differential of 25 percent over time).

Because of the job differences and differential labour market performance of postgraduates and college only workers that we have already shown, we question whether we should treat these different sorts of graduates as perfect substitutes in this way. The results of estimating equation (1) for E_1 as the postgraduate group and E_2 as the college only group that we now consider demonstrate why.[13]

[13] We were able to replicate the results of Autor, Katz and Kearney (2008) for time series running up to 2005 if we consider the college only/high school wage differential and relative supplies measured as college and high school equivalents (as defined in the Data Appendix). Much of the work in this area, following on from Katz and Murphy (1992), studies college versus high school comparisons. Like us others have used the framework to study particular pairwise comparisons of education groups of interest, like Goldin and Katz's (2008) historical study of

Column (1) of Table 7 reports estimates of α_1 and α_2, and of the associated elasticity of substitution between the two groups of college educated workers for time series data calculated from CPS March microdata from 1963 to 2012. The dependent variable (as in other papers in the literature and as above) is a composition-adjusted relative wage and the relative supply variable is constructed in terms of the relative group of equivalents (see the Data Appendix for more detail). In column (1), the estimated coefficient on the aggregate supply variable is negative and significant in both cases, and has a point estimate of -0.142 which corresponds to an elasticity of substitution of 7.0.

The estimate of α_1 also shows 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 point increase over the full 50 years. Demand driven increases in postgraduate/college only wage gaps have therefore been an important aspect of rising within-group inequality amongst graduates.

One extension that matters for the college only/high school wage differential that has been extensively studied is that this widened out differentially across different age or experience groups over time, an empirical observation that runs counter to the restriction imposed above that different age or experience groups with the same education level are perfect substitutes. Card and Lemieux (2011) 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

differences between high school graduates and high school dropouts, or Ottaviano and Peri's (2012) pairwise comparisons across four education groups (college, some college, high school graduates and high school dropouts).

different experience or age groups within the same education level.[14] In this case the relative wage equation becomes the following:

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

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 ω is an error term.[15]

Column (2) of Table 7 shows estimates of equation (2) within the graduate group. The estimated coefficient on the aggregate supply variable is negative and significant, with a point estimate of -0.160, implying an elasticity of substitution of 6.3. Interestingly, and unlike the studies of college only/high school wage differentials, there is no evidence at all of substitution across experience groups (i.e. we cannot reject the hypothesis that $1/\sigma_X = 0$). This is the reason why the estimates of equation (1) and (2) yield very similar substitution elasticities. Adding the Card-Lemieux nest to the production function does not matter for the within-graduate group extent of substitutability, as it does for the college only/high school comparison. Another way to note this similarity is that it occurs because the relative wages of postgraduate compared to college only workers do not show strongly different patterns over time for low versus high experience (or younger versus older) workers.

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 point increase over the

[14] 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).

[15] In practice, we estimate the equation from the two-level nested CES model 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 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.

full 50 years. Demand driven increases in postgraduate/college only wage gaps have therefore been an important aspect of rising within-group inequality amongst graduates.[16] We now move on to explore this further, by 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.

Technology-Skill Complementarities

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.[17] This work reveals that technology measures like R&D, innovation and 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:

$$\Delta S_{ejt} = \lambda_{1e} + \gamma_{1e}\Delta C_j + \omega_{1ejt} \quad (3)$$

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 (between 1989 and 2008) and ΔC_j is the change in the proportion of

[16] In an earlier version of this paper, we explored different ways of modelling the demand shift. 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, models incorporating the real ICT capital variable corroborate the findings from before and, if anything, turned out to generate stronger rejections of the hypothesis of constant wage evolutions for postgraduates and college only graduates.

[17] 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).

workers in industry j using a computer at work between 1984 and 2003 (from the October Current Population Survey Supplements).

To evaluate the longer run impact of computer use (since the initial introduction of computers in the PC era) we also augment equation (3) by the initial level of computer usage (in 1984) as follows:

$$\Delta S_{ejt} = \lambda_{2e} + \gamma_{2e}\Delta C_j + \varphi_{2e} C_j^{initial} + \omega_{2ejt} \qquad (4)$$

where $C_j^{initial}$ is the initial computer use proportion (measured in 1984). 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.

Estimates of equation (3) and (4) are reported for five education shares in Table 8. 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.[18] The two specifications showing the estimates of γ_{1e} from equation (3) and γ_{2e} and φ_{2e} from equation (4) are shown.

The upper panel in Table 8 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

[18] 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 (See the Appendix for more detail on the precise definitions used.)

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).[19] 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).[20] We will return to discuss the role of postgraduates in these polarization patterns in the next section.

The second panel in Table 8 shows estimates of equation (4) 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

[19] Like Autor, Katz and Kreuger (1998), we obtain a positive significant coefficient on computerization in the high school dropouts share equation. This ultimately arises, as Autor, Katz and Krueger clearly state, because the high school dropout share becomes very small in many industries in the latter period of the sample. As our data extend further, this is even more the case for our analysis, but 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.

[20] Our results are very much in line with Michaels, Natraj and Van Reenen (2014) who report cross-country evidence connecting polarization to computerization.

postgraduates possess skills that make them more complementary to computers, which is what we have seen already in the earlier sections of the paper.

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.

Routineness of Jobs and Complex/Basic Computer Use

In section 3 we disaggregated postgraduates and college graduates according to whether they were employed in non-routine or routine intensive jobs. We can do the same thing here which will allow us to directly link the polarization patterns observed from our labour demand shifts in Table 8 directly to routinization. Table 9 presents the estimates of equation (4) for our five education shares disaggregated according to whether occupations are non-routine or routine intensive. As one would expect, all the positive computerization effect for postgraduates (and the smaller effect for the initial level for all graduates) is observed amongst non-routine intensive employment. Contrariwise, all the positive computerization effect for high school drop outs is observed only for routine intensive jobs, whilst the hollowing out in the middle has occurred in both. Of course this is contrary to what we would expect since the routinization hypothesis would predict hollowing out for routine intensive jobs and high school drop-out employment growth from computerization in non-routine jobs.

To investigate this further, we exploit extra information in the computer usage data which allows us to disaggregate the computerization measure as to whether the computer is used for complex or basic tasks. We can only do this for a relatively more recent period since only the 1993 and 2003 CPS computer use supplements report whether computers are used for more complex tasks like programming as well as for a variety of other more basic purposes (see the Data Appendix for more detail). We therefore define complex use as computer programming and computer aided design (CAD) and basic use as all other computer use.

Table 10 reports the results, again disaggregating by non-routine and routine occupations in the second and third panels. In the first panel, 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.

The second and third panels now present a picture much more consistent with the routinization idea. The hollowing out is concentrated in routine intensive employment and is much more pronounced for complex computer use. There is much less employment growth for high school drop outs that is correlated with computerization but this is likely to be a consequence of only being able to analyse changes in computer use complexity over more recent years.

Overall, 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.[21]

5. Labour Market Polarization

As has already been noted, more recent work analysing the period of rising labour market inequality we study has pinpointed increased job polarization – with relatively fast job growth at the top and bottom end of the skill distribution, coupled with job falls in the middle - as a key aspect of changing employment and wage structures.[22] Empirical researchers have studied how this has interacted with technology and the tasks that workers perform in their jobs. In particular, the notion that middle skill jobs have been disproportionately lost as the job distribution has hollowed out in the middle has received significant attention.

We are interested to find out how the superior labour market performance and increased demand for postgraduates fits in to this framework. In the upper part of Figure 4 we therefore reproduce the pattern of labour market polarization that has been identified in US data (see Autor and Dorn, 2013, or Lindley and Machin, 2014) using US Census and American Community Survey data between 1980 and 2010. The horizontal axis of the Figure orders 1980 occupations from lowest to highest wage then shows the growth in hours at each decile of that initial skill distribution. The growth in hours is defined in relative terms so that a number above zero represents relative growth and a number below zero represents negative growth. A clear pattern of hours growth at the top end emerges, together with a hollowing out of the middle, but also positive growth at the bottom end in low wage jobs.

[21] In earlier versions of this paper (e.g. Lindley and Machin, 2011) we additionally looked at cost share equations, albeit implementing this analysis for a reduced number and more highly aggregated set of US industries (52) owing to the need for capital and output data. The findings from them were strongly supportive of the pattern seen 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. These results are available on request from the authors.

[22] See, among others, Autor and Dorn (2013), Goos and Manning (2007) or Goos, Manning and Salomons (2014).

Figure 4 also breaks down the patterns of relative growth by three education groups: it shows hours growth of postgraduate (the darkest grey bar), college only (the middle grey coloured bar) and less then college workers (the lightest grey bar) in each decile (which sum to the total). The Figure makes it very clear that the bulk of the hollowing out in the middle and the growth of low wage service jobs at the bottom is from changing job prospects of workers with less than a college education. At the top, however, the college graduates do well, with postgraduate job growth very strong in the top decile higher skill jobs. In fact the contribution of postgraduates to increased polarization at the top is stronger than for college only workers. This contribution to increased labour market polarization is consistent with our earlier findings that relative demand has shifted more rapidly for postgraduates owing to their superior skills and ability to use new technologies in the tasks required for high end jobs in modern workplaces. Carefully scrutinising the Figure also suggests the college only group are also affected a little in the hollowed out middle deciles.

