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1. Introduction

Lifelong learning is a generic term covering a variety of forms of human capital accumulation that occur after the cessation of an individual's first period of continuous education. One of the main distinctions within the literature is between vocationally-oriented and 'general' adult education and training (Green et al., 2000; Aspin et al., 2001; Wolf et al., 2006). Across the OECD there has been an increasing policy focus on lifelong learning that falls within the former of these categories, as it is seen as a key driver of economic growth and competitiveness (OECD, 2000; European Commission, 2001; Leitch, 2006). This growth in the perceived importance of vocational lifelong learning is based on a widely held belief, that the accelerated pace of technological change has increased the average rate of skill depreciation (OECD, 2004). As a result individuals need to regularly update their skills following entry into the labour market.

This focus on the development of work-related skills as the primary driver for participation in lifelong learning has faced some criticism. Aspin et al. (2001) point out that this view of lifelong learning as 'instrumental to an extrinsic [economic] goal' ignores the wider private and public benefits of education; with Wolf et. al. (2006) noting a perceived diminution of the role of lifelong learning in 'personal fulfilment or cultural development'. When one considers the literature on returns to lifelong learning this debate is broadly reflected in a distinction between studies that use (i) economic and (ii) sociological 'outcome' measures.

More specifically, a range of microeconometric studies use a version of the Mincerian framework to gauge the impact of later-life human capital accumulation on earnings (Kane and Rouse, 1995; Leigh and Gill, 1997; Jacobson et al., 2005 in the US: Stenberg and Westerlund, 2008 in Sweden: Dearden et al., 2004; De-Coulon and Vignoles, 2008; Blanden et al.

forthcoming 2009, in the UK). In contrast, Feinstein and Hammond (2004) evaluate the impact of adult learning on proxies for health and social capital and a range of reports detail the potential for wider social benefits arising from lifelong learning (Green et al. 2003; Parsons and Bynner, 2007). More recently lifelong learning is being presented in policy circles as an opportunity for individuals to get a 'second chance' and become socially mobile later in life (UK Cabinet Office, 2008)

However, relative to the extensive literature that has developed around the returns to years of (typically continuous) education (see for instance, Harmon et al., 2003; Psacharopoulos and Patrinos, 2004; Johnes and Johnes, 2004; Hanushek and Welch, 2006), this evidence base is small. This is surprising not only because of the increasing international policy focus, but also because later-life investment in human capital provides a particularly valuable framework for evaluation of returns. As Harmon, Oosterbeek and Walker (2003) underline, "panel data techniques can be used to address heterogeneity" (p146) when estimating the returns to education. Using panel data we can assume that unobserved unit hetereogeneity is a (time invariant) fixed effect and this has the potential to overcome a problem that, "has been the preoccupation of the empirical literature since the earliest contributions" (op. cit. p119). However, in order to utilise this framework we must observe returns (whether earnings or some other outcome of interest) both before and after the educational treatment (i.e. this must be learning after entry into the labour market). For the study of returns to education, panel data approaches are immensely valuable and it is therefore surprising that there are no existing studies (op. cit. p146).

This paper represents an important first step in overcoming this gap in the evidence base, using the 1991 to 2007 waves of the UK British Household Panel Survey. We estimate a fixed effects specification that has as outcomes (i) earnings and (ii) an indicator of social position

measured using the CAMSIS scale. Adopting a fixed effects specification enables us to isolate the role of lifelong learning on these two outcome measures, as distinct from other person-specific variables which might be correlated with wages and education level. As long as such factors are constant over time (for example parental occupation, or cognitive ability) then their influence will be differenced out of the coefficient for changes in lifelong learning. This is particularly important if those who engage in lifelong learning possess unobserved characteristics which are themselves associated with higher earnings. We are also able to inform the international literature on both the direct financial and wider social returns to lifelong learning.

In addition, we make some contribution to the wider literature on the returns to education, with the caveat that the returns to later-life learning are likely to be different to those arising as a result of continuous schooling in earlier years. Our study of the BHPS also adds an important dimension to the growing literature within the UK, where evaluation of the returns to lifelong learning has been very much focused on vocationally-oriented programmes (including National Vocational Qualifications or NVQs) and based on analysis of cohorts (Dearden et al., 2002; Jenkins et al, 2003; Dearden et al. 2004; De-Coulon and Vignoles, 2008).

The evidence arising from these UK studies of the returns to lifelong learning is mixed. De-Coulon and Vignoles (2008) find the strongest evidence that low level vocational qualifications (NVQ2) increase earnings for women. Jenkins et al (2003) identify a positive impact of lifelong learning on employment probabilities, with earnings impacts limited to men who left school with low level qualifications and subsequently obtained a degree. However, there is also evidence that some individuals who gain low level vocational qualifications (NVQs at levels 1 and 2) have lower earnings than those without these qualifications (Dearden et al. 2002). Dearden et al. (2004) and Greenwood et al. (2007) detail how the estimated returns to these NVQ qualifications vary for sub-groups of the population and across sectors/occupations.

Whilst Dearden et al. (2002) utilise the panel element of the Labour Force Survey in addition to analysis of cohort studies, this only allows consideration of individuals over a one year period and the authors are unable to account for unobserved heterogeneity. The use of the BHPS allows us to consider (i) long-term returns to lifelong learning (ii) that do not suffer from the potential for simultaneity that arise when one estimates returns using cohort studies. Our use of a distributed lag structure allows clear identification of whether human capital accumulation takes place before changes in earnings or other outcomes measures, in comparison to cohort studies.

However, these substantial benefits do represent something of a trade-off, as analysis of the BHPS also has some limitations. Primarily, these relate to the limited level of disaggregation by qualification type and personal characteristics that is possible; arising from both a problem of sample size and also issues with the categorisation of educational attainment within the BHPS. However, in this respect our paper serves to highlight the data-needs that surround the development of new panel data sets, for instance the proposed Longitudinal Household Survey within the UK.

The remainder of the paper is structured as follows. Section 2 sets out some of the theoretical considerations that underpin the analysis of returns to lifelong learning and Section 3 describes the data and key measures to be used in our analysis. Section 4 details our analysis strategy and model specification. In Section 5 we discuss results, before concluding in Section 6 with a consideration of the limitations of our analysis and the implications of our findings for the understanding of returns to lifelong learning.

2. Theoretical Background

According to Becker (1964; 1993), Mincer (1958; 1974) and Schultz (1960; 1961) time and money spent on education make individuals more productive and such individuals therefore experience higher earnings – a view that sees education as an investment in human capital and earnings as one of the returns. In this paper we focus on the returns to lifelong learning, which we define as, *the gaining of formal educational qualifications after entry into the labour market.*

What does human capital theory tell us about the returns to education acquired later in life? Firstly, it is important to underline that this study focuses on investments that lead to accredited awards. The signal that formal accreditation provides for the individual is more likely to be associated with poaching externalities (Stevens, 1999) and we may therefore expect firms to be less heavily involved in the investment decisions we investigate. Assuming that individuals are rational we may further expect them to invest in qualifications that signal transferable skills, as they would be unwise to invest in skills where there is a monopsony buyer (their present firm). The suggestion is that we are less likely to be considering the acquisition of only firm-specific skills (Becker, 1964; 1993). Any additions to human capital that arise from work-based training will only be captured if they are formally accredited and therefore we do not place this study within the wider literature on workplace training (see Bassanini et al. 2005 for a detailed discussion of the latter).

Within this framework we would expect, *ceteris paribus*, that the incentives for an individual to invest in accredited human capital will fall as they age, given that they have less time to reap the returns (see Urwin, 2006 for a discussion). In contrast, if we assume that human capital depreciates in the same way as physical capital, then later-life education may reflect an

updating of skills, with external shocks potentially accelerating the rate of depreciation and the concomitant need for retraining. The situation we observe with regard to lifelong learning is likely to be a combination of these effects, with skill depreciation acting as an encouragement to invest in further human capital, but time-limited careers acting to reduce the potential returns to any such investment (inferences that fit within the life-cycle human capital model originally described by Ben-Porath, 1967).

This slavish adherence to human capital theory ignores an important alternative model that views education simply as a method of screening individuals, so as to identify those who can 'signal' ability to potential employers (Spence, 1973). In its purest form, signalling theory rules out any direct contribution of education to individual productivity, and by contrast, argues that in the presence of asymmetric information about workers' productivity, educational qualifications provide signals to employers and offers them a screening device for identifying high-ability workers.

In this study, as in many others, signalling and human capital theory are to a large extent observationally equivalent; they both suggest that we observe higher productivity individuals having higher qualifications and that individuals will invest in education in order to balance the expected returns against the costs of gaining qualifications (this includes tuition fees, lost earnings and the disutility of study). Individuals may still obtain a return from lifelong learning even if the signalling model is correct as signals may need to be updated due to the passing of time or as a consequence of technological shocks. Thus, whilst the model of Ben-Porath (1967) was developed within the framework set out by Becker, it works for both signalling and human capital theories of individual investment in education over the lifecycle.

