LLAKES
CENTRE FOR LEARNING AND LIFE CHANCES IN KNOWLEDGE ECONOMIES AND SOCIETIES

IOE LONDON
Leading education and social research
Institute of Education
University of London

Industry knowledge spillovers: Do workers gain from their collective experience?

Rebecca Riley

LLAKES Research Paper 17

Centre for Learning and Life Chances in Knowledge Economies and Societies

LLAKES is an ESRC-funded Research Centre - grant reference RES-594-28-0001.

To request printed copies of this paper or other LLAKES Research Papers,
please contact the LLAKES Centre - llakescentre@ioe.ac.uk.

To view this and other LLAKES Research Papers online, please visit www.llakes.org.uk.

ISSN 2042-5929

Industry knowledge spillovers: Do workers gain from their collective experience?

Rebecca Riley[1]

National Institute of Economic and Social Research, London

LLAKES Research Paper

Abstract

Individuals acquire experience during their working lives. This is usually thought to contribute to individuals' human capital and is rewarded in terms of pay. This paper looks at whether individuals' pay is also affected by the general experience acquired by others working in the same firm or industry. The mechanism in mind is one where individual workers benefit from exchanges of ideas and learning opportunities that arise because of the human capital of their co-workers. Analysing repeated cross-sections of workers within industry sectors and longitudinal linked employer-employee data, I find the data to be consistent with the presence of knowledge spillovers from workers' general experience levels in the industry and the enterprise.

JEL classification: E24, J00, J24, O40.

Key words: human capital, education, work experience, age, externalities, spillovers.

[1] Correspondence: Rebecca Riley, National Institute of Economic and Social Research, 2 Dean Trench Street, Smith Square, London SW1P 3HE; Tel.: +44-207-222-7665; fax: +44-207-654-1900; *E-mail address:* r.riley@niesr.ac.uk

1. Introduction[2,3]

The importance of knowledge transfer between workers is central in the endogenous growth literature (Romer, 1986; Lucas, 1988). In this literature, human capital is not fully compensated for its contribution to economic growth, which partly occurs through the generation and sharing of ideas and practice. Existing study of the extent of such human capital externalities or knowledge spillovers focuses almost exclusively on formal education. Yet it is generally acknowledged that other forms of learning, such as work experience, may also contribute to human capital. Indeed, measures of work experience are often included as determinants of individuals' wages alongside other individual characteristics, and in many instances account for more of individuals' pay than formal qualifications.

This paper evaluates industry human capital externalities associated with work experience and, where possible, contrasts these with spillovers associated with formal education, adding to the evidence on the role of learning and knowledge transfer in generating growth and the way in which this takes place.[4] This paper also contributes to our understanding of the importance of individuals' life-long learning, although the analysis is not specific about the nature of this learning.

Human capital spillovers within industries are explored using a Mincerian approach to identification. The Mincerian approach to identifying human capital spillovers has

---

[2] The financial support of the Economic and Social Research Council (ESRC) and the European Commission is gratefully acknowledged. The work was part of the programme of the ESRC Centre for Learning and Life Chances in Knowledge Economies and Societies and benefits from work carried out in the INNODRIVE project financed by the EU 7th Framework Programme, No. 214576, and ESRC grant RES-000-22-1483. Thanks to Simon Kirby, Richard Harris, Richard Upward and the MAUS team at ONS for making available useful syntax and data items, and to John Forth, Geoff Mason and Martin Weale for comments and discussion.

[4] It is important to understand how different aspects of human capital contribute to economic output. Extending the Lucas endogenous growth model to allow human capital to depend on both formal education and experience acquired on the job, Hu and Mino (2005) suggest the endogenous growth framework accords better with the empirical relationship between education and growth.

typically been used to estimate spillovers arising from the geographical concentration of skilled workers (the literature on spatial human capital externalities is reviewed in Duranton, 2006; Mueller, 2007), although some industry level studies exist (e.g. Winter-Ebmer, 1994; Sakellariou and Maysami, 2004; Kirby and Riley, 2008). In industry studies, individuals' wages are found to depend on individual's own education as well as the level of education (schooling or qualifications) in the industry, e.g. because of relevant knowledge transfer between workers within firms and between firms within the industry; empirically no differentiation is made between the role of knowledge transfer within and between firms. Using a single cross-section of workers within establishments in Great Britain, Battu *et al.* (2003) find evidence of spillovers from the share of skilled workers in the workplace to employees' wages.

The analysis in this paper evaluates industry human capital spillovers associated with work experience using repeated cross-sections of workers in the UK Labour Force Survey (LFS), complemented with industry growth accounting data from EUKLEMS[5]. These data have previously been used to analyse spillovers associated with industry-level schooling (Kirby and Riley, 2008). I use a novel method of distinguishing between human capital externalities and other factors that may give rise to an association between individuals' wages and industry human capital (such as neoclassical supply effects and endogenous selection of high ability workers into skill-intensive industries). The analysis also makes use of longitudinal linked employer-employee data from the Annual Survey of Hours and Earnings (ASHE) and the Annual Business Inquiry (ABI). These data do not include information on individuals' schooling, but the longitudinal element of the data means such factors can be controlled for using person-specific fixed effects. With these data I analyse spillovers associated with workers' experience at both the enterprise and industry levels.

Here, as is often the case elsewhere, actual work experience is proxied by potential experience; and age where necessary. This raises a number of measurement issues, particularly for women. In the analysis here models are estimated for men and women

[5] http://www.euklems.net

separately and the female share of industry employment is included as an additional control; the relationship between individuals' wages and potential experience is specified as a cubic function at all levels of aggregation. The analysis provides evidence of positive human capital externalities associated with the average level of workers' general experience in the industry. The results also suggest that these externalities arise, at least in part, within the firm, and that in some instances spillovers from workers' experience may be at least as important as spillovers from formal education.