This is considered in more detail in the lower panel of the Figure which shows the decade by decade differences.[23] They highlight a couple of interesting observations. First, the only decade of U-shaped polarization is the 1990s. The 1980s actually saw relative growth at the top and falls at the bottom. In these two periods, the postgraduates did particularly well in terms of job growth. Second, is the lack of job growth at the top in the 2000s. This is what Autor (2014) refers to as the ‘downward ramp’ and, of course, is in line with the observation of Beaudry, Green and Sand (2013) who we have already noted demonstrate deterioration in the relative demand for college workers in the last decade of the three decades we study, although this does not mean there has been a fall in the proportion of jobs at the top. It only means that these employment shares have remained fairly constant in the 2000s. But at the top both

[23] As a lot of information is compressed on to these charts, and they are all set on the same scale to ensure comparability, magnified versions of these on scales specific to each chart are included in Appendix B for the reader who would like to inspect them more closely.

postgraduates and college only workers did not experience relative job growth in the 2000s and one can also detect a bumping down of the college only workers into the relative job losses in the middle part of the distribution. The postgraduates do not seem to experience this latter shift and their relative improvement in the graduate group occurs because the college only workers do badly.

In Figure 5 we further disaggregate by non-routine and routine occupations. Again the decile bars sum to the total, but we now have six groups (three education groups by two task measures) by which we decompose employment growth. The three shades of grey are used again to denote each of the graduate shares. The non-routine parts of the decomposition are surrounded by a black line and the routine parts do not have a surrounding line. This decomposition permits us to directly link labour market polarization to the routinization hypothesis. The results support routinization as a potential explanation of labour market polarization since most of the hollowing out in the middle of the distribution is for routine employment, whilst most of the growth in the tails has been for non-routine employment.

Moreover, we can see from the Figure which education groups have lost out the most. As one might expect, most of the hollowing out has been for non-college routine employment (the lightest grey bar with no outside shading). Also, the majority of the growth at the bottom end of the distribution has been for non-college non-routine (the lightest grey bar with black outside shading), whilst most at the top has been for postgraduate non-routine (the darkest grey bars with outside shading), closely followed by college non-routine (the middle grey coloured bar with outside shading). The decade by decade differences, in the lower panel, confirm that the college only routine employment group shows up as a feature of the jobs disappearing from the middle of the distribution in the 2000s.[24] This corroborates the main thesis of Beaudry,

[24] As with Figure 4, magnified versions of these on scales specific to each chart are included in Appendix B.

Green and Sand (2013) that, in terms of jobs, college only graduates in routine occupations did not do at all well through the 2000s.

6. Corroborative Evidence from Great Britain

In this section we widen our study of within-graduate wage inequality by presenting more evidence from another country, Great Britain. We are not able to cover all the ground we did with the earlier US analysis, mainly owing to data limitations, but we view consideration of evidence on the same issue from another country as potentially very useful from a corroborative perspective.

Changes in Relative Employment and Wages

Table 11 presents the employment shares by education in the upper panel and composition adjusted wage differentials in the lower panel, in the same way as was presented in Tables 1 and 2 for the US. These are taken from the Labour Force Survey (LFS) and are reported from 1996 to 2012, since the definition of postgraduate qualifications is only consistent from 1996 onwards.

The Table shows a rapid increase in the share of all graduates in employment (from 0.14 in 1996 to 0.32 by 2012). This reflects a longer run rapid increase in the graduate share, which has accelerated through time.[25] In the 1996 to 2012 period, there is also a sharper increase in the postgraduate share, from 0.042 in 1996, rising to 0.111 of the workforce in 2012. In terms of changing shares within the graduate group, in 1996 30 percent of graduates had a postgraduate qualification and this rises to 35 percent (interestingly, a very similar percentage as the US share) by 2012.

[25] 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).

The first three rows of the lower panel show wage differentials over time for the different graduate groups (college degree or higher, postgraduates, college only) measured relative to intermediate groups of workers (with intermediate 1 qualifications).[26] Again 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 64 with 0 to 39 years of potential experience.

The comparable wage gap for college degree or higher group relative to intermediate qualification workers was 0.47 in 1996 and remained statistically unchanged at 0.48 in 2012.[27] However, the postgraduate/high school graduate premium reaches 0.58 log points by 2012 (up by 8 percent from 0.50 in 1996). The college only/high school premium has fallen (by 3 percent from 0.46 to 0.42). Thus, just like in the US, the postgraduate/college only gap increases over time, even in the face of increased relative supply: it was 0.05 in 1996 and reached 0.16 by 2012.

Skills and Task Differences

We next draw upon the British 2006 and 2012 Skills Surveys that contain information on education levels of workers, but also on their specific skills in terms of the job tasks undertaken by workers. Table 12 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'.

[26] Intermediate 1 qualifications are A level and O level/GCSE qualifications. See the Data Appendix for more detail.
[27] 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).

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.[28] The computer usage breakdowns are also interesting, showing clearly that both 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 12 material as confirming that British postgraduates also 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 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. We are unable to estimate supply and demand models for Britain to look at this question in the same way as we did for the US in Section 4 above owing to only having a much shorter time series. Though we are able to directly link changes in employment shares and wages to routinization and look at industry level skill-demand shifts.

Changes in Relative Employment and Wages by Tasks

Given that British postgraduates are also employed in different jobs and perform more non-routine tasks than British college graduates, we split the employment shares and wage differentials presented in Table 11 by the routineness of occupations. We follow the same approach as we used for the US and code three digit SOC2000 occupations into broad routine and non-routine groups, again following the philosophy of Cortes et al. (2014).[29] Again we exclude farmers and military workers from the sample. In Table 13, the patterns of

[28] These are all skills that are becoming more highly valued in the labour market through time (see Green, 2012).
[29] For routine occupations these are SOC2000 codes 411-421, 711-721, 521-549 and 811-822, for non-routine occupations these are SOC2000 codes 111-118, 122-356, 611-629 and 912-925. Farmers and military are SOC2000 codes 121, 511 and 911.

employment shares and wages are roughly the same as those for the US. Postgraduates are mainly employed in non-routine jobs but the largest growth has been for the much smaller routine group. There are relatively more college only graduates employed in non-routine jobs but the percentage of these has fallen over time. Again it is the non-routine postgraduates that exhibit the highest wage differentials and wage growth relative to college only graduates in routine jobs.

Technology-Skill Complementarities

In this final sub section we show estimates of equation (8), this time for Great Britain. We now have 51 consistently defined industries and the change in the employment share for each education group in each industry is measured between 1996 and 2008, whilst the change in the proportion of workers, in each industry, using a computer at work is between 1992 and 2006 (taken from the 1992 Employment in Britain and the 2006 Skills Survey).

The upper panel in Table 14 gives the overall results. 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. 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 1 qualification group fares worst, whilst those at each end of the education spectrum (the postgraduates at the top and the intermediate 2 at the bottom) have the best outcomes in relative terms. In the lower two panels we distinguish between non-routine and routine jobs and again the results largely concur with those already presented for the US. Overall, the results support the routinization idea, with computerization complementarities only for postgraduate non-routine employment, though we are unable to further split by use computer complexity using these data.

7. Conclusions

This paper studies wage inequality amongst college graduates noting that, as this group has become much bigger over time, its increasingly heterogeneous nature warns against treating college graduates as a single group of workers in the labour market (or as a college equivalent group comprised of workers with different qualifications who are perfect substitutes in production). This observation of increased heterogeneity has been made in previous work (related to our study) that looks at wage differences between graduates who study different subjects at college and who attend different institutions. We focus on a different form of heterogeneity, singling out the post-college advanced degree holders as compared to college only/undergraduate educated workers. This is a surprisingly understudied area of research, despite postgraduates being the group that has made the largest human capital investment and which now forms a sizeable percentage of the adult workforce. Moreover, as we show in this paper, using data from the United States and Great Britain, they are the education group that has fared the best over time, even relative to college only graduates.

We show using data from the United States and Great Britain that, amongst all college graduates, the relative supply of postgraduate workers has increased through time, and so have their relative wages. Thus the relative demand for postgraduates has sharply increased and they are the education group that has fared the best over time. This is because of their superior skill sets and because they work in more productive jobs, namely non-routine occupations that have expanded their employment shares at the top end of the job growth distribution.

The fact that that the group with the most education has done best in the labour market over the last thirty years is significant when one recognises that, in the United States, the move to mass education has slowed down, especially for men. Up to the 1970s, as is documented very clearly by Goldin and Katz (2008), the US was the country at the forefront of mass education, since when it has been caught and then overtaken by other nations.[30] The (relatively poor) labour market performance of college only workers in the 2000s, the slowdown in the supply of college graduates, and the rising post-college wage premium all take on an additional importance for the future of evolution of wage inequality when seen in this light.

[30] The startling scale of the slowdown and the fact that more American males now have less education than their parents than have more (respectively 29 percent with less and 20 percent with more) is shown in OECD (2014).