However, this theoretical framework for consideration of the investment decisions and returns to lifelong learning is focused on private financial returns to the individual and does not necessarily capture the wider non-pecuniary returns that accrue at both the individual and societal levels. From the perspective of the economist, education and training provide both private returns that accrue to individuals, together with wider (external) benefits that accrue to society as a whole (for instance, more civic-mindedness amongst the better educated). In economics it is standard to think of private returns in terms of income and earnings. In this study, we also utilise the notion of social stratification, which draws together material with more social aspects of disadvantage, such as status, autonomy, and authority in employment relations. This enables us to evaluate whether education and training undertaken in adulthood might yield returns that would potentially go undetected in a standard econometric analysis of earnings.

For example, the concept of 'social mobility' cuts across consideration of returns to both the individual and society as a whole. Social mobility is often taken as an outward sign of democracy, allowing the most capable and hard-working individuals to rise to the highest rank, irrespective of social background. The allocation of individuals to their social position on the basis of ability rather than ascription, it can be argued, leads to more efficient utilisation of the available 'talent pool', and thereby improves economic efficiency and general standards of living for all. As well as these macro-considerations, there are also possible private returns to the individual, with the accrual of qualifications and skills seen as a crucial mediator between individual ability and socioeconomic achievement. Thus, individuals might see improvements in job security, status, and working conditions that enhance their private quality of life. While these features of an individual's working life are certainly correlated with earnings, they are not deterministic.

Finally, there may also be discernible benefits to lifelong learning that are unrelated to employment conditions; in terms of improved life-satisfaction, greater tolerance, interpersonal trust and more participation in community and political activities (Feinstein and Hammond 2004; Sturgis et al., 2007). Focusing solely on monetary returns to adult education may lead us to neglect other important social outcomes, such as higher levels of social status, work autonomy and social capital, all of which have been shown to have positive knock-on effects for the individual, their household and the community in which they live (Putnam 2000).

There are a number of key aspects to take from our brief discussion of the theoretical underpinnings of returns to lifelong learning. Firstly, we are faced with a number of possible factors that may motivate individuals to take up lifelong learning and, it is quite possible, that those who do take up education in later life are not representative of the population as a whole. Thus, simple OLS estimates of the returns to education will be biased as educational choice is endogenous. It is quite possible that many individuals invest in lifelong learning for reasons other than, or in addition to, any financial returns; which may be better captured by measures of social position. Also, one would wish to capture some aspect of the wider returns to society, though this is particularly tricky at the micro-level. As suggested in the introduction to this paper, our study of the BHPS is able to shed light on various of these aspects.

3. Data and Measures

Data

The first wave of the BHPS was conducted in 1991, with an achieved sample of 5,505 households, containing 10,264 individuals aged 15 or above. The BHPS employs a stratified,

multi-stage, random sample design, with annual face-to-face interviews conducted via computer assisted personal interview (CAPI) (see Lynn, 2006, for a detailed account of the BHPS sample design). At wave 1, the response rate for households where at least one individual was interviewed was 74%. In addition to these original sample members (OSMs), we include the children of the OSMs as they reach 16. We also include new entrants to the survey (after 1991) who become permanent sample members (PSMs) by virtue of having a child with an OSM. We do not include temporary sample members, the booster samples associated with Scotland, Wales and Northern Ireland, or the European Community Household Panel (ECHP) low income sub-sample, all of which were added to the BHPS in later years. When referring to sample size, we distinguish between 'respondents' and 'observations'. Respondents are the individuals in the sample, while observations are the *interviews* conducted with respondents across waves. These sample selection criteria yield a total of 130,563 observations from 13,022 respondents across the 16 waves from 1991 to 2006. Table 1 shows the total number of observations in each wave of the BHPS between 1991 and 2007.

Lifelong Learning

We operationalise lifelong learning by using information on qualifications obtained since the previous interview, approximately one year earlier. A focus on formally accredited human capital accumulation provides us with a clear indication that learning has taken place and distinguishes lifelong learning from work-based training. Whether a qualification counts as lifelong learning in our analysis depends upon the age and previous employment status of the respondent at the time of the observation. For observations where the respondent is aged 30 or over, any qualification obtained since the previous interview constitutes life long learning. For respondents who are aged 29 or under, qualifications obtained since the previous interview count as lifelong learning

only if the respondent has had at least two (necessarily contiguous) previous observations during which they were in employment – i.e. observations under age 29 were not unemployed, retired, in family care, a full-time student, sick/disabled, on maternity leave or in government training – prior to the observation in which the qualification was obtained. We apply this age-based definition so that lifelong learning is not ascribed to respondents who are still in the 'school-to-work' transition, such as people who obtain a degree after 'gap years' and the like. Figure 1 presents a histogram of the distribution of all qualifications and qualifications defined as lifelong learning by age.

Figure 1 shows pooled learning observations across time with the highest concentration of learning occurring near the ages of 18 and 21. This corresponds to qualifications obtained at the end of further education and higher education (qualifications obtained at age 16 are not shown because new qualifications cannot be identified until they are 17). Within this learning distribution the incidence of *lifelong* learning is very low for young people but increases steadily with age until at age 30 there is a somewhat smooth transition into total lifelong learning. The rising incidence of lifelong learners aged in their late 20s in addition to the falling incidence of 'normal' learners in their late 20s supports our cut-off point at age 30, where we consider all learning to be lifelong learning. A significant number of observations remain in the 'long tail' which indicates that lifelong learning events continue to occur frequently until age 50. After this the number of learning events drop with nearly no learning events occurring post age 65.

Table 2 shows the number of lifelong learners observed in each wave, and presents these as a proportion of all respondents, without limiting the sample to those in the labour force. Around 3-5 percent of respondents are gaining a lifelong learning qualification in each wave. In general lifelong learning appears equally prevalent among men and women. Lifelong learning

becomes more common in later waves of the survey, perhaps revealing a general trend; although some effect of the ageing of the sample cannot be ruled out.

Of course, using a simple dummy to capture a lifelong learning event is likely to mask a large amount of variability in the types of qualification being obtained. Table 3 breaks down the aggregate qualifications distribution into NVQ-equivalent levels 1-5. This shows that the most frequently obtained qualification type is 'other', which includes work-related qualifications of non-distinct types but which are accredited (e.g. technical and professional qualifications). We suspect that many qualifications at levels 1 and 2 may also be included here. Correlating these observations with some of the work-related training variables in the BHPS shows high positive correlations in the range 0.16-0.40 across individual waves and gender. This correlation range is much higher than when correlating training with other NVQ-equivalent types, where the range for all other levels is between 0.02-0.15 across waves and gender.

It would seem, then, that the primary form of lifelong learning that we detect in the sample is accredited work-related training. Ideally we would follow De-Coulon and Vignoles (2008) in isolating lifelong learning which raises the highest qualification of individuals. Unfortunately the prevalence of the 'other' qualifications renders this unfeasible. In addition, when specifying our criteria for acceptance of whether an event is counted as lifelong learning there is an implicit trade-off. We do not capture returns for those who are unemployed or inactive after leaving education, but then undertake lifelong learning and subsequently move into employment. Some of these individuals we might wish to count as undertaking lifelong learning, but many will be taking part in active labour market programmes that are likely to have an element of compulsion. It is not our aim to capture the latter of these as we are mainly interested in the returns to those who choose lifelong learning.

Earnings

We derive inflation-adjusted *usual* gross hourly earnings as our measure of earnings:

$$y = \frac{(Y)}{\frac{52}{12} \times (Hr + \lambda HrO)} \quad (1)$$

where Y is usual gross monthly earnings (deflated by the 2005 Consumer Price Index), Hr is the usual number of hours worked per week excluding overtime, HrO is the usual number of overtime hours worked per week and λ is the overtime rate (set at 1.5). This definition is similar to the one used by Booth et al. (2003). The mean gross earnings of our sample were £10.30 per hour for men (£8.44 median) and £7.83 per hour for women (£6.43 median).

Occupational social status

The CAMSIS scale is derived from multi-dimensional scaling analysis of cross-classified tables representing the occupations of individuals and their spouses or cohabiting partners. The data used to derive the scale is taken from the ONS Longitudinal Study (ONS-LS). The large sample size of the ONS-LS means that the full 3 digit standard occupational unit group coding can be used in deriving the scale. Similar measures to CAMSIS, which use the occupations of best friends rather than spouses (Chan and Goldthorpe 2004), necessarily entail an initial stage of aggregation across occupational unit groups. Thus, while the use of friendship rather than

spousal data may have some advantages[1], sample size limitations of existing data sources mean that it incorporates a degree of subjective judgement in the decisions taken over which occupations to place together in the aggregated list of occupations.