The remainder of this paper is structured as follows. The next section discusses identification of spillovers in production and presents the econometric models that are estimated. Section 3 discusses the data and measures of general work experience. Section 4 presents the results. Section 5 summarises and concludes.

2. Identifying knowledge spillovers

The Mincerian approach to identifying human capital externalities, first introduced by Rauch (1993) in the context of US cities, has become an increasingly popular means of estimating human capital externalities (see e.g. Acemoglu and Angrist, 2000; Moretti, 2004; Sakellariou and Maysami, 2004; Kirby and Riley, 2008). This is in part because it facilitates direct estimation of both the private and external returns to human capital. In this approach a Mincerian earnings equation including measures of individuals' human capital is augmented with aggregate (geography, industry or firm) level human capital terms. The coefficient on individual level human capital is then interpreted as the private return to human capital, and the coefficient on aggregate level human capital is interpreted as the external return to human capital or spillover effect.

Learning versus supply effects

A key difficulty in this approach is that human capital supply effects on the relative wage of skilled to unskilled workers are conflated with externality effects. If aggregate human capital rises (the supply of skilled workers rises), the relative wage of unskilled workers should also rise, unless skilled and unskilled workers are perfect substitutes, which seems unlikely (see e.g. Riley and Young, 2007). This has little to do with human capital externalities or spillovers per se, but in the Mincerian approach to identification these types of effects will affect the coefficient on aggregate human capital, and hence bias the estimate of human capital externalities. Indeed, Ciccone and Peri (2006) show that when aggregate level human capital mimics changes in skill supply, the Mincerian approach to identification overestimates the external effects of human capital.[6] Moretti (2004) deals with this problem by estimating an augmented Mincerian wage equation for different skill levels. He interprets the positive coefficient on the aggregate share of college graduates in US cities in a wage equation for college graduates alone as evidence of an external effect of college education. This method may be practical when analysing the external effects of a distinct aspect and specific level of human capital, as in Moretti (2004). It is less practical when human capital is measured continuously and when comparing the external effects of different aspects of human capital as in this paper. Furthermore, while this approach yields a strong test of whether or not there are any positive externalities from college education, it still conflates supply effects with externalities, because the wages of college graduates will be suppressed by increases in their supply.

The focus in this paper on industry level spillovers, rather than spillovers from the geographical concentration of workers and firms, probably means there can be less concern about confusing relative supply effects with spillovers in the Mincerian approach (as suggested in Kirby and Riley, 2008). This is because the number of skilled workers in an industry is unlikely to measure the supply of skilled workers in that industry; workers are likely to be more mobile across industries than they are between cities or regions. Certainly, when considering spillovers at the firm level, it is reasonable to assume that the number of skilled workers in the firm is not a measure of the supply of skilled workers available to it. Nevertheless, it seems unlikely that workers should be perfectly mobile across industries, at least not in the short term, as evidenced by persistent industry wage differentials for narrowly defined groups of workers. Switching costs may e.g. arise when

[6] Ciccone and Peri (2006) propose an approach to identification holding the skill composition constant over time.

workers have accumulated job-specific experience and training and when job search is costly.

For these reasons, the econometric model set out below does not assume that marginal human capital returns are independent of industry skill structures. Human capital externalities are separated from potential supply effects by allowing the returns to an individual's human capital to vary with the industry level of human capital. Specifically, the returns to an individual's schooling and potential experience are specified as flexible functional forms (cubics) in their industry level equivalents.

Endogenous selection

A number of selection issues arise in estimating the returns to human capital. Both individual and industry level schooling are potentially endogenous because of unobserved determinants of wages and schooling choices. The concern is that high ability individuals are more likely to self-select into education, such that it becomes difficult to separate the returns to schooling from the returns to ability. This is potentially a problem at both the individual and industry levels; although Gibbons and Katz (1992) find limited evidence of ability bias explaining inter-industry wage differentials.

The results presented in the next section do not instrument individual level schooling. This is because I cannot find valid instruments[7] and is complicated by the interaction of individual schooling with industry level schooling. Harmon *et al.* (2003) suggest that instrumental variables estimates of the returns to schooling may be biased upwards, and that the effect of measurement error and ability bias on OLS estimates of the returns to education may cancel themselves out.

The problem of endogenous selection of high skill and high ability workers into high human capital industries should be somewhat alleviated by allowing the return to

[7] Equation (1) was estimated instrumenting individual level schooling with two instruments proposed by Harmon and Walker (1999): a zero-one dummy differentiating between those affected by the increase in the minimum school leaving age in England and Wales in 1973 and those not; the sex- and cohort-specific proportion of 16 year olds in higher education in England and Wales. The Hansen's J-statistic casts doubt on the validity of these instruments in the current context.

individual level human capital to vary with industry level human capital. Endogenous selection into high human capital industries is less of an issue in the estimates based on the ASHE panel, which include person-specific fixed effects that should dummy out any ability bias that is constant over time.

Following Kirby and Riley (2008), I further attempt to minimise the problem of endogenous selection into industries of workers with particular human capital attributes by excluding from the sample workers under 30 years of age[8] and individuals with short job tenures (less than one year). Further to this, I discuss estimates where industry human capital terms are instrumented with their lagged values. However, a test for endogeneity of the industry human capital terms on the sample excluding short job tenures suggests exogeneity of these terms cannot be rejected.

All models estimated using the LFS control for industry and year effects, industry union density, ICT-capital to output ratios, and non-ICT capital to output ratios (coefficients allowed to vary for routine and non-routine employees) as well as industry employment growth in the last 5 years and hourly productivity. Controls for ICT capital are included to account for the effects on wages of skill-biased technologies (Iranzo and Peri, 2009); Kirby and Riley (2008) discuss the biases in human capital externalities that might arise without these controls. Controls also include the female share of employees to account for the tendency for women to concentrate in low-pay occupations and industries and to control for gender specific measurement error in potential experience. The analysis of firm-level spillovers associated with work experience includes variables to control for similar biases: firm-level capital-output ratios and productivity, as well as the distribution of workers in R&D and IT occupations.