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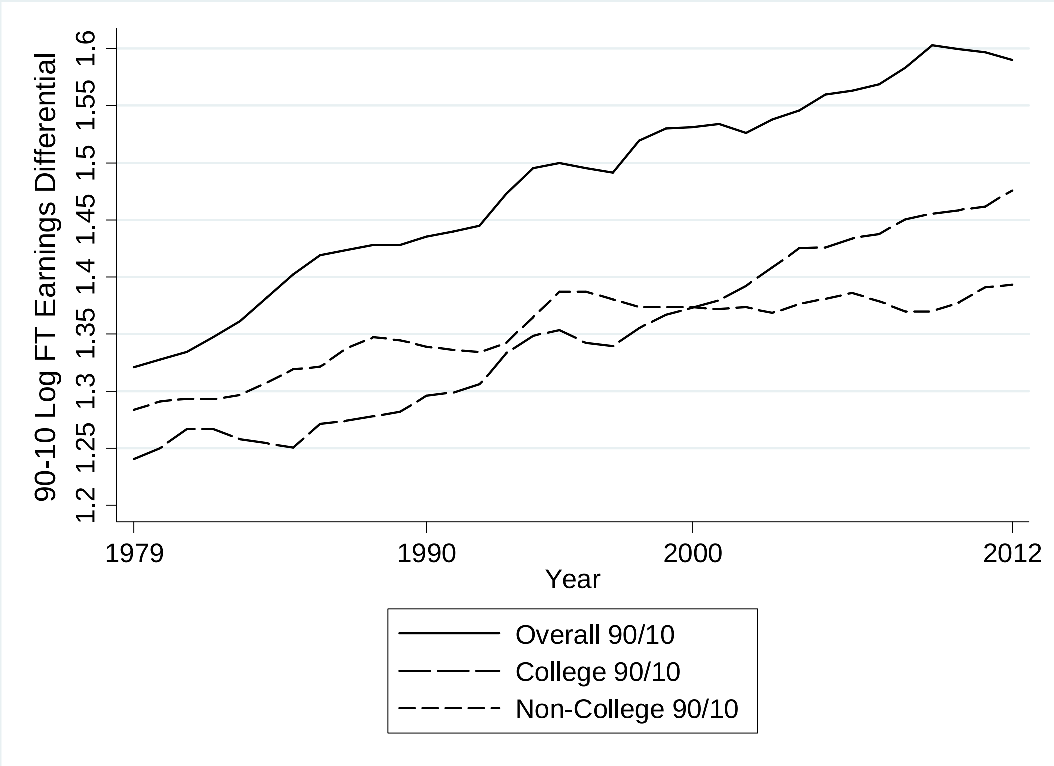
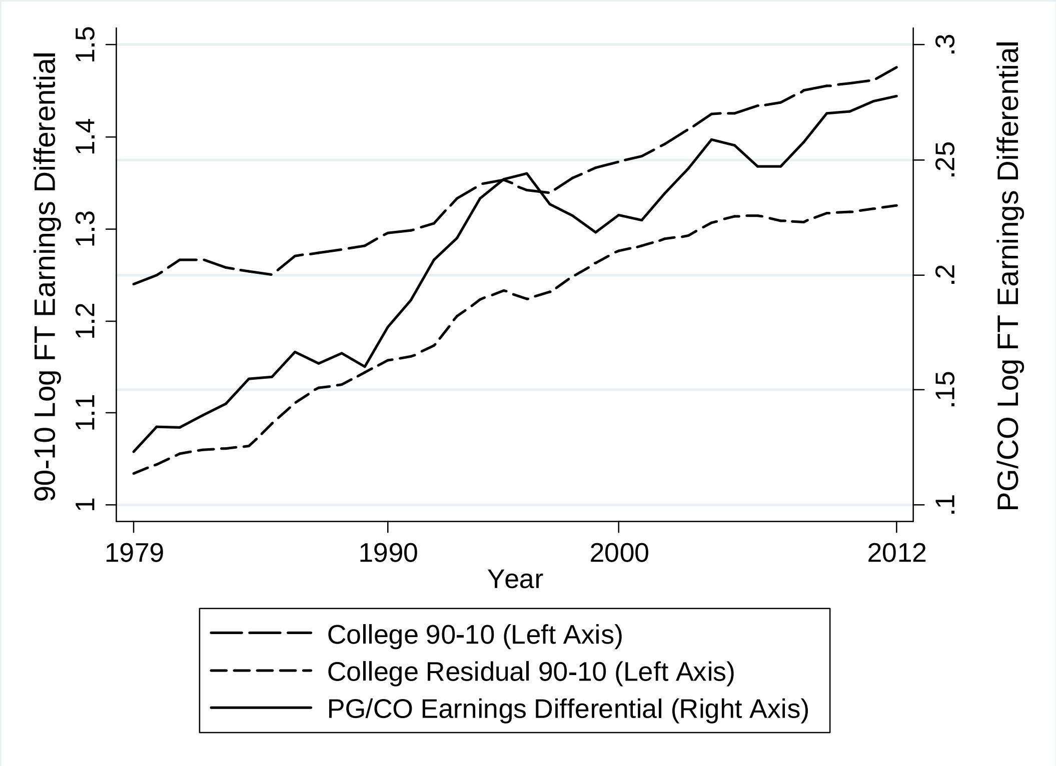
Figure 1:
US Wage Inequality Trends - Overall and Within Education Groups



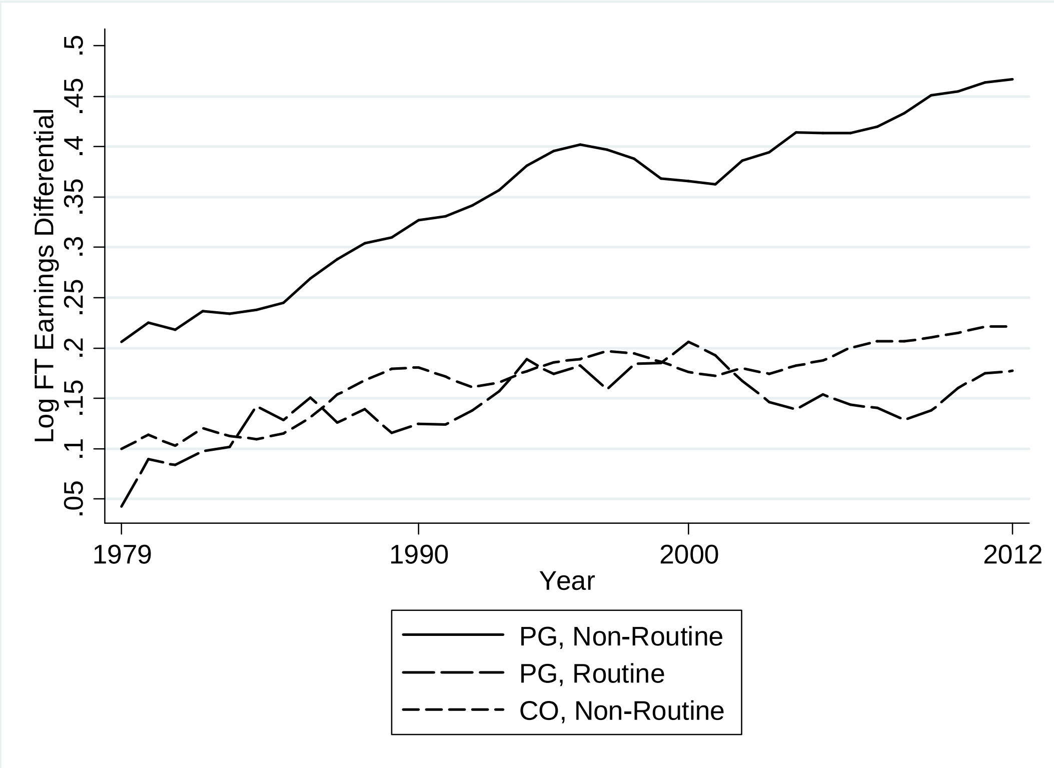
Notes: 90-10 Log(Earnings) differentials from March Current Population Surveys for earnings years 1979 to 2012 (survey years 1980 to 2013). Weekly earnings for full-time full-year workers aged 26-64 (during the earnings year) with 0-39 years of potential experience.

Figure 2:
US Within-College Wage Inequality Trends



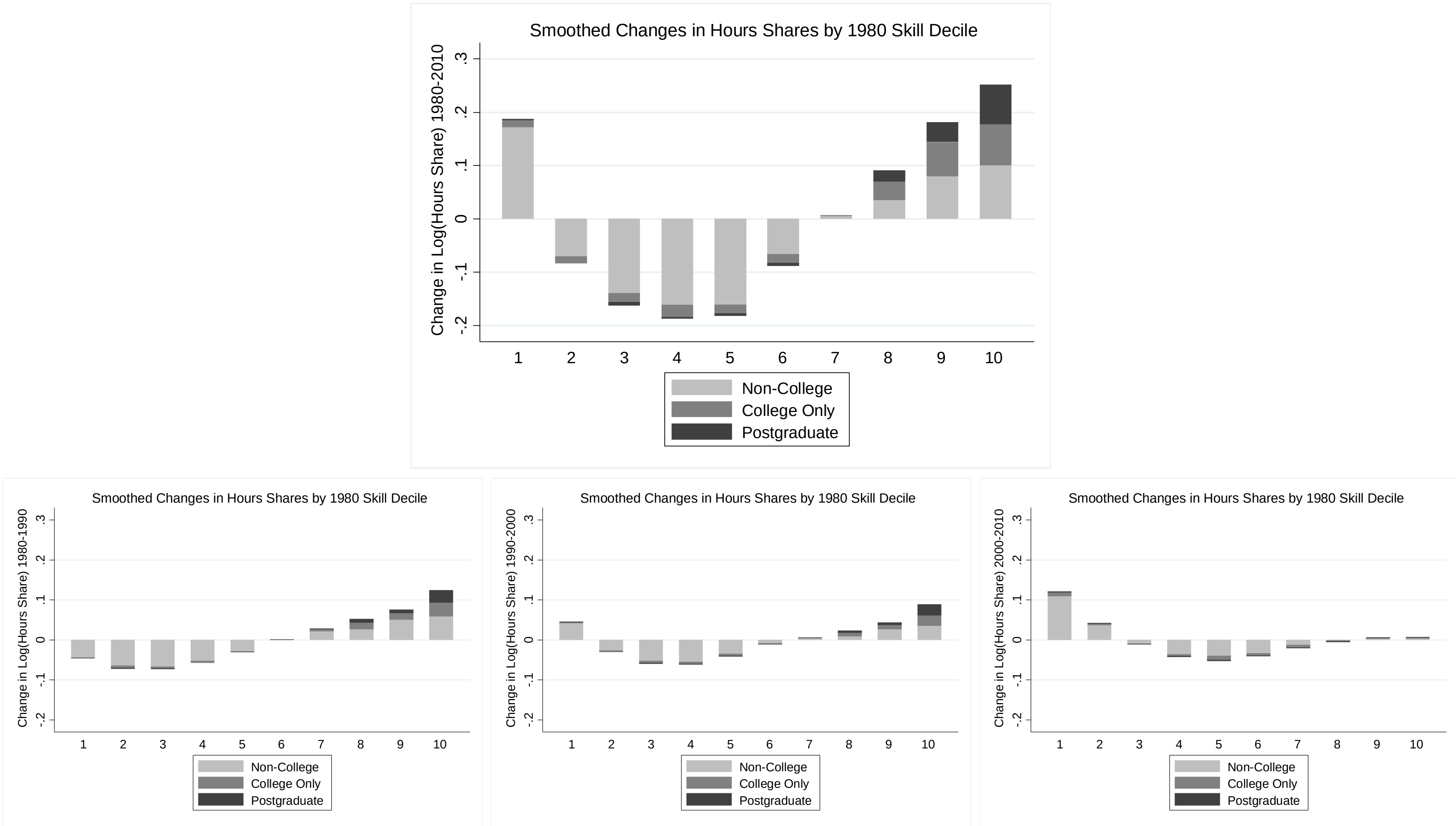
Notes: 90-10 Log(Earnings) differentials from March Current Population Surveys for earnings years 1979 to 2012 (survey years 1980 to 2013). Weekly earnings for full-time full-year college graduate workers aged 26-64 (during the earnings year) with 0-39 years of potential experience. PG denotes postgraduate and CO college only and the PG/CO differential is a composition adjusted differential obtained from separate yearly regressions of log(FT weekly earnings) on the dummy variable for PG (relative to CO), three potential experience dummies (10-19, 20-29 and 30-39 years relative to 0-9 years), a male dummy, three region dummies, black and other race dummies and interactions of the experience dummies with the other controls.