CAMSIS is based on the assumption that marriage partners are selected from occupations possessing a similar level of social status and material advantage; a lawyer is likely to marry a doctor but unlikely to marry a dustman. Thus, a measure of an individual's position within the social stratification hierarchy can be constructed *indirectly* from information about relative partnership propensities across occupational unit groups. CAMSIS is scaled such that a national population's distribution of scale scores (there are versions of CAMSIS for more than 30 different countries) should have a mean of 50 and standard deviation of 15.

Because CAMSIS measures the rather abstract notion of occupationally-based socio-economic advantage, units of the scale do not have an immediate intuitive interpretation. It is not possible, for instance, to relate x units of CAMSIS to some monetary value such as earnings in pounds. A higher score on CAMSIS, then, simply indicates greater advantage along the stratification dimension which the scores represent. As a uni-dimensional indicator of socio-economic disadvantage, CAMSIS is highly correlated with a range of normatively desirable outcomes, including but not limited to, mortality and morbidity; income; job satisfaction and a range of civic attitudes and behaviours (Feinstein and Hammond 2004; Sturgis et al. 2007). We can get a somewhat more concrete feel for the meaning of differences in CAMSIS scores by selecting some illustrative occupational unit groups from across the distribution of scale scores (Table 4). CAMSIS has also been shown to be strongly related to a range of important indicators of social and economic disadvantage such as health status, job satisfaction, income, education, and political engagement (Blanden et al. 2008).

[1] For instance, marriage often takes place during the early to mid-twenties, before many individuals have reached their highest occupational status, while friendship formation is more fluid throughout the life-course.

Missing values in earnings and CAMSIS

Naturally, estimation can only be carried out on observations where information on the outcome variable is present and information on both earnings and occupational status are only available when the respondent is in employment at the time of the interview. If the employment status for an observation is unemployment, retirement, family care, full-time student, sick/disabled, maternity leave or in government training, the observation cannot be included in the analysis. This restriction implies that the total number of observations eligible to be included in our analysis is reduced to 75,208 (39,498 observations for men and 35,710 observations for women).

Examining missing values for CAMSIS and earnings (see Table 5) within this new sample we find very few (189 observations for men and 158 observations women). However, approximately 17% of eligible observations have missing information on earnings, because the respondent did not supply this information (11% for women, 22% for men).

Respondents who report earnings information are approximately 5 years younger than those who do not; they are also less likely to have children; have a lower CAMSIS and the Registrar General's Social Class score; are less likely to work part-time; have a slightly lower level of educational attainment; are less likely to be married and more likely to have undertaken learning and lifelong learning.[2] However, we argue that the overall impact of this sample-selection is minimal because the proportion of missing earning responses is not large enough to significantly alter the average sample means. As there is no missing data bias for CAMSIS results using this variable as the outcome provides an interesting robustness check.

[2] We are happy to supply an additional appendix with detailed information regarding the t-tests and Hotelling's tests upon request

4. Modelling Strategy

We employ a finite distributed lag model within a fixed effects specification. A distributed lag model includes a set of lagged explanatory variables and allows us to examine how long it takes for any returns to lifelong learning to materialise. We omit contemporaneous lifelong learning (lag zero) because within an individual wave we are not able distinguish whether a change in earnings or occupational status occurred prior to, or at the same time, as the change in the qualification status. Furthermore, the fixed-effects specification allows us to condition out the influence of time-invariant person-level heterogeneity that is correlated both with the lifelong learning decision and with earnings.

Whilst the fixed effects specification removes individual heterogeneity that is time invariant, time-varying unobserved individual heterogeneity remains a potential problem. It is plausible, in this substantive context, that a variety of different 'life-events' might influence an individual to choose to take a new qualification. Many of the factors that might encourage an individual to undertake an additional qualification may also be those that lead to a career change, such as a shock in the labour market, a change of location, or a change in family circumstances. Some of these factors can be controlled for, by adding 'time-varying' variables to the regression that proxy these changes. We therefore also control for marital status, the number of children in the household and (previous) labour market status.

Finally, we include age (in years) and age squared in the model to capture the rise/fall in earnings/CAMSIS due to the experience profile of respondents. Our model, then, has the following form:

$$\ddot{y}_{it} = \alpha_i + \ddot{A}ge_{it} + \ddot{A}ge_{it}^2 + \sum_{k=1}^{K} \ddot{L}LL_{it-k} + \sum_{k=1}^{K} \ddot{X}_{it-k} + \ddot{e}_{it} \quad (2)$$

where $\ddot{y}_{it}$ is individual *i*'s time-demeaned CAMSIS score (or logged gross hourly earnings) at time *t*, $\ddot{A}ge_{it}$ and $\ddot{A}ge_{it}^2$ are the time-demeaned age variables, $\ddot{L}LL$ is a series of variables indicating whether individual *i* obtained a lifelong learning qualification at time *t-k*, $\ddot{X}$ is a vector of time (varying)-demeaned lagged exogenous individual characteristics and $\ddot{e}_{it}$ is a person *i* specific time-demeaned error term which is time varying. *K* is the number of lags used in the model for the qualification dummy and time varying characteristics respectively. Although the theoretical maximum number of lags in our dataset is 15, we set K to a maximum of 10, as going beyond this number introduces problems of differential attrition and multicollinearity. Simple-to-general specification tests (Greene, 2008; p. 676) which support the choice of a 10 lag maximum are available from the corresponding author upon request. Models are run separately for men and women. This reflects the rather different status hierarchy of occupations for men and women (Stewart et al.,1980).

In addition to the effect of gaining a qualification on our outcomes for particular values of K, we are interested in total effect across all values of K. For instance, it might be the case that we observe small and non-significant coefficient for several lagged coefficients but, when combined, these show a larger and statistically significant effect. The total effect of gaining a qualification across all lags is known as the long-run multiplier (Green, 2008; p 673) and, in this case, is calculated as:

$$\sum_{k=1}^{K} \beta_{it-k} \quad (3)$$

Finally, as we use 16 waves of data we are not able to look back the full 10 periods for each observation, i.e. when observed at wave 5, we are only able to look back over four possible episodes of lifelong learning. Rather than excluding this observation due to the lack of information in higher lags we can include a set of missing dummies for lifelong learning at each lag. This implies that we can use the maximum number of observations if we set lagged lifelong learning to zero when it is not observed. The advantage of this approach is that it does not introduce further selection problems by keeping the maximum possible number of observations. A disadvantage is that higher lags will have a reduced number of observations within their cells as more observations are placed into the missing dummies. This will increase the standard error of higher order lags and subsequently make higher order lag results more 'noisy'. A similar procedure is adopted to account for missing values in the other explanatory variables.

5. Results

First we present results for models which assess the returns for *any lifelong learning,* which are presented in Table 6. We have compared estimates from the fixed effects models with those obtained from a random effects model, where the random effects models include additional time-invariant controls. A Hausman test (Hausman, 1978) rejects the random effects model and so the fixed effects specification is used throughout the rest of the paper.

The coefficients reported in Table 6 are the estimated effect of gaining lifelong learning qualification, *T* years ago, on current individual earnings and occupational status. We also report in Table 6 the intermediate and long-run multipliers computed according to (3).

We find that for men, there is little initial effect of lifelong learning on hourly earnings. Lags up to 5 years indicate no statistically significant coefficients. However, significant effects are identified at lags 6, 7 and 9, which suggests that returns to earnings, though evident, take a long time to materialise for men. CAMSIS returns for men suggest that significant positive effects are identified at lags 2, 4, 5 and 6 which suggests a more immediate 'pay-off' from lifelong learning. For women we find that the effect of lifelong learning materialises somewhat less glacially, with a significant increase in earnings apparent at lags 4, 5, 6 and 7. The CAMSIS return for women is even more pronounced with positive returns at lags 1, 2, 3, 4 and 5.

However, the short run coefficients reported in Table 6 are the effects of gaining a lifelong learning qualification in a particular year, independent of the effect of lifelong learning in other years. The summation of the coefficients will provide information on the cumulative effects of gaining a lifelong learning qualification. This information is provided at the bottom of Table 6, or – for a graphical depiction of this information – in Figure 2.

The diagrammatic exposition of the results suggest that, for both men and women, lifelong learning has a positive and significant effect on hourly earnings and CAMSIS scores after 10 years. However, examining the temporal dynamics we see that, as suggested earlier, women appear to experience the positive effects of lifelong learning earlier than men (this is especially pronounced for earnings). Our results suggest that women who gain a lifelong learning qualification see a small rise in earnings (not distinguishable from zero) in the first three years after gaining a qualification. After this the return to earnings accelerates rapidly to the point where after 5 years women experience approximately an 11% rise in hourly earnings. The rise in earnings then decelerates, although a steady increase is still observed, until at 10 years women earn approximately 22% more. For men, we also observe substantial earnings increases after 10 years (approximately 18%), although this earnings trajectory is somewhat more gradual than for

women. We can only distinguish a lifelong learning effect which is significantly different from zero after 6 years for men.