[8] Workers under 30 are significantly more likely to switch industries than workers age 30+. According to longitudinal LFS data 1999-2007, 22 (13) per cent of workers age 16-24 (25-29) switch their industry of employment over the course of 12 months (using the industry sectoral breakdown in this paper). This compares to an average of 8 per cent for workers age 30+.

Models for estimation

The investigation of spillovers from industry level human capital to individual wages in this paper is based on estimation of the augmented Mincerian wage equation in (1):

$$\begin{aligned}\ln Y_{ijt} &= \beta'_{P1,IN} P_i + \beta'_{P2,IN} P_i^2 + \beta'_{P3,IN} P_i^3 + \beta'_{P1,EX} \overline{P}_{jt} + \beta'_{P2,EX} \overline{P}_{jt}^2 + \beta'_{P3,EX} \overline{P}_{jt}^3 \\ &\quad + \beta'_{S,IN} S_i + \beta'_{S,EX} \overline{S}_{jt} + \gamma'_1 X_i + \gamma'_2 \overline{X}_{jt} + \delta_j + \delta_t + u_{jt} + \varepsilon_i \qquad (1)\end{aligned}$$

where ln Y_{ijt} is the log hourly wage of individual i in industry j at time t, P_i (S_i) is a measure of years of potential work experience (schooling) for individual i, $\overline{P}_{jt}$ ($\overline{S}_{jt}$) is a measure of average years of potential work experience (schooling) held by those working in industry j at time t, X_i is a vector of individual characteristics, $\overline{X}_{jt}$ is a vector of industry and time specific characteristics, and δ_j and δ_t are industry and year fixed effects. The coefficients $\beta_{P1,IN}$, $\beta_{P2,IN}$, $\beta_{P3,IN}$ and $\beta_{S,IN}$ on individual experience and schooling measure the private returns to human capital. The cubic in individual experience is standard and reflects the fact that returns to experience do not accumulate *ad infinitum*; possibly reflecting human capital obsolescence. The coefficients $\beta_{P1,EX}$, $\beta_{P2,EX}$, $\beta_{P3,EX}$ and $\beta_{S,EX}$ on industry level experience and schooling measure the indirect or spillover effects of human capital, *i.e.* the returns to the individual that accrue from the work experience and education of his co-workers in the industry. These are the parameters of interest. The rationale for the cubic in industry experience is the same as for individual experience. The random part of the model comprises an industry-year specific component, u_{jt}, and an individual component, ε_i.

To capture the possibility that industry skill-structure is correlated with the private returns to skill, for the reasons discussed above, the marginal returns to own level human capital are modeled as flexible functions of industry level human capital as in equations (2a) and (2b):

$$\beta'_{S,IN} = \alpha_{S0} + \alpha_{S1}\overline{S}_{jt} + \alpha_{S2}\overline{S}_{jt}^2 + \alpha_{S3}\overline{S}_{jt}^3 \qquad (2a)$$

$$\beta'_{P1,IN} = \alpha_{P0} + \alpha_{P1}\overline{P}_{jt} + \alpha_{P2}\overline{P}_{jt}^{\,2} + \alpha_{P3}\overline{P}_{jt}^{\,3} \tag{2b}$$

If more and less skilled workers are complements in production and workers are not perfectly mobile, one might expect to see α_{S1}>0 and α_{S2}<0 (α_{P1}>0 and α_{P2}<0). With this parameterization the marginal return to individual human capital is increasing in industry human capital in industries where workers tend to be low skilled. Conversely, the marginal return to human capital is decreasing in industry human capital in industries where workers tend to have high levels of human capital. Instead, if high ability/high skilled workers tend to self-select into high skilled industries, one might find α_{S1}<0 and α_{S2}>0 (α_{P1}<0 and α_{P2}>0).

In analysing firm-level spillovers I estimate equation (3) rather than equation (1). This exploits the longitudinal element of the ASHE-ABI panel.

$$\begin{aligned}\ln Y_{ijt} &= \beta'_{P1,IN}P_{it} + \beta'_{P2,IN}P_{it}^{\,2} + \beta'_{P3,IN}P_{it}^{\,3} + \beta'_{P1,EX}\overline{P}_{jt} + \beta'_{P2,EX}\overline{P}_{jt}^{\,2} + \beta'_{P3,EX}\overline{P}_{jt}^{\,3} \\ &\quad + \gamma'_1 X_{it} + \gamma'_2\overline{X}_{jt} + \delta_i + \delta_t + u_j + \varepsilon_{it} \end{aligned} \tag{3}$$

In (3) ln Y_{ijt} is the log hourly wage of individual *i* in enterprise *j* at time *t*, P_{it} is a measure of years of potential work experience for individual *i*, $\overline{P}_{jt}$ is a measure of average years of potential work experience held by those working in enterprise *j* at time *t*, X_{it} is a vector of individual characteristics that vary over time, $\overline{X}_{jt}$ is a vector of enterprise and time specific characteristics, and δ_i and δ_t are person and year fixed effects. I also include industry fixed-effects. The person fixed effects soak up variation related to individual schooling and qualifications (acquired before entering the work force), and all other time-invariant personal characteristics. The person fixed effects also absorb the majority of any firm-specific time-invariant variation, as only 10 per cent of employees in the sample switch firms over the period in which they are included in the sample. The random part of the model comprises an enterprise-specific component, u_j, and an individual component,

ε_{it}.[9] The coefficients $\beta_{P1,EX}$, $\beta_{P2,EX}$, and $\beta_{P3,EX}$ on enterprise level experience capture the returns to the individual that accrue from the work experience of his colleagues in the enterprise.