Figure 3:
Postgraduate and College Only Wage Differentials by Routineness of Occupation



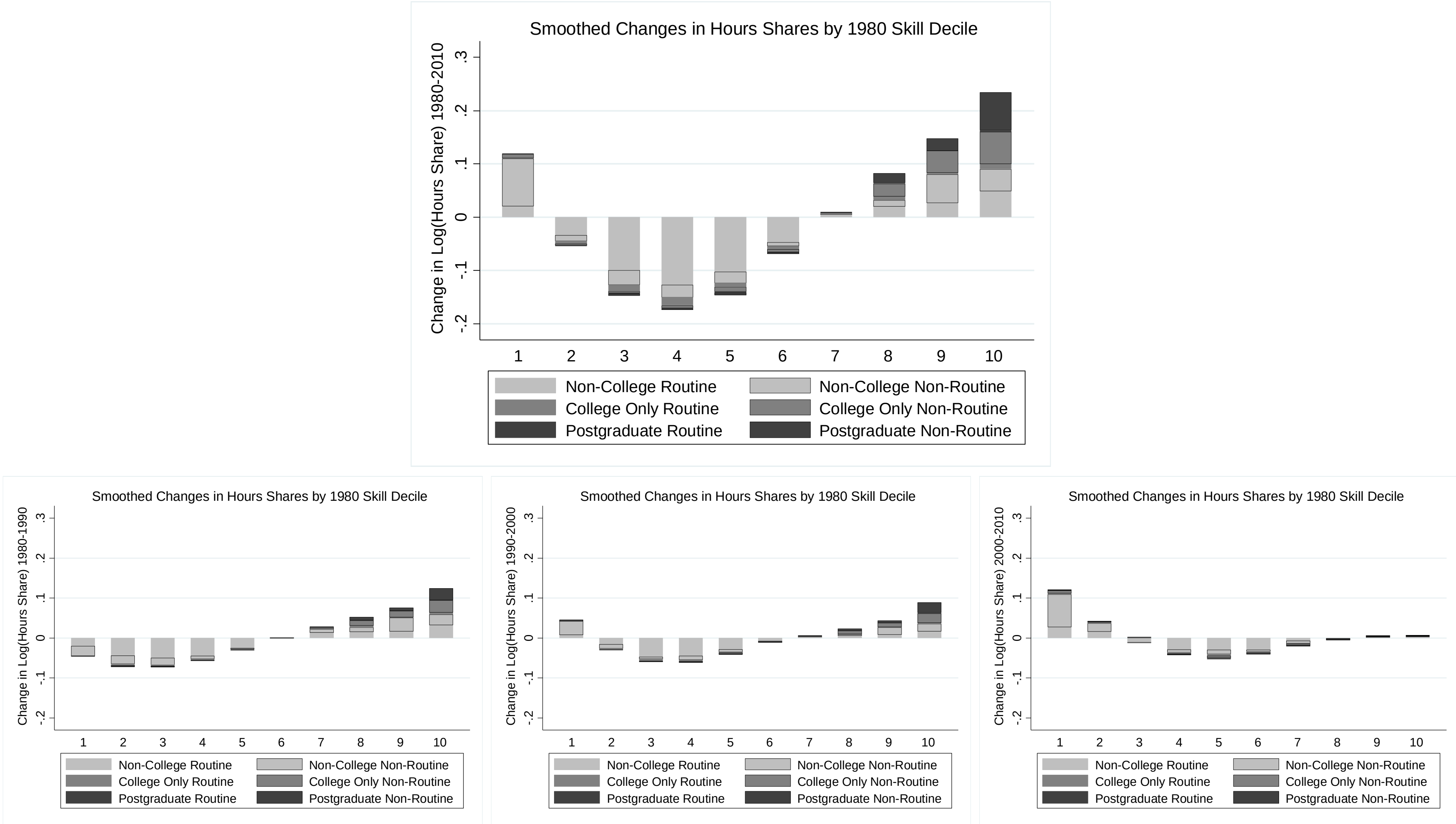
Notes: Log(Earnings) differentials from March Current Population Surveys for earnings years 1979 to 2012 (survey years 1980 to 2013). Weekly earnings for full-time full-year college graduate workers aged 26-64 (during the earnings year) with 0-39 years of potential experience. PG denotes postgraduate and CO college only and the PG/CO differentials are composition adjusted differentials obtained from separate yearly regressions of log(FT weekly earnings) on the dummy variable of interest (PG, Non-Routine; PG, Routine; CO, Non-Routine each relative to CO, Routine), three potential experience dummies (10-19, 20-29 and 30-39 years relative to 0-9 years), a male dummy, three region dummies, black and other race dummies and interactions of the experience dummies with the other controls. The definitions of Non-Routine and Routine occupations are given in the Data Appendix.

Figure 4: Job Polarization Broken Down by Education, 1980 to 2010 and by Decade



Notes: Based on 320 consistently defined non-farm occupations from the 1980 US Census and the pooled 2009 to 2011 American Community Surveys. Skill deciles are based on the hours weighted 1980 mean occupational log(hourly wage).

Figure 5: Job Polarization Broken Down by Education and Routineness, 1980 to 2010 and by Decade



Notes: Based on 320 consistently defined non-farm occupations from the 1980 US Census and the pooled 2009 to 2011 American Community Surveys. Skill deciles are based on the hours weighted 1980 mean occupational log(hourly wage).

Table 1: College Degree Group Employment Shares, US

Survey/Census Year	1980	1990	2000	2012	2012 – 1980 Change
A. March CPS					
All					
College Degree or Higher	0.236	0.280	0.317	0.383	0.147
Of which:					
Postgraduate Degree	0.076	0.093	0.110	0.142	0.066
College Degree Only	0.160	0.187	0.207	0.241	0.081
College Degree or Higher					
Postgraduate Degree	0.323	0.331	0.346	0.371	0.048
Sample Size	54164	56303	51492	72924	
B. Census/ACS					
All					
College Degree or Higher	0.233	0.274	0.311	0.368	0.135
Of which:					
Postgraduate Degree	0.085	0.103	0.116	0.140	0.055
College Degree Only	0.148	0.171	0.195	0.228	0.080
College Degree or Higher					
Postgraduate Degree	0.365	0.375	0.373	0.381	0.016
Sample Size	3312656	4357861	5169385	1035723	
C. CPS MORGs					
All					
College Degree or Higher	0.247	0.289	0.325	0.393	0.146
Of which:					
Postgraduate Degree	0.081	0.097	0.112	0.144	0.063
College Degree Only	0.166	0.192	0.213	0.249	0.083
College Degree or Higher					
Postgraduate Degree	0.328	0.335	0.348	0.367	0.041
Sample Size	141913	149434	133358	132676	

Notes: Employment shares are defined for people in work with 0 to 39 years of potential experience and aged 26 to 64. The Census samples for 1980, 1990 and 2000 are 5 percent samples of the US population and the 2012 American Community Survey is a 1 percent sample. Sample sizes are for All in each year.