For CAMSIS we find that the temporal effect from lifelong learning is relatively similar for both men and women, perhaps with a suggestion that women experience CAMSIS returns somewhat quicker than men. However, comparing CAMSIS returns to hourly earnings returns we find that for both men and women the returns to CAMSIS materialise far quicker than returns to earnings. Whilst we have previously stated that CAMSIS returns lack a clear interpretation, there is a suggestion in our results that lifelong learning leads to improved occupational standing before it leads to improved earnings power.

Finally, it ought to be noted, that the plotted confidence interval in Figure 2 increases substantially the 'further back in time we go'. Partly this is because of a reduction in the number of observations in the higher order lifelong learning lags due to imperfect information. This results in a larger standard error and hence, as can be seen from Figure 2, our point estimates in the later years are subject to a fair degree of variability

Using relevant information in our data we are able to use the point estimates to transform the return to lifelong learning into £ and % changes. This information is given in Table 7.

Table 7 suggests that after 10 years the return to a lifelong learning qualification for men is an hourly increase in earnings of £1.90, which corresponds to a yearly rise of £4,307. The CAMSIS return for men after 10 years is 5.12 points which equates to a CAMSIS increase of 10% for the average man. For women, gaining a lifelong learning qualification will lead to a £1.84 rise in hourly earnings after 10 years. However, because women's mean earnings are lower this equates

to only increasing yearly earnings by £2,986. The occupational status return for women is similar to that experienced by men. Gaining a lifelong learning qualification will lead to a 5.97 point rise in CAMSIS which equates to an increase of 11%.

At first glance then, our evidence suggests that *in general terms* returns to lifelong learning are positive and significant for both men and women, although there is a suggestion that women experience these returns more rapidly than men. Perhaps this is due to sample selection into work; women who enter the labour force may be more conscious of reaping possible rewards when compared to men and are thus able to extract positive earning differentials more rapidly than men. Whatever the reason, compared to some of the previous UK-based evidence, we believe that our approach allows us to remove a lot of ambiguity regarding the causal nature of the effect of learning on earnings (or CAMSIS) in addition to providing us with a not-seen-before insight into temporal aspects of the returns to learning in adulthood.

However, so far all our results have been based on treating all qualifications as equivalent measures of lifelong learning. We relax this assumption by specifying separate variables for each level of qualification, as described in Table 4. We are limited, however, by sample size; due to the small number of observations in some of the cells we must shorten the lag structure to 7 in order to maintain robust inference. As an additional consequence of the small sample sizes in some of the cells, the potential influence of outliers becomes more germane. We therefore omit observations from 1st and 99th percentiles of the earnings sample. This has the result of reducing some extreme estimates that are found when using the full sample. Results for the full sample are available from the corresponding author upon request. Results are presented in Table 8.

However, the complexity of Table 8 reduces its direct interpretability and, as before, we use the point estimates in Table 8 to compute the cumulative point estimates and transform these into £ and % to ease interpretation. These results are presented in Table 9.

Examining the returns to lifelong learning by NVQ-equivalent levels we find that returns to earnings differ substantially over the type of level acquired. In the context of the current UK policy focus on NVQ qualifications at level 1 and 2, perhaps the most noteworthy feature of Table 8 is that, while there are no earnings effects for either of these types of qualifications, there is evidence of positive returns to occupational status for women at level 1 (with a suggestion of a possible effect at level 2). It may be the case, then, that these qualifications offer broader, non-pecuniary returns of a sort that have not been investigated empirically in the past.

Returns to level 3 lifelong learning qualifications are large and substantial for earnings, but insignificant for occupational status. Gaining a level 3 qualification leads to a 30+% increase in hourly earnings for men and women after 7 years. This equates to, approximately, £3.52 per hour (£8,000 per year) for men. Further supporting evidence that these substantial observed returns are not artificial is provided by the commensurate estimates for women, who also stand to increase their earnings by around a third for this level of qualification, though the estimates for women do not reach statistical significance at the 5% level of confidence. However, it should be noted, from Table 8, that the standard errors associated with the returns to level 3 qualifications are some of the highest in the model. In part this is because the cell sizes for level 3 returns are the smallest in the model (see Table 3), but also it is because there appears to be a lot of variability in the returns to level 3. Level 3 returns were particularly susceptible to outliers. Nonetheless, the high returns to level 3 for men and women cannot be explained away by outliers and small sample size and there is sufficient evidence to suggest that there are significant

positive returns to level 3 qualifications. Unfortunately, our sample size limitations mean that we cannot probe these estimates further.

Gaining a level 4-equivalent qualification – of which a substantial proportion are nursing and teaching qualifications – results in a positive and significant impact on earnings for men (£1.90 per hour, £4,300 per year). However, this effect appears to be transient in nature as the statistical significance of the point estimates is lost after 4 years. We are unable to comment on whether this effect is short-run or whether the imprecise long run estimation 'hides' the true point estimates within larger standard errors. However, it does appear that the monetary returns to level 4 qualifications rapidly peak after three years and then 'flatten' into a long run trajectory. The coefficient for level 4 on occupational status is non-significant for both men and women, although there is a suggestion of a similar positive but transient effect for men.

The effect of gaining a level 4/5 (academic) qualification is positive and significant on earnings for both men and women; our models suggest that individuals attaining qualifications at this level can expect quite substantial earnings returns in future years. Men increase their annual earnings by £8,000 seven years after obtaining a qualification at this level, whilst women can expect an increase of £3,800 after seven years. There is also an occupational status return for men obtaining level 4; men who gain a diploma or degree type qualification later in life can expect an increase of 12 % to their CAMSIS score after 7 years. An effect of similar magnitude is found for women but remains insignificant.

Finally, examining NVQ equivalent 'other' qualifications we see that significant earnings returns are only observed for women, whilst occupational status returns are found for both men and women. Women who gained an 'other' level qualification experienced a 17% increase in hourly wages of after 7 years (£1.33 per hour or £2,200 per annum). Both men and women

experience similar occupational status returns at this qualification level, with both sexes seeing increases of 6.5% in their CAMSIS score after seven years. We have previously argued that 'other' level qualifications are likely to consist of accredited work related training and our results suggest that returns to such qualifications are beneficial in terms of occupational standing and, for women, in terms of hourly earnings.

6. Conclusions

Our analysis of the returns to any form of lifelong learning suggests there are significant positive returns for men and women, in terms of both earnings and CAMSIS. The magnitude of effect is similar for both genders, with men and women experiencing a 20 per cent increase in hourly earnings 10 years after gaining a lifelong learning qualification. With respect to CAMSIS, both genders experience a 10 per cent return over the same period. However, interpretation of the time dynamics imply that women experience returns from an investment in lifelong learning sooner than men, as we observe a significant increase in earnings four years after the event; compared to six years for men. Considering changes to CAMSIS arising from participation in lifelong learning the difference is only one year and returns to women materialising after one year. The implication for the wider literature is that social status returns seem to be more immediate for both sexes, but for women both pecuniary and non-pecuniary returns are realised sooner than is the case for their male counterparts.

Disaggregating the lifelong learning variable into its NVQ-equivalent levels pushes the BHPS data to its limits. As is the case in the existing UK literature a more complicated story emerges. Broadly, our findings can be seen to validate the existing findings from studies by De-

Coulon and Vignoles (2008) and Dearden et. al. (2004). For level 1 equivalent-qualifications we find no effect on earnings, but some return to women in terms of enhanced CAMSIS score. For both men and women, for CAMSIS and earnings, the lack of any significant returns at level 2 equivalent qualifications seems at first to be counter to the findings of the existing studies. However, the returns we identify across CAMSIS for men and women (as well as earnings for women) when considering the 'other' qualifications category may explain this apparent anomaly. Whilst we do find a significant return for the earnings of men who obtain a level 3-equivalent qualification, any effect for women is only significant at the 10% level, and there is a lack of significance for any occupational returns for both genders.

At higher levels of NVQ-equivalent qualifications we distinguish between academic and vocationally-oriented lifelong learning qualifications and for the former there are returns identified across both men and women for earnings (and for men with respect to CAMSIS). This is in contrasts to a lack of any apparent impact of attaining vocational level 4 qualifications and it is not necessarily the case that this is driven by small cell sizes (which are larger than those we observe for level 3 equivalent qualifications). This lack of significance for such a high-level of vocational attainment is something of a new finding.

The use of a fixed effects specification with distributed lags has allowed us to shed light on the time dynamics of the returns arising from the accumulation of lifelong learning and also to produce evidence that is much less likely to suffer from problems of unobserved heterogeneity. We have also used measures of both financial and social status returns to capture a broader range of potential benefits from lifelong learning. As we mention elsewhere there are limitations to our study, which should be considered in future research. We are unable to address the potential for differential effects arising from lifelong learning that reflect a movement along,

as opposed to a movement up, the educational ladder; we are forced to use indicators of lifelong learning that are relatively aggregated and also we have a large group of 'other' qualifications.