3. Data and measurement

Data

The model specified in equations (1), (2a) and (2b) is estimated using pooled cross-sections from the UK LFS 1994-2004.[10] The LFS has previously been used to study the private and industry level returns to schooling (Kirby and Riley, 2008); it has frequently been used to examine the private returns to schooling and potential experience (e.g. Shields and Wheatley Price, 1998; Harmon *et al.*, 2003). Individuals' years of schooling are defined as years spent in continuous full-time education, assuming a school starting age of 5. Potential experience is measured as age in the survey week less age left full-time education. Industry-year aggregates of these individual human capital measures are constructed from the full sample of paid employees. Earnings responses in the LFS are recorded at the last of 5 survey waves.[11] In addition to the exclusions discussed above, I also exclude workers with less than 10 years to retirement (women age 50+ and men age 55+).[12] Characteristics of individual and industry human capital measures in this LFS sample are shown in Appendix Table A1. In estimation I control for many other individual and industry level characteristics that influence wages (detailed in the notes to

---

[9] In theory the enterprise-specific component can also be included as a fixed effect. The model can then be estimated using a two-way fixed effects estimator. In practice the inclusion of both person-specific and firm-specific effects completely saturates the model.

[10] At the time of analysis the annual LFS data are available to 2008. The years 2005-2008 are not included because the EUKLEMS data, from which detailed sectoral controls are obtained, are not available for this period.

[11] Since 1997 individuals are also asked to record their earnings in the first survey wave. In estimation respondents in the first survey wave are excluded in order to maintain consistency across the sample and to avoid the complications of having two observations for some persons in the sample.

[12] Following Kirby and Riley (2008) I also exclude non-white and non-native individuals. The exclusions help to achieve a relatively homogeneous sample and to minimise self-selection into industries. To reduce measurement error I exclude individuals with less than 9 years of schooling or more than 22 years of schooling, and, given the age restrictions, men with more than 40 years potential experience and women with more than 35 years potential experience.

Tables 1 and 2). Industry information on ICT capital (computers, software and other ICT technology), non-ICT capital (structures, vehicles and non-ICT equipment), gross value-added and employment growth are from EUKLEMS. The sample covers all industries in Great Britain aggregated into 54 industry groupings.

The model specified in equation (3) is estimated using employees in the ASHE linked to enterprises in the ABI 1998-2006.[13] The ABI is a census of firms in Great Britain with more than 250 employees (excluding financial services firms), and collects detailed financial information at the establishment level. A random sample of smaller firms is also included every year. The ASHE is a 0.6% sample of employees in Great Britain (typically a 1% sample of employees in enterprises that include ASHE employees), and collects detailed pay roll information, including workers' age, occupation, industry, hours worked and pay. Employees are selected on the basis of their National Insurance numbers and should remain in the sample as long as they retain employee status.

I construct individual and matched firm level data on potential experience and the occupational structure[14] from the ASHE. Enterprises with less than 10 linked employees in the ASHE and firms with average turnover less than 1.3 £mn per annum are excluded from the sample; the number of ASHE employees needs to be large enough to derive firm-level estimates of human capital (the cut-off is admittedly arbitrary). Potential experience is measured as age at the time of the survey (April) less age left compulsory full-time education. This is less perfect than the measure of potential experience that can be constructed from the LFS, where it is possible to take into account the age at which an individual leaves continuous full-time education. Even so, the correlation across sector-years (54 industry sectors, 1998-2004) of mean employee potential experience in the ASHE and the LFS is 0.9332 (significant at the 1% level). Measures of enterprise-level

[13] The process of linking enterprises to the ASHE is described in Upward, R. (2007) 'Linking the ASHE and the BSD', University of Nottingham, mimeo.

[14] Occupations are detailed in the notes to Table 3. These groupings were constructed for the INNODRIVE project financed by the European Commission and are intended to distinguish between highly-skilled/highly-paid occupations that contribute to different aspects of intangible capital formation and lower-skill/lower-pay occupations.

productivity and capital-output ratios are constructed from the ABI.[15] Characteristics of individual and industry human capital measures in the ASHE-ABI sample used here are shown in Appendix Table A2. The number of firms and workers in the sample are detailed in Tables 3 and 4. Comparing Tables A1 and A2, the characteristics of the potential experience data look reasonably similar in the two samples. Comparing the share of high-skilled occupations in the industry across the two samples, it is clear that the ASHE-ABI sample excludes a relatively high proportion of women in low skilled industries.

Measuring work experience

As described above, general work experience is measured here as potential experience, defined as current age less age left school (and in the ASHE, less age left compulsory schooling). This measure is often used in empirical labour economics to proxy work experience (see e.g. Lemieux *et al.*, 2009; Bratsberg and Terrell, 1998; Shields and Wheatley Price, 1998), although it is typically used due to lack of a better measure of actual labour market experience. It is perhaps particularly inaccurate for women (Heywood, 1988; Miller, 1993; Anderson *et al.*, 2000), who are more likely than men to engage in part-time work and have extended periods of absence from the labour market associated with family responsibilities. Indeed it is typically found that the marginal return to potential experience diminishes more quickly for women than for men, suggesting that potential experience may overestimate actual work experience for women in comparison to men. While it is possible to look at men and women separately, as is done here, when potential experience is aggregated to the industry level this is of little help. All models include controls for the female share of the workforce to help control for the correlation between measurement error in potential experience and gender. This variable always has a negative and statistically significant association with individual wages; partly capturing the fact that women tend to be employed in low-paying industries.

[15] Plant-level capital stock data were kindly made available by Richard Harris and are described in Harris & Drinkwater (2000) and Harris (2005).

Potential experience is likely to capture a variety of factors that contribute to life-long learning. It is a very general term. An alternative measure of work experience available in the LFS is tenure with current employer. In comparison to potential experience, tenure is more likely to capture job-specific experience. At the same time, because it only captures experience with a recent employer, it underestimates work experience for individuals who have changed employer at some point in the past. Furthermore, tenure may reflect a variety of other factors distinct from work experience that are correlated with wages. For example, high tenure may result from a lack of outside opportunities for low-ability individuals.[16] For these reasons, potential experience is the preferred measure of work-experience here.