Table 2: Composition Adjusted Wage Differentials by College Degree Group, US

Survey/Census Year	1980	1990	2000	2012	2012 – 1980 Change
A. March CPS					
All					
College Degree or Higher	0.368 (0.007)	0.518 (0.007)	0.630 (0.007)	0.698 (0.007)	0.329 (0.010)
Postgraduate Degree	0.454 (0.010)	0.623 (0.009)	0.778 (0.010)	0.862 (0.008)	0.410 (0.014)
College Degree Only	0.327 (0.007)	0.466 (0.007)	0.549 (0.008)	0.599 (0.007)	0.272 (0.001)
College Degree or Higher					
Postgraduate Degree	0.127 (0.010)	0.157 (0.010)	0.230 (0.010)	0.264 (0.008)	0.137 (0.014)
Sample Size	29925	34938	31226	42357	
B. Census/ACS					
All					
College Degree or Higher	0.390 (0.001)	0.552 (0.001)	0.623 (0.001)	0.690 (0.002)	0.300 (0.002)
Postgraduate Degree	0.461 (0.001)	0.664 (0.001)	0.744 (0.001)	0.849 (0.002)	0.388 (0.002)
College Degree Only	0.352 (0.001)	0.484 (0.001)	0.551 (0.001)	0.589 (0.002)	0.233 (0.002)
College Degree or Higher					
Postgraduate Degree	0.109 (0.002)	0.180 (0.002)	0.192 (0.001)	0.259 (0.002)	0.150 (0.003)
Sample Size	2469882	3164726	3836508	805086	
C. CPS MORGs					
All					
College Degree or Higher	0.359 (0.004)	0.510 (0.004)	0.601 (0.004)	0.645 (0.004)	0.287 (0.006)
Postgraduate Degree	0.445 (0.006)	0.644 (0.005)	0.738 (0.006)	0.785 (0.006)	0.342 (0.009)
College Degree Only	0.320 (0.005)	0.445 (0.004)	0.528 (0.005)	0.565 (0.005)	0.244 (0.007)
College Degree or Higher					
Postgraduate Degree	0.125 (0.006)	0.199 (0.006)	0.209 (0.006)	0.220 (0.006)	0.095 (0.010)
Sample Size	80640	96811	92826	94469	

Notes: Log(Earnings) differentials based on weekly earnings for full-time full-year workers in the March CPS and Census/ACS and for full-time workers in the CPS MORGSs for those aged 26-64 (during the earnings year which is the year prior to the survey year for the March CPS and Census/ACS, and we match the year prior for the CPS MORGs) with 0-39 years of potential experience. The reported differentials are composition adjusted differentials obtained from separate yearly regressions of log(FT weekly earnings) on the education dummy variable of interest, three potential experience dummies (10-19, 20-29 and 30-39 years relative to 0-9 years), a male dummy, three region dummies, black and other race dummies and interactions of the experience dummies with the other controls. In the All panel estimates of education wage differentials are relative to high school graduates and in the College Degree or Higher they are relative to college degree only. Standard errors in parentheses.

Table 3: Top Ten Occupations - College Only and Postgraduates, US, 2012

US, March 2012, 454 Detailed Occupations			
College Only		Postgraduates	
Top 10 Occupations	Share (%)	Top 10 Occupations	Share (%)
1. Registered Nurses	5.1	1. Elementary and middle school teachers	8.2
2. Elementary and middle school teachers	4.4	2. Lawyers, judges, magistrates and other judicial	6.2
3. Managers, all other	4.1	3. Postsecondary teachers	5.6
4. Accountants and auditors	3.2	4. Physicians and surgeons	5.0
5. First-line supervisors/managers of retail sales workers	2.3	5. Secondary school teachers	3.9
6. Chief executives	2.2	6. Managers, all other	3.6
7. Secretaries and administrative assistants	1.8	7. Education administrators	3.0
8. Financial managers	1.8	8. Chief executives	2.3
9. Sales representatives, wholesale and manufacturing	1.7	9. Software developers, applications and systems software	2.1
10. Software developers, applications and systems software	1.7	10. Counsellors	2.1
Share of top 10	28.4		42.1

Notes: US source March 2012 Current Population Survey. For workers aged 26-64 with 0-39 years of potential experience.

Table 4: Changes in Job Tasks Postgraduates and College Only Workers

	1980				2012				Difference-in-Difference of Regression Corrected Gap
Job Tasks	PG	CO	PG/CO Gap	Regression Corrected Gap	PG	CO	PG/CO Gap	Regression Corrected Gap	
Non-Routine									
Analytical (GED Maths)	5.493	4.904	0.589 (0.196)	0.495 (0.192)	5.670	4.922	0.747 (0.223)	0.714 (0.216)	0.219 (0.096)
Interactive (DCP of Others)	4.656	4.026	0.631 (0.416)	0.379 (0.424)	4.866	3.952	0.913 (0.463)	0.848 (0.461)	0.470 (0.208)
Routine									
Cognitive (SLTS)	2.340	3.425	-1.085 (0.332)	1.052 (0.322)	2.459	3.548	-1.089 (0.318)	-0.111 (0.324)	-0.058 (0.232)
Manual (Finger Dexterity)	3.474	3.552	-0.078 (0.212)	-0.049 (0.199)	3.518	3.519	-0.002 (0.261)	-0.005 (0.260)	0.054 (0.093)
Aptitudes									
Numeracy	5.969	5.449	0.520 (0.222)	0.450 (0.217)	6.122	5.427	0.695 (0.246)	0.680 (0.240)	0.230 (0.079)
Verbal	7.545	6.737	0.808 (0.222)	0.771 (0.216)	7.599	6.621	0.979 (0.208)	0.964 (0.210)	0.193 (0.080)
General Learning	7.668	6.917	0.751 (0.208)	0.714 (0.203)	7.738	6.811	0.927 (0.201)	0.911 (0.202)	0.197 (0.080)
Temperaments									
Influencing People	2.972	2.002	0.970 (0.561)	0.955 (0.564)	2.524	1.705	0.819 (0.518)	0.856 (0.526)	-0.099 (0.137)
Performing Under Stress	0.377	0.617	-0.234 (0.155)	-0.199 (0.120)	0.519	0.943	-0.424 (0.212)	-0.454 (0.233)	-0.255 (0.132)
Dealing With People	7.799	7.081	0.718 (0.275)	0.785 (0.290)	7.764	7.034	0.730 (0.275)	0.722 (0.272)	-0.062 (0.194)

Notes: From 1980 Census and 2012 ACS. All estimates are weighted using individual person weights and standard errors are clustered on three digit occupation. Tasks are matched to individual Census/ACS data on three digit occupation from the 1980 DoT definitions of task inputs. DCP is the direction, control and planning of others. STLS is setting limits, tolerances and standards. Sample sizes are 267697 (151777) for postgraduates and 562455 (262788) for college only in 1980 (2012).

Table 5: College Degree Employment Shares by Routineness

Survey/Census Year	1980	1990	2000	2012	2012 – 1980 Change
A. March CPS					
Postgraduate Non-Routine	0.294	0.289	0.314	0.340	0.046
Postgraduate Routine	0.027	0.038	0.030	0.037	0.010
College Only Non-Routine	0.496	0.461	0.456	0.446	-0.050
College Only Routine	0.183	0.211	0.201	0.177	-0.006
Sample Size	12647	15257	14712	27727	
B. Census/ACS					
Postgraduate Non-Routine	0.321	0.330	0.331	0.343	0.022
Postgraduate Routine	0.044	0.045	0.041	0.038	-0.007
College Only Non-Routine	0.444	0.428	0.444	0.442	-0.002
College Only Routine	0.191	0.197	0.183	0.177	-0.014
Sample Size	761861	1148586	1529518	392854	
C. CPS MORGs					
Postgraduate Non-Routine	0.298	0.295	0.313	0.331	0.033
Postgraduate Routine	0.030	0.041	0.035	0.036	0.006
College Only Non-Routine	0.495	0.456	0.460	0.457	-0.038
College Only Routine	0.177	0.209	0.191	0.176	-0.001
Sample Size	35096	43343	43631	53464	

Notes: As for Table 1, except the sample is only for college graduates.

Table 6: Composition Adjusted Wage Differentials by Routineness

Survey/Census Year	1980	1990	2000	2012	2012 – 1980 Change
A. March CPS					
Postgraduate Non-Routine	0.241 (0.016)	0.312 (0.014)	0.369 (0.016)	0.445 (0.013)	0.206 (0.023)
Postgraduate Routine	0.065 (0.036)	0.144 (0.029)	0.182 (0.033)	0.185 (0.026)	0.121 (0.051)
College Only Non-Routine	0.132 (0.015)	0.190 (0.013)	0.173 (0.015)	0.218 (0.012)	0.086 (0.022)
Sample Size	7417	10119	9756	17095	
B. Census/ACS					
Postgraduate Non-Routine	0.235 (0.002)	0.292 (0.002)	0.340 (0.002)	0.433 (0.003)	0.198 (0.004)
Postgraduate Routine	0.049 (0.004)	0.110 (0.003)	0.106 (0.003)	0.182 (0.006)	0.133 (0.008)
College Only Non-Routine	0.139 (0.002)	0.135 (0.002)	0.170 (0.002)	0.212 (0.003)	0.074 (0.004)
Sample Size	515019	806477	1103255	304382	
C. CPS MORGs					
Postgraduate Non-Routine	0.226 (0.010)	0.349 (0.009)	0.395 (0.009)	0.423 (0.008)	0.198 (0.015)
Postgraduate Routine	0.062 (0.021)	0.110 (0.017)	0.138 (0.018)	0.126 (0.018)	0.064 (0.033)
College Only Non-Routine	0.114 (0.009)	0.173 (0.008)	0.224 (0.008)	0.247 (0.008)	0.133 (0.014)
Sample Size	19388	27709	30118	37898	

Notes: As for Table 2, except the sample is only for college graduates.

Table 7: Estimates of Supply-Demand Models of Postgraduate/College Only Wage Differentials, US

	United States, 1963-2012	
	(1)	(2)
Log(Aggregate Relative Supply)	-0.142 (0.059)	-0.160 (0.051)
Trend	0.005 (0.001)	0.005 (0.001)
Log(Experience Specific Relative Supply) - Log(Aggregate Relative Supply)		0.001 (0.031)
Sample Size	50	200
R-Squared	0.89	0.73

Notes: The dependent variable is the log of the relevant fixed weighted (composition adjusted) postgraduate/college only wage differentials. Standard errors in parentheses. Four experience specific groups (0-9, 10-19, 20-29, 30-39) are considered in column (2) whose specification includes 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 8: Education Labour Demand Shifts and Changes in Computer Usage

	United States, 215 Industries				
Change in Employment Shares, 1989-2008	Postgraduates	College Only	Some College	High School Graduates	High School Dropouts
A. No Initial Computer Variable					
Change in Computer Use, 1984-2003	0.079	0.005	-0.046	-0.094	0.054
	(0.022)	(0.026)	(0.028)	(0.036)	(0.025)
R-Squared	0.06	0.01	0.01	0.03	0.02
B. With Initial Computer Variable					
Change in Computer Use, 1984-2003	0.105	0.026	-0.080	-0.140	0.086
	(0.019)	(0.025)	(0.024)	(0.030)	(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	0.30	0.12	0.29	0.33	0.34

Notes: Standard errors in parentheses. All changes are annualised. Employment shares are from the 1989 and 2008 Merged Outgoing Rotation Groups of the CPS; Computer usage from the 1984 and 2003 October CPS. All regressions weighted by the average employment share in total industry averaged across the two years.