However, our analysis fills a substantial gap in a variety of existing literatures. It provides robust evidence that there are returns to later life education and suggests that in many other studies the use of earnings as a measure of return may potentially miss some of the benefits of lifelong learning. We add to existing UK evidence that is predominantly based on the analysis of NVQ qualifications using Cohort studies and at the international level we provide a starting point for an approach to the analysis of lifelong learning that can be more easily compared across national boundaries.

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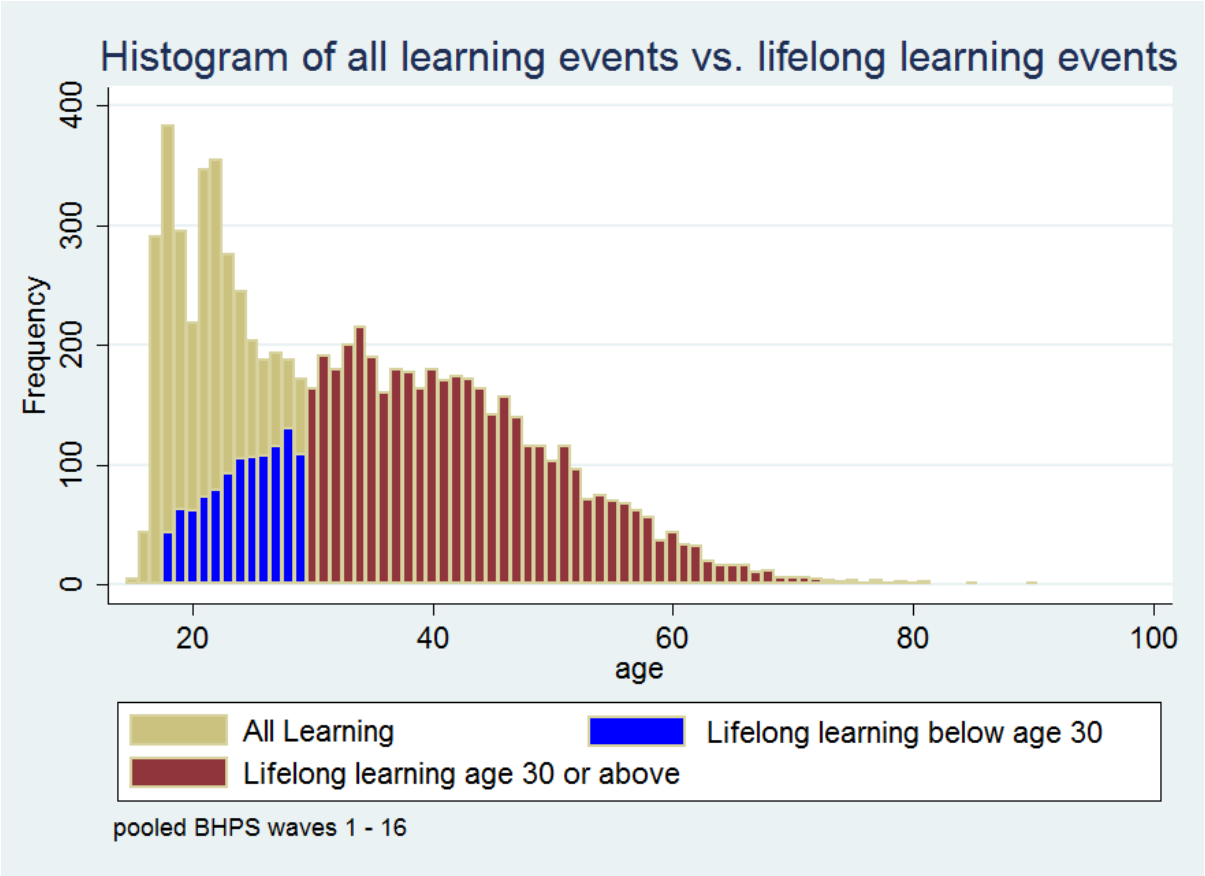
Figure 1 Distribution of learning and lifelong learning events by age



Source: BHPS

Figure 2 Cumulative Impulse Response Functions using any type of lifelong learning qualification

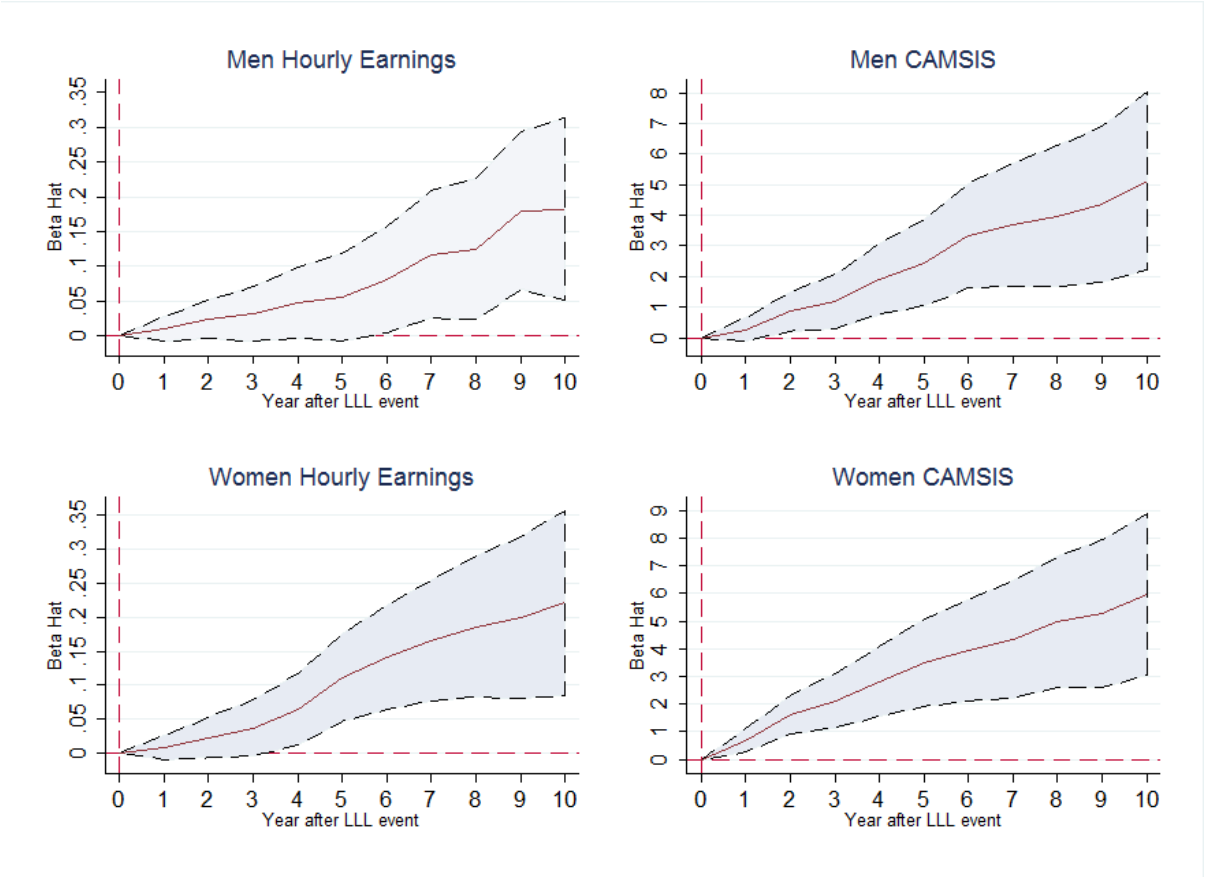


Table 1 Number of observations in each wave of BHPS

BHPS	OSMs	PSM	Total (OSM +PSM)
Wave 1	10264	0	10264
Wave 2	9281	10	9291
Wave 3	8862	29	8891
Wave 4	8554	77	8631
Wave 5	8252	120	8372
Wave 6	8261	179	8440
Wave 7	8102	240	8342
Wave 8	7936	291	8227
Wave 9	7765	359	8124
Wave 10	7600	351	7951
Wave 11	7448	339	7787
Wave 12	7299	310	7609
Wave 13	7120	299	7419
Wave 14	7030	289	7319
Wave 15	6897	281	7178
Wave 16	6785	273	7058
Total	127456	3447	130903