4. Results

Table 1 shows the main results; I report the estimated returns to industry and individual level potential experience and schooling that arise from estimating the model described by equations (1), (2a), and (2b) using the LFS cross-sections.[17] The coefficients on individual years of schooling and potential experience vary with the level of human capital in the industry; coefficients are reported for the sample mean value of mean years of schooling in the industry and mean years of potential experience of workers in the industry. The estimated individual return to schooling is very much as found elsewhere in the literature (Walker and Zhu, 2001), and implies a wage gain of 5 to 6 per cent for each additional year of schooling. The cubic in own level potential experience suggests the return to potential experience is similar for men and women until 13 years of potential experience are accumulated. Thereafter the return to potential experience increases for men in comparison to women. This broadly coincides with the time at which women will typically take on caring responsibilities for children.

[16] Although the focus of this paper is different, the LFS question on whether an individual has undergone job-related training may provide another opportunity to get a handle on the importance for earnings and economic growth of human capital acquired outside the formal schooling and higher education system. Explorations of these data suggest this variable is highly endogenous to wages and schooling.
[17] Full regression results for the models reported in this paper are available upon request.

Like several other studies of industry human capital spillovers (Winter-Ebmer, 1994; Sakellariou and Maysami, 2004; Kirby and Riley, 2008) I find a statistically significant positive coefficient on the industry aggregate measure of schooling, consistent with spillovers from industry level schooling. The coefficient on industry level schooling implies that a one year increase in industry mean schooling raises average wages by 5.2 per cent over and above any returns to individual schooling. This coefficient is very similar for men and for women in Table 1. Note that estimates of the model in equation (1) without the extensions in equations (2a) and (2b) that allow for individual skill returns to vary with industry level human capital, result in much larger coefficients on industry level schooling for women than for men (0.10 for women and 0.03 for men, as opposed to the 0.05 reported in Table 1 for both men and women). This gives some confidence in the ability of the extended model to net out changes in average wages associated with industry schooling that arise for reasons other than spillover effects.

In Table 1, there is evidence of a statistically significant cubic in industry level potential experience for both women and men. The estimated coefficients imply a statistically positive and significant effect of industry potential experience on women's wages for all values of industry potential experience. The estimates imply that wages are 28 per cent higher in industries where workers have on average 10 years of experience than in industries where workers have on average 5 years of experience, over and above wage differences generated by differential returns to individuals' own human capital. The equivalent wage differential between workers in industries where workers have on average 20 years of experience as opposed to 10 years of experience is 5 per cent. Much as with individual level experience, wage spillovers from industry level potential experience do not increase *ad infinitum*. Indeed, the estimated cubic suggests that, although spillovers from industry experience remain positive, these are smaller in industries where workers are significantly more experienced and older than average.

In contrast to the results for women, the estimated coefficients imply that the effect of industry potential experience on male wages is statistically negligible. In other words, while I find evidence of spillovers from the average level of experience in the industry to women's wages, I find no such effect for men. Note that estimates of the model in equation (1) without the extensions in equations (2a) and (2b) are little different than those shown in Table 1.

In Table 2 the regressions include controls for the occupational structure in the industry, and provide a check on whether the estimated gains to individuals' wages associated with the work experience of other workers in the industry arise because more experienced workers are more likely to be in higher skilled occupations. This does not appear to be the case, as the estimated returns to industry level potential experience in Table 2 are little different than those reported in Table 1. In contrast, the estimated returns to industry level schooling in Table 2 become statistically insignificant for women, and increase in magnitude and statistical significance for men. It is likely that these changes arise because of the strong correlation between high-skilled occupations and schooling levels; indeed the negative and strongly significant coefficients on the share of industry workers in R&D and marketing occupations in the regressions for men suggest this is so.

As discussed in previous sections a number of steps have been taken to control for the potential endogeneity of industry human capital. The Hausman Chi-squared statistics in Table 1 suggest that exogeneity of the industry human capital terms cannot be rejected. This may indicate that the controls included and the sample restrictions imposed are sufficient in dealing with individual selection into industries. In Table 2, where I include controls for the industry occupational structure, the Hausman Chi-squared statistic remains statistically insignificant for women. However, it becomes significant at the 10 per cent level for men. Estimates of the model in Table 2 for men, when the industry level human capital terms are instrumented with their lagged values, also suggest that spillovers from the experience of other workers in the industry to male wages are negligible.

In Table 3 the model given by equation (3) is estimated using the sample of workers and firms in the linked ASHE-ABI. In these regressions I find evidence of a statistically significant cubic in enterprise-level potential experience for men. The evidence is less strong for women. Evaluated at the sample mean, the estimates imply an average wage gain of 17 per cent associated with mean experience across employees in the firm (in comparison to the case where all workers are inexperienced). Perhaps more informative, the estimates suggest that wages are 10 per cent higher in firms where workers have on average 15 years of experience in comparison to firms where workers have on average 5 years of experience; this is over and above any wage differences that arise from the return to individuals' own experience. There is no difference between wages in firms where workers have on average 20 years of experience in comparison to firms where workers have on average 10 years of experience; other than that which arises from the return to individuals' own experience. The estimates for women are not hugely different to those for men, but statistically they are not very significant.[18]

The results in Table 3 suggest that wage spillovers from the work experience of other workers in the firm are positive and significant for men, but statistically less important for women. The results in Tables 1 and 2 suggest that wage spillovers from the work experience of other workers in the industry are positive and significant for women, but statistically unimportant for men. An obvious question to ask is whether the gender differences that arise differently at the level of the firm and at the level of the industry stem from differences in the two samples of workers analysed (the samples are different in terms of the time period covered, establishment size, and employee qualifications). In Table 4, the model in equation (3) is again estimated on the ASHE sample, but the firm-level measures of human capital are replaced with industry-level measures of human capital. In Table 4, the gender differences in spillovers from the work experience of others in the industry look similar to those reported in Tables 1 and 2. This suggests that there may be genuine differences in the way that spillovers from work experience come about for male and female workers. For women, the results suggest that spillovers from work experience may largely occur between firms within the same industry, rather than within firms. For men the opposite appears to be the case: positive spillovers from work

[18] Note that the coefficients on the individual occupation groups are much smaller than in Table 2. This is because these are identified off individuals that switch occupations; most of the differences between occupations is absorbed in the person-specific fixed effects.

experience occur within firms, but do not occur between firms in the same industry. It is not clear what might drive these gender differences in the way that spillovers arise.