Table 9: Education Labour Demand Shifts and Computers By Routineness

	United States, 215 Industries				
Change in Employment Shares, 1989-2008	Postgraduates	College Only	Some College	High School Graduates	High School Dropouts
Non-Routine Intensive:					
Change in Computer Use, 1984-2003	0.102	0.013	0.018	-0.072	-0.004
	(0.019)	(0.024)	(0.021)	(0.020)	(0.016)
Computer Use, 1984	0.005	0.005	-0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)
R-Squared	0.33	0.20	0.01	0.06	0.08
Routine Intensive:					
Change in Computer Use, 1984-2003	0.003	0.013	-0.098	-0.067	0.082
	(0.004)	(0.013)	(0.022)	(0.027)	(0.022)
Computer Use, 1984	-0.001	-0.001	-0.006	-0.008	0.004
	(0.0001)	(0.004)	(0.001)	(0.001)	(0.001)
R-Squared	0.01	0.04	0.30	0.31	0.18

Notes: Standard errors in parentheses. All changes are annualised. Employment shares are from the 1989 and 2008 Merged Outgoing Rotation Groups of the CPS; Computer usage from the 1984 and 2003 October CPS. All regressions weighted by the average employment share in total industry averaged across the two years.

Table 10: Education Labour Demand Shifts and Changes in Complex/Basic Computer Use

	United States, 215 Industries				
Change in Employment Shares, 1998-2008	Postgraduates	College Only	Some College	High School Graduates	High School Dropouts
Change in Complex Computer Use, 1993-2003	0.063 (0.026)	0.023 (0.062)	-0.049 (0.039)	-0.057 (0.042)	0.020 (0.030)
Change in Basic Computer Use, 1993-2003	0.075 (0.027)	0.081 (0.038)	-0.064 (0.040)	-0.101 (0.043)	0.009 (0.031)
Complex Computer Use, 1993	0.012 (0.002)	0.003 (0.003)	-0.014 (0.003)	-0.002 (0.003)	0.001 (0.002)
Basic Computer Use, 1993	0.003 (0.001)	0.004 (0.001)	-0.006 (0.001)	-0.006 (0.002)	0.004 (0.001)
R-Squared	0.25	0.04	0.22	0.08	0.12
Non-Routine Intensive:	Postgraduates	College Only	Some College	High School Graduates	High School Dropouts
Change in Complex Computer Use, 1993-2003	0.063 (0.025)	-0.021 (0.036)	0.054 (0.033)	0.012 (0.027)	0.006 (0.016)
Change in Basic Computer Use, 1993-2003	0.086 (0.026)	0.090 (0.037)	-0.027 (0.034)	-0.012 (0.030)	0.007 (0.017)
Complex Computer Use, 1993	0.011 (0.002)	0.005 (0.003)	-0.008 (0.003)	0.003 (0.002)	0.004 (0.001)
Basic Computer Use, 1993	0.004 (0.001)	0.006 (0.001)	-0.001 (0.001)	-0.0001 (0.001)	0.002 (0.001)
R-Squared	0.24	0.14	0.09	0.01	0.10
Routine Intensive:	Post-Graduates	College Only	Some College	High School Graduates	High School Dropouts
Change in Complex Computer Use, 1993-2003	-0.0001 (0.007)	0.045 (0.030)	-0.102 (0.034)	-0.069 (0.040)	0.012(0.027)
Change in Basic Computer Use, 1993-2003	-0.009 (0.008)	-0.006 (0.031)	-0.034 (0.035)	-0.088 (0.041)	0.001(0.028)
Complex Computer Use, 1993	0.002 (0.001)	-0.002 (0.002)	-0.005 (0.002)	-0.005 (0.003)	0.001(0.002)
Basic Computer Use, 1993	-0.001 (0.001)	0.003 (0.001)	-0.005 (0.001)	-0.006 (0.002)	0.002 (0.001)
R-Squared	0.05	0.06	0.16	0.11	0.04

Notes: All changes are annualised. Employment shares are from the 1999 and 2008 Merged Outgoing Rotation Groups of the CPS; Computer usage from the 1993 and 2003 October CPS. Complex computer usage is for programming, CAD and other Design. 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 11: Education Shares and Composition Adjusted Wage Differentials, Great Britain

Survey Year	1996	2012	2012 - 1996 Change
A. Education Shares			
All			
College Degree or Higher	0.142	0.320	0.178
Of which:			
Postgraduate Degree	0.042	0.111	0.069
College Degree Only	0.100	0.209	0.109
College Degree or Higher			
Postgraduate Degree	0.296	0.348	0.052
Sample Size	146598	95008	
B. Wage Differentials			
All			
College Degree or Higher	0.471 (0.010)	0.483 (0.008)	0.012 (0.013)
Postgraduate Degree	0.504 (0.016)	0.585 (0.010)	0.081 (0.020)
College Degree Only	0.456 (0.011)	0.424 (0.008)	-0.032 (0.015)
College Degree or Higher			
Postgraduate Degree	0.048 (0.018)	0.161 (0.012)	0.113 (0.023)
Sample Size	18774	21122	

Notes: Samples are for British born people in work with 0 to 39 years of potential experience and aged 26 to 64.

Table 12: Skills and Job Tasks of British Postgraduate and College Only Graduates, Great Britain

Skill/Job Task	PG	CO	Gap	Regression Corrected Gap
Cognitive Skills				
Literacy	4.040	3.704	0.336 (0.054)	0.324 (0.054)
Simple Numeracy (Basic Arithmetic)	3.589	3.536	0.053 (0.063)	0.025 (0.062)
Advanced Numeracy (Maths and Stats)	3.138	2.718	0.420 (0.070)	0.360 (0.069)
Problem Solving Skills				
Thinking of Solutions to Problems	4.342	4.219	0.122 (0.044)	0.113 (0.044)
Analysing Complex Problems	4.286	3.843	0.444 (0.055)	0.404 (0.054)
People Skills				
Making Speeches/Presentations	3.701	3.149	0.552 (0.063)	0.514 (0.062)
Teaching People	3.978	3.846	0.132 (0.057)	0.141 (0.057)
Dealing With People	4.663	4.684	-0.021 (0.033)	-0.019 (0.032)
Firm Specific Skills				
Knowledge of Products/Services	3.766	3.828	-0.062 (0.061)	-0.066 (0.061)
Specialist Knowledge or Understanding	4.689	4.513	0.176 (0.038)	0.173 (0.038)
Computer Usage				
Using a Computer or Computerised Equipment	4.592	4.421	0.171 (0.046)	0.172 (0.046)
Proportion That Do Not Use a Computer	0.019	0.045	-0.026 (0.009)	-0.024 (0.009)
Simple Computer Users	0.082	0.104	-0.022 (0.014)	-0.033 (0.014)
Moderate Computer Users	0.412	0.489	-0.077 (0.023)	-0.061 (0.023)
Complex Computer Users	0.487	0.363	0.124 (0.023)	0.119 (0.022)
Routineness of Job				
Performing Short Repetitive Tasks	2.794	2.989	-0.195 (0.051)	-0.200 (0.050)
Variety in Job	4.214	4.114	0.099 (0.045)	0.117 (0.044)
Sample Size	676	2358		

Notes: Using the 2006 and 2012 Skills Surveys. All estimates are weighted using individual person weights. 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 13: College Degree Employment Group and Wage Differentials by Routineness, Great Britain

Survey Year	1996	2012	2012 - 1996 Change
A. College Degree Group Shares			
Postgraduate Non-Routine	0.284	0.331	0.047
Postgraduate Routine	0.012	0.017	0.005
College Only Non-Routine	0.634	0.566	-0.068
College Only Routine	0.069	0.085	0.016
Sample Size	20378	29631	
B. College Degree Group Wage Differentials			
Postgraduate Non-Routine	0.388 (0.034)	0.501 (0.022)	0.113 (0.046)
Postgraduate Routine	0.096 (0.076)	0.128 (0.050)	0.032 (0.103)
College Only Non-Routine	0.360 (0.032)	0.370 (0.021)	0.010 (0.044)
Sample Size	3129	7167	

Notes: Samples are for British born college graduates in work with 0 to 39 years of potential experience and aged 26 to 64. Routine occupations are SOC2000 codes 411-421, 711-721, 521-549 and 811-822. Non-routine occupations are SOC2000 codes 111-118, 122-356, 611-629 and 912-925. Farmers and military are excluded from the sample and these are SOC2000 codes 121, 511 and 911.