Source: BHPS

Table 2 Proportion of lifelong learning incidents of in the BHPS

BHPS	Men QFX	Women QFX	Men LLL	Women LLL
Wave 1	n/a	n/a	n/a	n/a
Wave 2	5.33	4.42	2.41	2.13
Wave 3	6.06	4.62	3.83	2.86
Wave 4	5.93	5.09	3.68	3.28
Wave 5	5.54	5.74	3.63	3.92
Wave 6	6.62	6.31	4.63	4.02
Wave 7	6.57	6.50	4.32	4.33
Wave 8	6.45	7.00	4.79	5.06
Wave 9	6.68	6.78	4.84	5.23
Wave 10	7.08	7.64	5.19	5.59
Wave 11	7.06	7.16	5.42	5.51
Wave 12	5.80	6.45	4.48	4.99
Wave 13	6.88	7.14	5.37	5.21
Wave 14	6.47	6.94	4.96	5.19
Wave 15	7.46	8.04	5.69	5.86
Wave 16	7.48	7.46	5.47	5.53
Obs.	3,587	4,153	2,510	2,917
All BHPS Obs.	60,415	70,148	60,415	70,148

Source: BHPS

Note: 'w'QFX is the name of the BHPS variable which measures changes in qualifications compared to the prior wave. 'w'LLL is our lifelong learning transformation of this variable

Table 3 NVQ Equivalent scale

NVQ Equivalent	Definition	QFX		LLL	
		Observations	Individuals	Observations	Individuals
NVQ 1	Includes: Youth Training, Trade Apprenticeships, Clerical & Commercial, NVQ/SVQ level 1, City and Guilds level 1, GCSE, SCE, CSE, RSA stage 1 and other vocational qualifications (BTEC, BEC, SCOTVEC general certificate)	1,358 (1.04)	1,062 (8.16)	848 (0.64)	671 (5.15)
NVQ 2	Includes: NVQ/SVQ level 2, City and Guilds level 2, RSA diploma, AS-level, 1 A-level and other vocational qualifications (BTEC, BEC, SCOTVEC diploma)	719 (0.55)	593 (4.55)	489 (0.37)	403 (3.09)
NVQ 3	Includes: NVQ/SVQ level 3, City and Guilds level 3, RSA advanced diploma, 2+ A-level, other vocational qualifications (BTEC, BEC, SCOTVEC, national certificate)	369 (0.28)	311 (2.39)	298 (0.23)	242 (1.86)
NVQ 4 (Vocational)	HNC, HND, RSA BTEC higher diploma, teaching & nursing degrees, other qualifications below degree level	821 (0.63)	647 (4.97)	409 (0.31)	331 (2.54)
NVQ4 (Academic) & NVQ 5	Diploma in Higher Education, First Degree, Post-graduate Degree, PhD, Other Degree	961 (0.73)	759 (5.83)	399 (0.30)	307 (2.36)
NVQ Other	Other qualifications including technical and professional qualifications – mainly work related qualifications	3,975 (3.04)	2,453 (18.84)	3,276 (2.50)	2,012 (15.45)

Source: BHPS Wave 1 to 16.

Numbers in parenthesis are percent our BHPS sample.

Table 4 CAMSIS scores for Exemplar Occupational Unit Groups for Men and Women

SOC90 UNIT GROUP	CAMSIS SCORE Men	SOC90 UNIT GROUP	CAMSIS SCORE Women
933 Refuse and salvage collectors	19.8	557 Clothing cutters, milliners, furriers	19.7
922 Rail construction maintenance track length-men	24.9	955 Lift and car park attendants	25.0
500 Bricklayers, masons fixer	33.9	592 Dental technicians denture foreman	34.4
521 Electricians, electrical maintenance fitters	45.4	641 Hospital ward assistants	44.3
526 Computer engineers, installation and maintenance	54.1	461 Receptionists/ telephonist	54.7
131 Bank, Building Society and Post Office managers	65.1	651 Playgroup leaders	65.1
252 Actuaries, economists and statisticians	75.3	250 Chartered and certified accountants	75.6
240 Judges and officers of the court	85.7	224 Veterinarians	88.4

Table 5 Sample sizes and selected descriptive statistics

Sample	*Max Possible Obs*	Age *Mean*	Hr Earnings *Mean*	CAMSIS *Mean*	Education* *Mean*	Happiness *Mean*	UK Born *Mean*
				Men			
OSM and PSM	60,415	44.79	10.89	50.57	2.20	1.99	0.95
OSM and PSM employed	39,498	39.91	11.16	50.83	2.52	1.97	0.94
OSM and PSM employed & CAMSIS not missing	39,290	39.87	11.16	50.83	2.52	1.97	0.94
OSM and PSM employed & income not missing	30,577	38.64	11.16	50.64	2.56	1.97	0.94
				Women			
OSM and PSM	70,148	46.40	8.03	52.54	1.81	2.04	0.94
OSM and PSM employed	35,710	39.66	8.21	53.05	2.26	2.02	0.94
OSM and PSM employed & CAMSIS not missing	35,545	39.61	8.21	53.05	2.26	2.02	0.94
OSM and PSM employed & income not missing	31,876	39.24	8.21	52.77	2.23	2.02	0.94

Source: BHPS

* Education is initial education level and is measured on a scale of 0 – 5 (5 being the highest); Happiness is measured on a scale of 1 – 4 (1 being the highest)

Table 6 Returns to Lifelong Learning for Men and Women using any type of lifelong learning qualification

	Men		Women	
	Log Hr. Earnings	CAMSIS	Log Hr. Earnings	CAMSIS
Short run multiplier:				
Lifelong learning (LLL_{t-1})	0.010	0.270	0.008	0.689**
	(0.009)	(0.198)	(0.009)	(0.214)
Lifelong learning (LLL_{t-2})	0.014	0.588**	0.015	0.926***
	(0.009)	(0.208)	(0.010)	(0.215)
Lifelong learning (LLL_{t-3})	0.011	0.316	0.015	0.511*
	(0.010)	(0.223)	(0.010)	(0.236)
Lifelong learning (LLL_{t-4})	0.013	0.748**	0.027**	0.689**
	(0.010)	(0.251)	(0.010)	(0.238)
Lifelong learning (LLL_{t-5})	0.008	0.535*	0.046***	0.680*
	(0.011)	(0.251)	(0.011)	(0.271)
Lifelong learning (LLL_{t-6})	0.025*	0.876**	0.030*	0.458
	(0.012)	(0.278)	(0.013)	(0.273)
Lifelong learning (LLL_{t-7})	0.035**	0.360	0.025*	0.387
	(0.013)	(0.315)	(0.012)	(0.307)
Lifelong learning (LLL_{t-8})	0.008	0.288	0.020	0.625
	(0.014)	(0.326)	(0.014)	(0.324)
Lifelong learning (LLL_{t-9})	0.055***	0.374	0.014	0.292
	(0.015)	(0.358)	(0.015)	(0.393)
Lifelong learning (LLL_{t-10})	0.003	0.766	0.022	0.715
	(0.018)	(0.466)	(0.019)	(0.473)
Constant	2.155***	50.900***	2.140***	54.629***
	(0.039)	(0.545)	(0.023)	(0.491)

	Men		Women	
	Log Hr. Earnings	CAMSIS	Log Hr. Earnings	CAMSIS
Intermediate and long run multipliers:				
$\beta_{t-1}+\beta_{t-2}$	0.024†	0.858**	0.023	1.615***
	(0.014)	(0.322)	(0.015)	(0.354)
$\beta_{t-1}+...+\beta_{t-3}$	0.031†	1.174**	0.037†	2.126***
	(0.020)	(0.455)	(0.021)	(0.50)
$\beta_{t-1}+...+\beta_{t-4}$	0.048†	1.922***	0.064*	2.816***
	(0.026)	(0.592)	(0.027)	(0.643)
$\beta_{t-1}+...+\beta_{t-5}$	0.056†	2.457***	0.111***	3.496***
	(0.032)	(0.721)	(0.033)	(0.799)
$\beta_{t-1}+...+\beta_{t-6}$	0.081*	3.333***	0.141***	3.954***
	(0.039)	(0.872)	(0.039)	(0.940)
$\beta_{t-1}+...+\beta_{t-7}$	0.117*	3.693***	0.166***	4.341***
	(0.047)	(1.022)	(0.045)	(1.075)
$\beta_{t-1}+...+\beta_{t-8}$	0.125*	3.981***	0.186***	4.966***
	(0.052)	(1.167)	(0.053)	(1.211)
$\beta_{t-1}+...+\beta_{t-9}$	0.180**	4.355***	0.200***	5.259***
	(0.058)	(1.296)	(0.061)	(1.364)
$\beta_{t-1}+\beta_{...}+\beta_{t-10}$	0.182**	5.121***	0.221***	5.973***
	(0.067)	(1.471)	(0.070)	(1.481)
N	30203	38564	31553	35112
R-sq	0.318	0.031	0.239	0.044
Hausman Test				

Controls include: centered age, centered agesq, lagged marriage, lagged no. child, lagged previous labour market status and lagged indicators of missing values

Standard errors in parentheses: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001
Observations aged greater than 65 are exlcuded