5. Summary and conclusions

The analysis presented in this paper examined the evidence for industry level spillovers from work experience alongside industry level spillovers from formal schooling using pooled cross sections from the UK Labour Force Survey and longitudinal linked employer-employee data. The latter data were also used to assess the importance of spillovers from colleagues' work experience within the firm. The analysis adopted a novel approach to distinguishing between human capital externalities and other influences of industry human capital on wages.

The evidence presented is consistent with the presence of substantial knowledge spillovers or learning effects from work experience. The analysis pointed to positive and significant spillovers to women's wages from work experience at the industry level. These effects were not prevalent for men. Spillovers from the level of schooling in the industry were found for both men and women, and were comparable in magnitude when the analysis controlled for the interaction between the returns to individual's own education and the level of schooling in the industry. At the level of the firm, the analysis pointed to positive and significant spillovers to male wages from the work experience of other workers in the firm. Similar effects were found for women, but these were not statistically significant. Although the analysis is imprecise about the form of work experience that generates these spillovers, it nevertheless lends support to the notion that life-long learning is an important driver of economic performance.

The paper points to differences between men and women in the way they learn or interact. Both men and women appear to benefit from the educational level of their co-workers in the industry. But, where women seem to benefit from the work experience of their co-workers in the industry, men seem to benefit from the work experience of their colleagues in the same firm.

References

Acemoglu, D. and J. Angrist (2000) 'How large are human-capital externalities? Evidence from compulsory schooling laws.' In: B. Bernanke and K. Rogoff (eds) *NBER Macroeconomics Annual, Vol. 15.* MIT Press, Cambridge, MA, pp. 9-59.

Anderson, D., M. Binder and K. Krause (2000) 'The Motherhood Wage Penalty Revisited: Experience, Heterogeneity, Work Effort and Work-Schedule Flexibility', doi:10.2139/ssrn.258750

Battu, H., C. Belfield and P. Sloane (2003) 'Human Capital Spillovers within the Workplace: Evidence from Great Britain', *Oxford Bulletin of Economics and Statistics*, 65, pp. 575-594.

Bratsberg, B. and Terrell, D. (1998) 'Experience, Tenure, and Wage Growth of Young Black and White Men', *Journal of Human Resources*, 33, pp. 658-682.

Ciccone, A. and G. Peri (2006) 'Identifying Human-Capital Externalities: Theory with Applications', *Review of economic Studies*, 73, pp. 381-412.

Duranton, G. (2006) 'Human Capital Externalities in Cities: Identification and Policy Issues.' In R. Arnott and D. McMillen (eds) *A Companion to Urban Economics*. Blackwell Publishing Ltd., Oxford.

Gibbons, R. and L. Katz (1992) 'Does Unmeasured Ability Explain Inter-Industry Wage Differentials?', *Review of Economic Studies*, 59, pp. 515-535.

Harmon, C., V. Hogan and I. Walker (2003) 'Dispersion in the economic return to schooling', *Labour economics*, 10, pp. 205-214.

Harmon, C. and I. Walker (1999) 'The marginal and average returns to schooling in the UK', *European Economic Review*, 43, pp. 879-887.

Harris, R.I.D. (2005) *Deriving Measures of Plant-level Capital Stock in UK Manufacturing, 1973-2001*. Report to the DTI, London.

Harris, R.I.D. and Drinkwater, S. (2000) 'UK Plant and Machinery Capital Stocks and Plant Closures', *Oxford Bulletin of Economics and Statistics*, 62, pp. 239-261.

Heywood, J. (1988) 'The union wage profile of women: Potential vs. actual experience', Economics Letters, 27, pp. 189-193.

Hu, Y. and K. Mino (2005) 'Schooling, Working Experiences, and Human Capital Formation', *Economics Bulletin*, 15, pp. 1−8.

Kirby, S. and R. Riley (2008) ‘The external returns to education: UK evidence using repeated cross-sections’, *Labour Economics*, 15, pp. 619-630.

Lemieux, T., MacLeod, W.B., and D. Parent (2009) ‘Performance pay and wage inequality’, *Quarterly Journal of Economics*, 124, pp. 1-49.

Lucas, R. E. (1988) ‘On the mechanics of economic development’, *Journal of Monetary Economics*, 22, pp. 3-42.

Miller, C. (1993) ‘Actual Experience, potential experience or age, and labor force participation by married women’, *Atlantic Economic Journal*, 21, pp. 60-66.

Moretti, E. (2004) ‘Estimating the social return to higher education: evidence from longitudinal and repeated cross-section data’, *Journal of Econometrics*, 121, pp. 175-212.

Mueller, N. (2007) ‘(Mis-) Understanding Education Externalities’, MPRA Paper No. 5331, Munich.

Rauch, J. (1993) ‘Productivity Gains from Geographic Concentration of Human Capital: Evidence from Cities’, *Journal of Urban Economics*, 34, pp. 380-400.

Riley, R. and G. Young (2007) ‘Skill Heterogeneity and Equilibrium Unemployment’, *Oxford Economic Papers*, 59, pp. 702-725.

Romer, P. (1986) ‘Increasing Returns and Long-Run Growth’, *Journal of Political Economy*, 94, pp. 1002-37.