Table 14: Education Labour Demand Shifts and Computers by Routineness, Great Britain

	Great Britain, 51 Industries				
Change in Employment Shares, 1996-2008	Postgraduates	College Only	Intermediate 1	Intermediate 2	No Qualifications
All					
Change in Computer Use, 1992-2006	0.133 (0.033)	0.054 (0.053)	0.235 (0.058)	0.094 (0.079)	-0.037 (0.038)
Computer Use, 1992	0.009 (0.002)	0.004 (0.003)	-0.001 (0.003)	-0.021 (0.004)	0.009 (0.002)
R-Squared	0.38	0.05	0.26	0.38	0.33
Non-Routine Intensive:					
Change in Computer Use, 1992-2006	0.133 (0.033)	0.061 (0.052)	-0.202 (0.049)	0.074 (0.058)	-0.071 (0.036)
Computer Use, 1992	0.008 (0.002)	0.003 (0.003)	0.002 (0.003)	-0.003 (0.003)	0.008 (0.002)
R-Squared	0.38	0.05	0.30	0.06	0.33
Routine Intensive:					
Change in Computer Use, 1992-2006	0.001 (0.004)	0.001 (0.001)	-0.033 (0.024)	0.020 (0.063)	0.034 (0.046)
Computer Use, 1992	0.0004 (0.002)	0.001 (0.001)	-0.003 (0.001)	-0.018 (0.003)	0.001 (0.002)
R-Squared	0.07	0.05	0.09	0.38	0.01

Notes: All changes are annualised. Employment shares are from the 1996 and 2008 Labour Force Survey; computer usage from the 1992 Employment for Britain and 2006 Skills Surveys. All regressions weighted by the average employment share in total industry averaged across the two years. Routine occupations are SOC2000 codes 411-421, 711-721, 521-549 and 811-822. Non-routine occupations are SOC2000 codes 111-118, 122-356, 611-629 and 912-925. Farmers and military are excluded from the sample and these are SOC2000 codes 121, 511 and 911.

Data Appendix

United States Data

1. Basic Processing of the March CPS Data

We use the March Current Population Survey from 1964 to 2013 (corresponding to earnings years 1963 to 2012 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 Census and ACS Data

We use the 5% PUMS 1980, 1990 and 2000 Decennial Census data, as well as the 1 % samples from the 2012 American Community Surveys. Our basic sample consists of all working individuals aged 26-64 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 workers. 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 was reported in a single variable, which was top-coded at values between $75,000 in 1980 and $200,000 in 2012. Following Katz and Murphy (1992), we multiply the top-coded earnings value by 1.5. Earnings numbers are inflated into 2012 prices using the PCE deflator.

3. Basic Processing of the CPS MORG Data

We use the Merged Outgoing Rotation Groups for 1979 to 2012 for all employed workers. Our basic sample consists of workers aged 26-64 with 0 to 39 years of potential experience. Hours are measured using usual hours worked in the previous week. Full-time weekly earnings are calculated as the logarithm of weekly earnings over for full-time workers. Weights are used in all calculations. Top codes are handled by multiplying the top code by 1.5. Earnings numbers are deflated using the PCE deflator.

4. Coding of Education and Potential Experience in the CPS, Census, ACS

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.

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 the Census and ACS data we construct consistent educational categories again using the method proposed by Jaeger (1997). For the pre 1990 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 1990 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.

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 and for our relative supply measures, we consider ages 26 to 64.

5. Construction of the Relative Wage Series

We calculate composition-adjusted relative wages overall and by age and experience using the CPS, Census, ACS and LFS samples described above, excluding the self-employed. For Table 7, the March CPS data are sorted into gender-education-experience groups based on a breakdown of the data by gender, the two education categories, 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.

6. Construction of the Relative Supply Measures

For Table 7 we calculate relative supply measures using the March 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 64 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 percent 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.

7. Occupation Data for the Task and Polarization Analysis

In this part of the analysis we used data from the 5% PUMS 1980 Decennial Census data, as well as the 1 % samples from the 2009, 2010 and 2011 American Community Surveys (we refer to the pooled 2009-2011 sample as 2010). The basic sample consists of all working individuals aged 18-65. Hours are measured using usual hours worked in the previous year. We construct consistent educational categories in the 1980 and 2010 data as described in 3. above. The skill percentiles are based upon 320 consistently defined occupations for all those in employment (hours > 0). The procedures followed in Autor and Dorn (2013) and Lefter and Sand (2011) were used to obtain the consistent definitions. The 320 occupations are divided into employment weighted percentiles and deciles based upon the mean occupational wage in 1980.

For tasks, we use the 1980 Dictionary of Titles (DoT) occupational task data matched to the 320 occupations of workers in the 1980 Census and 2010 ACS where we have large enough samples to observe how the tasks have grown over time, separately for postgraduates and college only workers. We first use the same occupational task measures as Autor, Levy and Murnane (2003), which were kindly provided to us by David Dorn. Each occupation is evaluated by the DoT team to determine the extent of involvement for each task.

For the non-routine/routine part of the analysis we look at the following measures: analytical non-routine task content (based on the General Educational Development of worker's mathematics skills); interactive non-routine tasks (based on the extent to which worker's direct, control and plan for others); cognitive non-routine tasks (based on how often worker's set limits, tolerances and standards); and manual non-routine tasks (based on the finger dexterity of workers).

We also look at other task measures, also taken from the DoT. These are based on a selection of relevant aptitudes of workers which are taken from the United States Employment Services General Aptitude Test Battery (GATB) and the temperaments required by workers who are employed in a given occupation.

We also class each three digit occupation as routine intensive or non-routine intensive using the same broad definitions as used in Cortes et al. (2014). These are given in detail in Appendix A of their paper.

8. Industry Level MORG CPS Data

For the US industry level analysis, we use the Merged Outgoing Rotation Groups for 1989 and 2008 for all employed workers, excluding farmers and military 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.

9. Computer Use Data

The US computer use data are taken from the October 1984, 1993 and 2003 CPS supplements. CPS computer use is derived from the question `Do you use a computer at work?'. 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.

<u>Great Britain Data</u>

1. Basic Processing of the LFS Data

We use the 1996 to 2012 Quarterly Labour Force Surveys. 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. We also exclude all foreign born workers as a consequence of the change in the recording of foreign qualifications from `other' up to 2010, to their British equivalents from 2011 onwards. 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.

2. Coding of Education and Potential Experience in the LFS Data

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. Years of potential experience were calculated as age minus age left full time education.

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 64.

3. Industry Level LFS Data

We use the Quarterly Labour Force Survey for 1996 and 2008 for all British born 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.

4. Computer Use Data

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. In the EIB and the SS the 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.

5. 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.