Table 7 Predicted Earnings and CAMSIS Returns for Men and Women

				Men		
Years after LLL event	Hr Earnings	Yearly Earnings	P-Value	CAMSIS	CAMSIS %	P-Value
1	£0.09	£211.45	0.279	0.270	0.53%	0.149
2	£0.23	£533.07	0.103	0.858	1.69%	0.006
3	£0.34	£781.37	0.096	1.174	2.31%	0.008
4	£0.47	£1,059.81	0.082	1.922	3.78%	0.001
5	£0.54	£1,222.69	0.102	2.457	4.83%	0.000
6	£0.80	£1,817.95	0.049	3.333	6.55%	0.000
7	£1.18	£2,677.05	0.018	3.693	7.26%	0.000
8	£1.27	£2,879.91	0.024	3.981	7.82%	0.000
9	£1.88	£4,270.53	0.004	4.355	8.56%	0.001
10	£1.90	£4,306.84	0.010	5.121	10.06%	0.000
				Women		
Years after LLL event	Hr Earnings	Yearly Earnings	P-Value	CAMSIS	CAMSIS %	P-Value
1	£0.06	£99.43	0.361	0.689	1.29%	0.001
2	£0.17	£281.37	0.136	1.615	3.03%	0.000
3	£0.29	£464.11	0.073	2.126	3.99%	0.000
4	£0.49	£802.14	0.018	2.816	5.29%	0.000
5	£0.87	£1,412.99	0.001	3.496	6.56%	0.000
6	£1.13	£1,825.86	0.000	3.954	7.43%	0.000
7	£1.34	£2,178.64	0.000	4.341	8.15%	0.000
8	£1.52	£2,465.03	0.000	4.966	9.33%	0.000
9	£1.64	£2,664.05	0.001	5.259	9.88%	0.000
10	£1.84	£2,986.37	0.001	5.973	11.22%	0.000

Results are in 2005 prices and based on the fixed effects model. Results are based on sample means.

Table 8 Returns to Lifelong Learning for Men and Women using any NVQ levels of lifelong learning

	Men		Women	
	Controls		Controls	
	Log Hr. Earnings	CAMSIS	Log Hr. Earnings	CAMSIS
Short run multiplier:				
Lifelong learning (NVQ1)	0.004	0.059	-0.003	0.740
(LLL_{t-1})	(0.018)	(0.568)	(0.015)	(0.383)
Lifelong learning (NVQ1)	-0.016	0.265	0.009	0.627
(LLL_{t-2})	(0.021)	(0.568)	(0.018)	(0.409)
Lifelong learning (NVQ1)	-0.024	0.615	-0.016	0.265
(LLL_{t-3})	(0.023)	(0.589)	(0.019)	(0.409)
Lifelong learning (NVQ1)	-0.024	0.680	-0.012	0.247
(LLL_{t-4})	(0.026)	(0.677)	(0.018)	(0.480)
Lifelong learning (NVQ1)	0.018	0.563	0.024	1.193*
(LLL_{t-5})	(0.026)	(0.617)	(0.018)	(0.473)
Lifelong learning (NVQ1)	0.006	0.405	0.013	0.422
(LLL_{t-6})	(0.023)	(0.644)	(0.019)	(0.566)
Lifelong learning (NVQ1)	0.035	1.078	0.006	1.423**
(LLL_{t-7})	(0.024)	(0.676)	(0.020)	(0.522)
Lifelong learning (NVQ2)	0.013	-0.323	-0.039	0.907
(LLL_{t-1})	(0.022)	(0.530)	(0.027)	(0.792)
Lifelong learning (NVQ2)	0.021	-0.278	0.031	1.192
(LLL_{t-2})	(0.023)	(0.580)	(0.027)	(0.618)
Lifelong learning (NVQ2)	0.027	0.494	0.039	0.829
(LLL_{t-3})	(0.022)	(0.527)	(0.025)	(0.676)
Lifelong learning (NVQ2)	0.030	0.056	-0.004	0.595
(LLL_{t-4})	(0.024)	(0.527)	(0.029)	(0.813)
Lifelong learning (NVQ2)	0.039	-0.948	0.025	0.904
(LLL_{t-5})	(0.025)	(0.768)	(0.028)	(0.730)
Lifelong learning (NVQ2)	0.019	-0.311	0.014	0.847
(LLL_{t-6})	(0.026)	(0.759)	(0.031)	(1.038)
Lifelong learning (NVQ2)	-0.013	-0.837	-0.047	1.044
(LLL_{t-7})	(0.041)	(0.884)	(0.035)	(0.905)
Lifelong learning (NVQ3)	-0.003	0.175	-0.001	0.031
(LLL_{t-1})	(0.031)	(0.744)	(0.033)	(0.722)
Lifelong learning (NVQ3)	0.025	0.179	0.038	0.875
(LLL_{t-2})	(0.026)	(0.751)	(0.039)	(0.915)
Lifelong learning (NVQ3)	0.046	1.206	0.042	0.635
(LLL_{t-3})	(0.034)	(0.849)	(0.041)	(1.023)
Lifelong learning (NVQ3)	0.034	0.617	0.055	0.965
(LLL_{t-4})	(0.031)	(1.018)	(0.041)	(0.927)
Lifelong learning (NVQ3)	0.102*	0.743	0.078	-0.205
(LLL_{t-5})	(0.041)	(1.205)	(0.044)	(1.021)
Lifelong learning (NVQ3)	0.046	0.772	0.107*	-0.147
(LLL_{t-6})	(0.036)	(1.035)	(0.052)	(1.175)
Lifelong learning (NVQ3)	0.067	1.642	0.055	2.061
(LLL_{t-7})	(0.047)	(1.334)	(0.061)	(1.437)

continued

Table 8 continued

	Men Controls		Women Controls	
	Log Hr. Earnings	CAMSIS	Log Hr. Earnings	CAMSIS
Lifelong learning (NVQ4 Vocational)	0.068*	0.379	0.014	1.057
(LLL_{t-1})	(0.027)	(0.667)	(0.024)	(0.617)
Lifelong learning (NVQ4 Vocational)	0.049	1.769**	0.016	0.514
(LLL_{t-2})	(0.026)	(0.667)	(0.023)	(0.560)
Lifelong learning (NVQ4 Vocational)	0.018	0.189	0.025	1.010
(LLL_{t-3})	(0.027)	(0.676)	(0.022)	(0.649)
Lifelong learning (NVQ4 Vocational)	0.014	0.060	-0.007	-0.688
(LLL_{t-4})	(0.034)	(0.853)	(0.021)	(0.851)
Lifelong learning (NVQ4 Vocational)	-0.018	-0.924	-0.014	-0.093
(LLL_{t-5})	(0.032)	(0.675)	(0.021)	(0.870)
Lifelong learning (NVQ4 Vocational)	0.020	0.681	0.025	-0.555
(LLL_{t-6})	(0.029)	(0.800)	(0.022)	(0.703)
Lifelong learning (NVQ4 Vocational)	0.035	1.409	0.025	-0.758
(LLL_{t-7})	(0.030)	(0.840)	(0.023)	(0.762)
Lifelong learning (NVQ4/5 Academic)	0.037	1.209	0.020	0.522
(LLL_{t-1})	(0.026)	(0.761)	(0.022)	(0.737)
Lifelong learning (NVQ4/5 Academic)	0.051	0.637	0.057*	0.783
(LLL_{t-2})	(0.026)	(0.657)	(0.024)	(0.735)
Lifelong learning (NVQ4/5 Academic)	0.067*	1.848**	0.049*	1.078
(LLL_{t-3})	(0.026)	(0.691)	(0.023)	(0.806)
Lifelong learning (NVQ4/5 Academic)	0.049	1.031	0.072**	1.030
(LLL_{t-4})	(0.027)	(0.708)	(0.025)	(0.782)
Lifelong learning (NVQ4/5 Academic)	0.043	0.297	0.076***	0.902
(LLL_{t-5})	(0.033)	(0.675)	(0.021)	(0.798)
Lifelong learning (NVQ4/5 Academic)	0.004	0.992	-0.003	1.078
(LLL_{t-6})	(0.046)	(0.803)	(0.034)	(0.903)
Lifelong learning (NVQ4/5 Academic)	0.068	0.053	0.007	0.274
(LLL_{t-7})	(0.039)	(0.828)	(0.045)	(0.755)
Lifelong learning (NVQ 'other')	-0.002	0.189	0.022*	0.496
(LLL_{t-1})	(0.009)	(0.227)	(0.009)	(0.256)
Lifelong learning (NVQ 'other')	0.007	0.571*	-0.001	0.795**
(LLL_{t-2})	(0.009)	(0.237)	(0.010)	(0.262)
Lifelong learning (NVQ 'other')	0.002	-0.122	0.013	0.277
(LLL_{t-3})	(0.009)	(0.270)	(0.011)	(0.292)
Lifelong learning (NVQ 'other')	0.007	0.707*	0.038***	0.897**
(LLL_{t-4})	(0.010)	(0.313)	(0.011)	(0.311)
Lifelong learning (NVQ 'other')	0.001	0.741*	0.043***	0.477
(LLL_{t-5})	(0.011)	(0.306)	(0.012)	(0.344)
Lifelong learning (NVQ 'other')	0.009	1.043**	0.017	0.517
(LLL_{t-6})	(0.012)	(0.324)	(0.015)	(0.362)
Lifelong learning (NVQ 'other')	0.032*	0.131	0.034*	0.008
(LLL_{t-7})	(0.013)	(0.390)	(0.016)	(0.444)
Constant	2.359***	52.136***	2.099***	55.000***
	(0.012)	(0.270)	(0.012)	(0.314)
N	29588	38564	30915	35112
R-sq	0.337	0.030	0.281	0.045