Sakellariou, C. and R. Maysami (2004) ‘Lucas type external effects of human capital: strong evidence using microdata’, *Applied Economics Letters*, 11, pp. 343-346.

Shields, M. and S. Wheatley Price (1998) ‘The earnings of male immigrants in England: evidence from the quarterly LFS’, *Applied Economics*, 30, pp. 1157-1168.

Walker, I. and Y. Zhu (2001) *The Returns to Education: Evidence from the Labour Force Surveys*. Department for Education and Skills Research Report No. 313.

Winter-Ebmer, R. (1994) ‘Endogenous growth, human capital and industry wages’, *Bulletin of Economic Research*, 46, pp. 289-314.

Appendix

Table A1. LFS sample characteristics

	Women age 30-49		Men age 30-54	
	Mean	Std. Dev.	Mean	Std. Dev.
Mean years of potential experience of workers in the industry	21.24	2.82	21.59	2.43
Individual potential experience	22.31	6.42	24.23	7.80
Mean years of schooling of workers in the industry	12.57	0.86	12.20	0.86
Individual years of schooling	12.23	2.27	12.25	2.56
Share of high qual occupations in the industry	0.15	0.10	0.20	0.12
Observations	79993		92550	

Notes: Sample period 1994-2004; High qual occupations include R&D, ICT, management, and marketing occupations; Sample includes employees in the fifth survey waves of the Quarterly Labour Force Surveys (LFS), excluding employees who have been with their current employer for less than 12 months; Industry statistics calculated from the full LFS sample.

Table A2. ASHE sample characteristics

	Women age 30-49		Men age 30-54	
	Mean	Std. Dev.	Mean	Std. Dev.
Mean years of potential experience of workers in the industry	22.13	2.46	23.89	2.27
Mean years of potential experience of workers in the firm	21.86	4.38	24.15	4.04
Individual potential experience	23.18	5.89	25.87	7.40
Share of high qual occupations in the industry	0.20	0.10	0.22	0.11
Share of high qual occupations in the firm	0.20	0.17	0.24	0.20
Observations	47356		85859	

Notes: Sample period 1998-2006; High qual occupations include R&D, ICT, management, and marketing occupations; Sample includes employees in the Annual Survey of Hours and Earnings (ASHE) linked to enterprises in the Annual Business Inquiry (ABI), excluding enterprises with less than 10 linked employees in the ASHE, and enterprises with real turnover less than 1.3 £mn on average over the sample; Industry statistics calculated from the full ASHE sample.

Tables

Table 1. OLS estimates of industry human capital spillovers

	Women age 30-49		Men age 30-54	
Mean years of potential experience of workers in the industry	0.13044***	(0.03296)	0.02084	(0.02306)
Mean years of potential experience squared of workers in the industry	-0.00583***	(0.00165)	-0.00224**	(0.00109)
Mean years of potential experience cubed of workers in the industry	0.00007***	(0.00002)	0.00004**	(0.00002)
Mean years of schooling in the industry	0.05311**	(0.02546)	0.05229**	(0.02140)
Potential experience	0.05835***	(0.00693)	0.0489***	(0.00390)
Potential experience squared	-0.00263***	(0.00033)	-0.00160***	(0.00017)
Potential experience cubed	0.00004***	(0.00000)	0.00002***	(0.00000)
Years of schooling	0.06005***	(0.00105)	0.05199***	(0.00102)
Observations	79993		92550	
Rsq	0.473		0.437	
Hausman Chisq(4); (p-value)	4.878	(0.300)	5.416	(0.247)

Notes: Dependent variable is log hourly earnings in 2002 prices; Models include year fixed effects and industry fixed effects; Sample period 1994-2004; Standard errors in parentheses corrected for clustering on industry-year groups; *** significant at the 1 per cent level, ** significant at the 5 per cent level, * significant at the 10 per cent level; Models include additional employee-level indicator variables for quarter, region, occupation (8 categories: blue-collar occupations=reference category, lower-skilled administrative occupations, non-production occupations in production and transport n.e.c., service sector occupations n.e.c., R&D, ICT, management, and marketing occupations), marriage, working full-time, workplace size, routine employee, proxy response, and a quadratic in years of tenure with current employer; Models include additional industry-level controls for industry union density, ICT-capital to output ratio, and non-ICT capital to output ratio (coefficients allowed to vary for routine and non-routine employees), as well as real gross value-added per hour worked, industry employment growth in the last 5 years, and the share of female employees in the industry; Coefficients on potential experience and years of schooling are interacted with linear, quadratic and cubic terms in their industry-level equivalents (coefficients shown for sample average values of industry means); The sample excludes individuals who have been with their current employer for less than one year, and individuals with less than 9 years schooling and with more than 22 years schooling; Sample includes white UK born individuals included in the UK Labour Force Survey 1994-2004; Hausman endogeneity test of the industry human capital terms is evaluated using lagged values of the industry human capital terms as additional instruments.

Table 2. OLS estimates of industry human capital spillovers, controlling for occupations