Figures Appendix: Magnified Versions of Decade Specific Polarization Figures

Figure A1: Job Polarization Broken Down by Education, 1980 to 1990

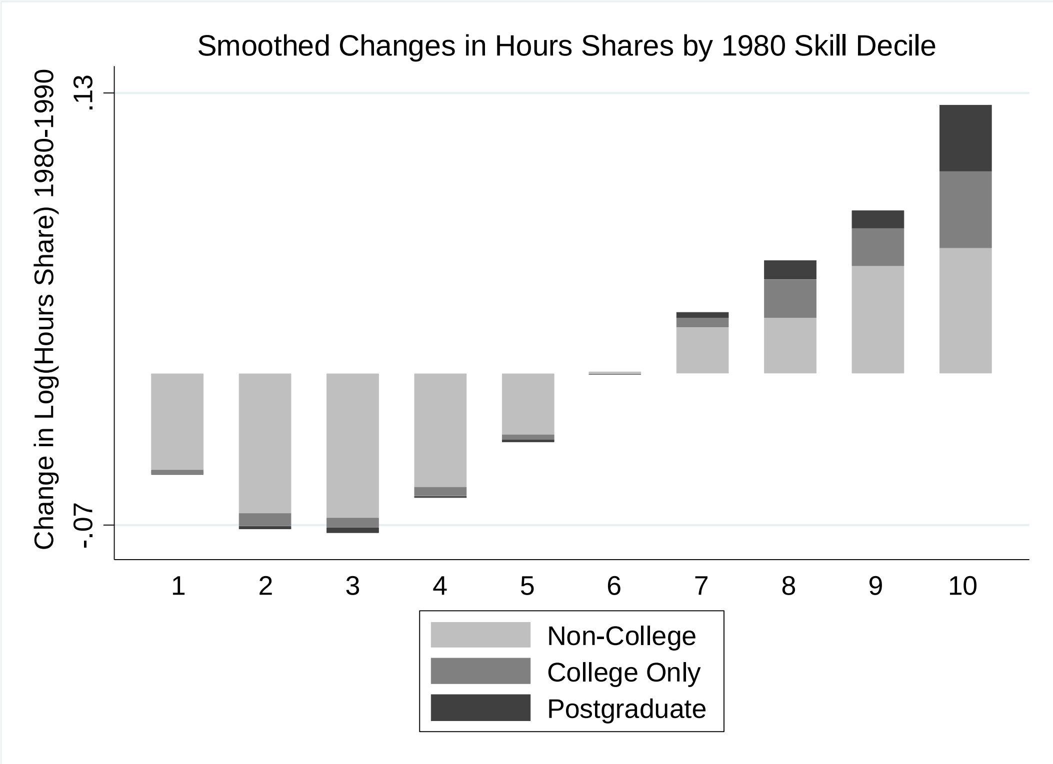


Figure A2: Job Polarization Broken Down by Education, 1990 to 2000

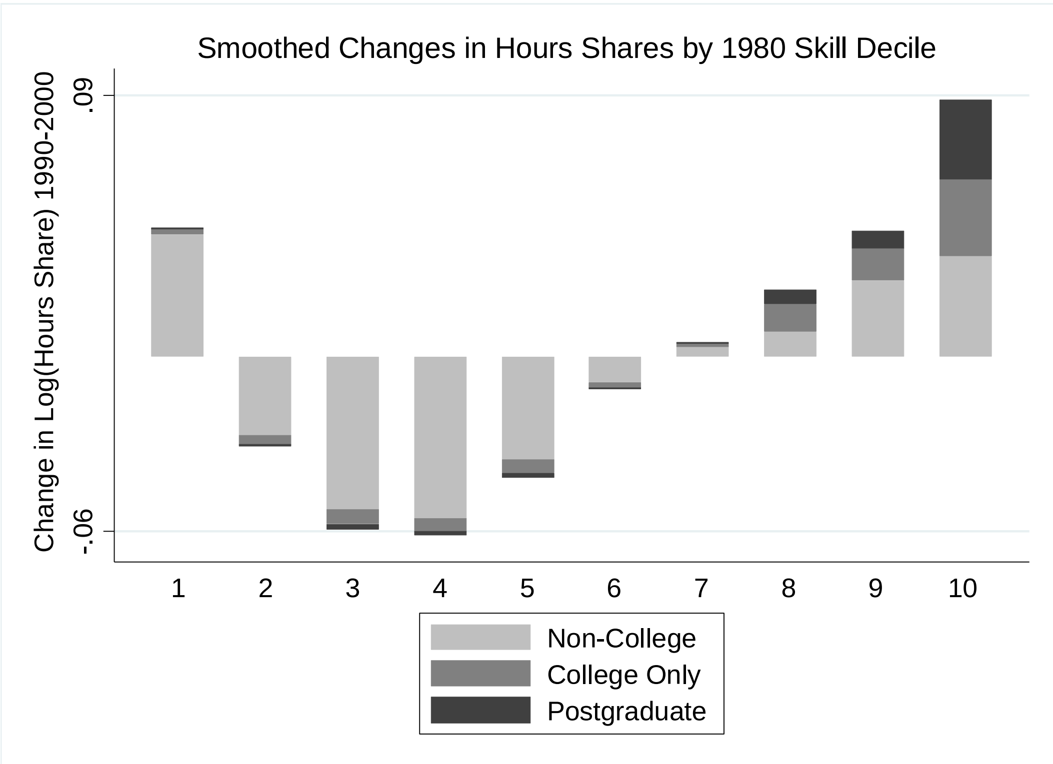


Figure A3: Job Polarization Broken Down by Education, 2000 to 2010

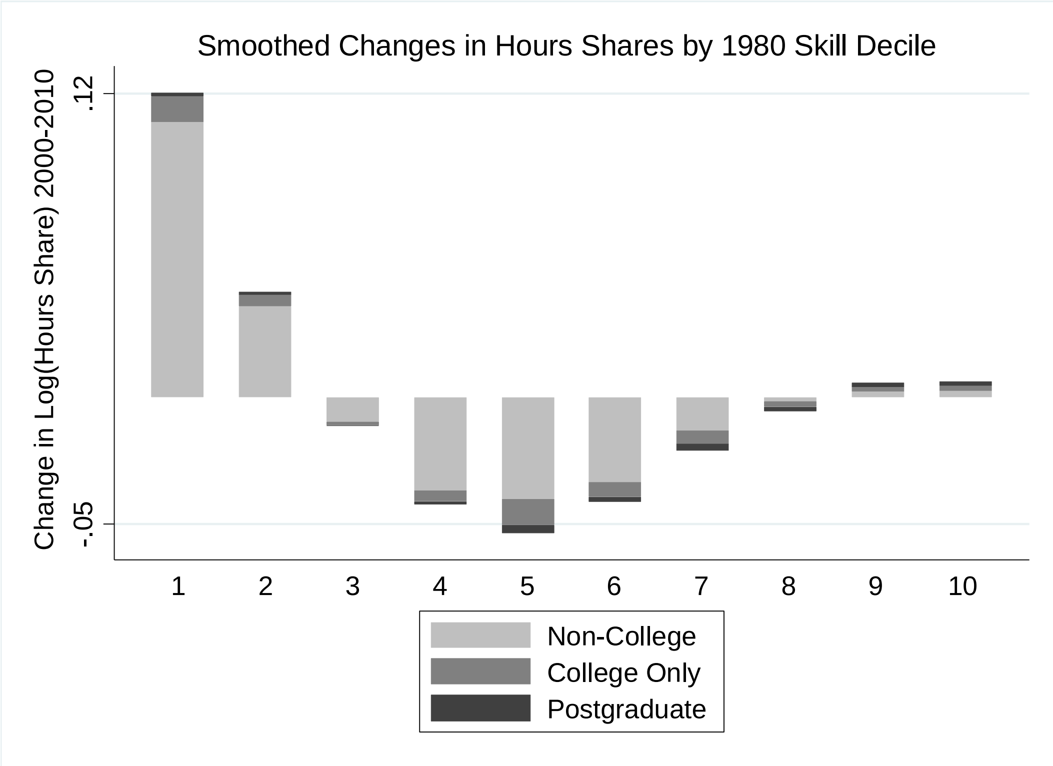


Figure A4: Job Polarization Broken Down by Education and Routineness, 1980 to 1990

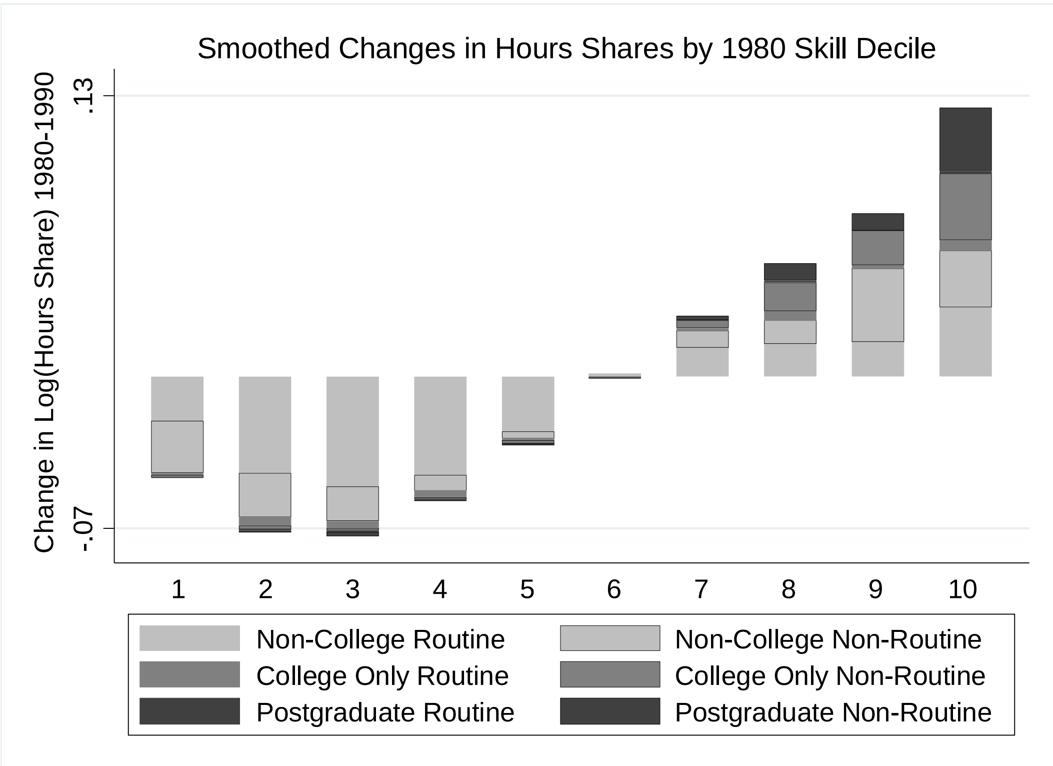


Figure A5: Job Polarization Broken Down by Education and Routineness, 1990 to 2000

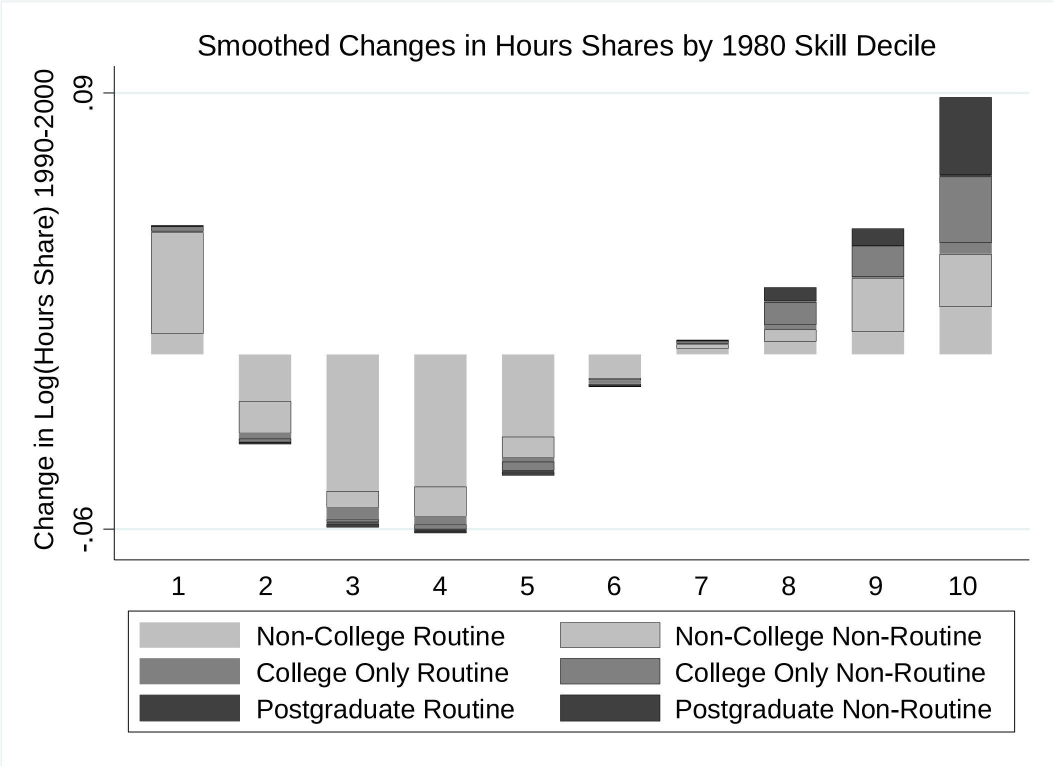


Figure A6: Job Polarization Broken Down by Education and Routineness, 2000 to 2010