Controls include: centered age, centered agesq, lagged marriage, lagged no. child, lagged previous labour market status and lagged indicators of missing values (attrition dummies)

Earnings results are based on a 98% subsample of the entire sample due to influential outliers in some cells. Observations aged greater than 65 are excluded

Standard errors in parentheses: † p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 9 Cumulative Predicted Earnings and CAMSIS Returns for Men and Women: by NVQs

	Men				Women				Men			Women		
Years after LLL event	%Increase	Hr Earnings	Yearly Earnings	P-value	%Increase	Hr Earnings	Yearly Earnings	P-value	CAMSIS	% CAMSIS	P-Value	CAMSIS	% CAMSIS	P-value
Level 1														
1	0.35%	£0.04	£89	0.845	-0.29%	-£0.02	-£35	0.848	0.059	0.12%	0.918	0.740	1.39%	0.054
2	-1.20%	-£0.10	-£232	0.721	0.65%	£0.05	£79	0.822	0.323	0.64%	0.741	1.366	2.57%	0.038
3	-3.60%	-£0.31	-£708	0.470	-0.96%	-£0.07	-£115	0.818	0.938	1.84%	0.499	1.631	3.06%	0.074
4	-5.96%	-£0.52	-£1,172	0.390	-2.15%	-£0.16	-£256	0.694	1.618	3.18%	0.363	1.878	3.53%	0.121
5	-4.11%	-£0.36	-£812	0.639	0.25%	£0.02	£30	0.970	2.182	4.29%	0.312	3.071	5.77%	0.041
6	-3.56%	-£0.30	-£678	0.734	1.55%	£0.12	£188	0.835	2.587	5.08%	0.302	3.493	6.56%	0.055
7	-0.04%	£0.01	£32	0.998	2.11%	£0.16	£257	0.806	3.664	7.20%	0.201	4.916	9.23%	0.019
Level 2														
1	1.35%	£0.11	£259	0.542	-3.89%	-£0.28	-£459	0.155	-0.323	-0.63%	0.542	0.907	1.70%	0.252
2	3.44%	£0.30	£681	0.355	-0.81%	-£0.06	-£97	0.853	-0.601	-1.18%	0.546	2.099	3.94%	0.077
3	6.15%	£0.56	£1,261	0.221	3.08%	£0.23	£377	0.600	-0.107	-0.21%	0.930	2.927	5.50%	0.079
4	9.14%	£0.85	£1,925	0.126	2.68%	£0.20	£327	0.720	-0.051	-0.10%	0.972	3.522	6.61%	0.116
5	13.08%	£1.24	£2,820	0.071	5.15%	£0.39	£637	0.564	-0.999	-1.96%	0.605	4.426	8.31%	0.095
6	15.02%	£1.45	£3,284	0.085	6.52%	£0.50	£811	0.539	-1.310	-2.57%	0.591	5.273	9.90%	0.100
7	13.75%	£1.31	£2,978	0.170	1.79%	£0.13	£218	0.883	-2.147	-4.22%	0.476	6.317	11.86%	0.086
Level 3														
1	-0.32%	-£0.02	-£51	0.919	-0.13%	-£0.01	-£15	0.969	0.175	0.34%	0.814	0.031	0.06%	0.966
2	2.13%	£0.21	£486	0.639	3.71%	£0.28	£455	0.564	0.353	0.69%	0.792	0.906	1.70%	0.514
3	6.71%	£0.68	£1,551	0.347	7.93%	£0.61	£994	0.415	1.560	3.06%	0.388	1.542	2.90%	0.462
4	10.12%	£1.05	£2,396	0.259	13.44%	£1.07	£1,733	0.292	2.177	4.28%	0.351	2.506	4.71%	0.362
5	20.32%	£2.15	£4,888	0.082	21.28%	£1.76	£2,856	0.167	2.919	5.74%	0.327	2.301	4.32%	0.493
6	24.89%	£2.67	£6,064	0.065	31.99%	£2.80	£4,539	0.074	3.691	7.25%	0.241	2.154	4.05%	0.594
7	31.63%	£3.52	£7,990	0.041	37.51%	£3.38	£5,479	0.074	5.333	10.48%	0.148	4.215	7.91%	0.342

	Men				Women				Men			Women		
Years after LLL event	%Increase	Hr Earnings	Yearly Earnings	P-value	%Increase	Hr Earnings	Yearly Earnings	P-value	CAMSIS	% CAMSIS	P-Value	CAMSIS	% CAMSIS	P-value
Level 4 (Vocational)														
1	6.75%	£0.63	£1,439	0.012	1.40%	£0.10	£170	0.559	0.379	0.74%	0.571	1.057	1.99%	0.087
2	11.69%	£1.14	£2,582	0.013	3.01%	£0.23	£368	0.457	2.148	4.22%	0.039	1.571	2.95%	0.105
3	13.50%	£1.34	£3,033	0.028	5.49%	£0.42	£680	0.313	2.337	4.59%	0.079	2.582	4.85%	0.061
4	14.93%	£1.48	£3,370	0.062	4.77%	£0.36	£589	0.468	2.397	4.71%	0.158	1.893	3.56%	0.349
5	13.14%	£1.31	£2,973	0.184	3.42%	£0.26	£419	0.647	1.472	2.89%	0.450	1.801	3.38%	0.479
6	15.11%	£1.51	£3,428	0.180	5.91%	£0.45	£733	0.486	2.153	4.23%	0.308	1.246	2.34%	0.666
7	18.61%	£1.90	£4,305	0.147	8.38%	£0.65	£1,053	0.365	3.562	7.00%	0.125	0.488	0.92%	0.885
Level 4/5 (Academic)														
1	3.67%	£0.35	£789	0.161	1.99%	£0.15	£243	0.375	1.209	2.38%	0.112	0.522	0.98%	0.478
2	8.72%	£0.85	£1,940	0.049	7.73%	£0.60	£968	0.036	1.846	3.63%	0.093	1.305	2.45%	0.293
3	15.39%	£1.55	£3,521	0.015	12.60%	£1.00	£1,616	0.011	3.694	7.26%	0.017	2.383	4.47%	0.169
4	20.29%	£2.09	£4,741	0.014	19.77%	£1.62	£2,631	0.003	4.725	9.28%	0.016	3.413	6.41%	0.126
5	24.63%	£2.60	£5,900	0.017	27.41%	£2.34	£3,793	0.000	5.022	9.87%	0.023	4.315	8.10%	0.113
6	25.02%	£2.65	£6,009	0.059	27.11%	£2.31	£3,747	0.002	6.014	11.82%	0.024	5.393	10.13%	0.094
7	31.78%	£3.49	£7,923	0.039	27.84%	£2.38	£3,862	0.014	6.066	11.92%	0.041	5.667	10.64%	0.107
Level 'Other'														
1	-0.20%	-£0.02	-£46	0.818	2.20%	£0.17	£267	0.015	0.189	0.37%	0.406	0.496	0.93%	0.053
2	0.51%	£0.04	£85	0.725	2.12%	£0.16	£258	0.179	0.760	1.49%	0.039	1.290	2.42%	0.003
3	0.74%	£0.06	£130	0.718	3.39%	£0.26	£415	0.140	0.637	1.25%	0.237	1.567	2.94%	0.010
4	1.40%	£0.12	£264	0.594	7.18%	£0.55	£895	0.013	1.345	2.64%	0.064	2.464	4.63%	0.002
5	1.47%	£0.11	£257	0.655	11.47%	£0.90	£1,459	0.001	2.086	4.10%	0.020	2.941	5.52%	0.003
6	2.32%	£0.18	£417	0.560	13.18%	£1.04	£1,692	0.003	3.129	6.15%	0.004	3.458	6.49%	0.003
7	5.51%	£0.48	£1,086	0.234	16.56%	£1.33	£2,161	0.002	3.260	6.41%	0.012	3.465	6.51%	0.010

Earnings results are based on a 98% subsample of the entire sample. Top/bottom 1% are cut due to influential outliers in some cells. Observations aged greater than 65 are exlcuded

Results are in 2005 prices