	Women age 30-49		Men age 30-54	
Mean years of potential experience of workers in the industry	0.14760***	(0.03156)	0.02347	(0.02345)
Mean years of potential experience squared of workers in the industry	-0.00696***	(0.00158)	-0.00228**	(0.00113)
Mean years of potential experience cubed of workers in the industry	0.00009***	(0.00002)	0.00004**	(0.00002)
Mean years of schooling in the industry	0.02728	(0.02714)	0.06963***	(0.02200)
Share of Research & Development occupations in the industry	-0.24164	(0.23076)	-0.34795***	(0.12876)
Share of ICT occupations in the industry	0.17261	(0.29197)	0.31609	(0.19755)
Share of management occupations in the industry	-0.08298	(0.20105)	-0.17919	(0.13779)
Share of marketing occupations in the industry	-0.02884	(0.23354)	-0.45394***	(0.17457)
Potential experience	0.05847***	(0.00692)	0.05206***	(0.00103)
Potential experience squared	-0.00263***	(0.00033)	-0.00160***	(0.00017)
Potential experience cubed	0.00004***	(0.00000)	0.00002***	(0.00000)
Years of schooling	0.06050***	(0.00108)	0.04876***	(0.00390)
Research & Development occupations	0.19745***	(0.02168)	0.12039***	(0.00700)
ICT occupations	0.16643***	(0.01514)	0.18391***	(0.00950)
Management occupations	0.23860***	(0.01342)	0.21325***	(0.00580)
Marketing occupations	0.23217***	(0.01334)	0.25832***	(0.00817)
Observations	79993		92550	
Rsq	0.473		0.437	
Hausman Chisq(11); (p-value)	14.822	(0.191)	18.823	(0.064)

Notes: See notes to Table 2; Models include additional employee-level indicator variables for occupation (4 categories in addition to those shown: blue-collar occupations=reference category, lower-skilled administrative occupations, non-production occupations in production and transport n.e.c., service sector occupations n.e.c.); Models include additional industry-level controls for the share of workers in lower-skilled administrative occupations, the share of workers in non-production occupations in production and transport n.e.c., the share of workers in service sector occupations n.e.c..

Table 3. OLS estimates of firm-level human capital spillovers using ASHE-ABI data

	Women age 30-49		Men age 30-54	
Mean years of potential experience of workers in the firm	0.02451*	(0.01270)	0.03226**	(0.01307)
Mean years of potential experience squared of workers in the firm	-0.00093	(0.00063)	-0.00129**	(0.00062)
Mean years of potential experience cubed of workers in the firm	0.00001	(0.00001)	0.00001*	(0.00001)
Share of high qual occupations in the firm	0.27674	(0.20553)	0.00607	(0.09569)
Potential experience	0.03001*	(0.01778)	0.05582***	(0.01347)
Potential experience squared	-0.00117	(0.00072)	-0.00169***	(0.00039)
Potential experience cubed	0.00001	(0.00001)	0.00002***	(0.00000)
Research & Development occupations	0.07111**	(0.02939)	0.01367	(0.01554)
ICT occupations	0.05816***	(0.02110)	0.02973	(0.01976)
Management occupations	0.07165***	(0.01682)	0.04965***	(0.01580)
Marketing occupations	0.04276*	(0.02263)	0.05208***	(0.01726)
Observations	44901		82215	
Person groups	17439		27210	
Firm groups	1364		1459	
Rsq	0.2493		0.1307	

Notes: Dependent variable is log hourly earnings in 2000 prices; Models include person fixed effects, year fixed effects and industry fixed effects; Sample period 1998-2006; Standard errors in parentheses corrected for clustering on firm groups; *** significant at the 1 per cent level, ** significant at the 5 per cent level, * significant at the 10 per cent level; Models include additional employee-level indicator variables for working full-time, lower-skilled administrative occupations, non-production occupations in production and transport n.e.c., service sector occupations n.e.c. (blue-collar occupations is the reference category); Models include additional employer-level variables: real gross value-added (2000 prices) per hour worked, ratio of capital stock to output, share of female employees; "high qual occupations in the firm" include R&D, ICT, management, and marketing occupations; Sample includes employees in the Annual Survey of Hours and Earnings (ASHE) linked to enterprises in the Annual Business Inquiry (ABI) 1998-2006, excluding enterprises for which there is not full financial information in the ABI, enterprises with less than 10 linked employees in the ASHE, and enterprises with real turnover less than 1.3 £mn on average over the sample.

Table 4. OLS estimates of industry human capital spillovers using ASHE data

	Women age 30-49		Men age 30-54	
Mean years of potential experience of workers in the industry	0.05645**	(0.02692)	0.00596	(0.02480)
Mean years of potential experience squared of workers in the industry	-0.00142**	(0.00069)	-0.00036	(0.00056)
Share of high qual occupations in the industry	0.23810	(0.16829)	-0.00435	(0.12078)
Potential experience	0.03610**	(0.01608)	0.05328***	(0.00925)
Potential experience squared	-0.00146**	(0.00060)	-0.00158***	(0.00028)
Potential experience cubed	0.00002**	(0.00001)	0.00001***	(0.00000)
Research & Development occupations	0.05359**	(0.02364)	0.01164	(0.01202)
ICT occupations	0.05922***	(0.01754)	0.03082**	(0.01269)
Management occupations	0.07181***	(0.01617)	0.05054***	(0.00934)
Marketing occupations	0.03930**	(0.02168)	0.04728***	(0.01327)
Observations	47356		85859	
Person groups	18622		28595	
Industry-year groups	452		462	
Rsq	0.1917		0.1034	

Notes: Dependent variable is log hourly earnings in 2000 prices; Models include person fixed effects, year fixed effects and industry fixed effects; Sample period 1998-2006; Standard errors in parentheses corrected for clustering on industry-year groups; *** significant at the 1 per cent level, ** significant at the 5 per cent level, * significant at the 10 per cent level; Models include additional employee-level indicator variables for working full-time, lower-skilled administrative occupations, non-production occupations in production and transport n.e.c., service sector occupations n.e.c. (blue-collar occupations is the reference category); "high qual occupations in the industry" include R&D, ICT, management, and marketing occupations; Sample includes employees in the Annual Survey of Hours and Earnings (ASHE) linked to enterprises in the Annual Business Inquiry (ABI) 1998-2006, excluding enterprises with less than 10 linked employees in the ASHE, and enterprises with real turnover less than 1.3 £mn on average over the sample.

For more information, please contact
llakescentre@ioe.ac.uk
LLAKES Centre
Institute of Education
20 Bedford Way
WC1H 0AL
London
UK

National Institute of Economic and Social Research

University of BRISTOL

UNIVERSITY OF Southampton School of Education

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL