The productivity impact of skills in English manufacturing, 2001: evidence from plant-level matched data[1]

Richard Harris[*], **Qian Cher Li[*]** and Catherine Robinson[†]
(Corresponding author: q.li@socsci.gla.ac.uk)

Abstract

Microeconomic analyses of productivity for the UK have generally not been able to control for the quality of the labour input, primarily due to data availability, and yet the supply of suitably skilled labour is thought to be a major contributing factor to productivity levels. This paper combines the Annual Respondents Database with the Employers' Skills Survey for 2001, which allows for a more detailed analysis of the role of skills in determining plant level productivity. Using an augmented Cobb-Douglas production function, the analysis shows that plants experiencing skills shortages were generally less productive than those who did not perceive a skills gap, having controlled for industry and regional effects. In more detail, the analysis reveals some interesting results: the impact that skills gaps have on productivity vary by industry, and higher qualifications do not always result in higher productivity, although innovative plants are seen to be on average 5 per cent more productive, as a result of their more qualified workforce.

[1] The financial support of the DTI is gratefully acknowledged. This work contains statistical data from ONS which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data.

[*] University of Glasgow

[†] National Institute of Economic and Social Research

1. Introduction

Labour is a fundamental input for the production process, and the quality of the labour force is thought to have considerable impact on productivity levels and differences across plants, firms and countries. However, heterogeneity in the labour input is often difficult to account for within micro economic estimation of productivity because of data availability. The purpose of this paper is to outline the results from merging two UK plant level datasets, one of which contains financial data, while the other contains detailed data on skills and skills shortages, in order to provide preliminary productivity estimates which incorporate variables to account for labour heterogeneity[2].

The Annual Respondents Database (ARD) contains no direct information on the human capital attributes of the workforce and therefore cannot be readily used to consider such issues as whether plants that employ more skilled workers benefit in terms of higher levels of (total factor) productivity. The Employers Skills Survey datasets for 1999 and 2001 have previously been merged with the ARD (see Hawkes, 2002) for use in analysing the impact of skills on productivity (see, for example, Haskel et. al., 2003; Galindo-Rueda and Haskel, 2005). Thus, the merging of the ESS and ARD produces a potentially significant resource for conducting appropriate micro-level analysis of the link between TFP and the quality of the workforce employed in UK firms.

This paper is structured as follows; Section 2 reviews current evidence on the role of skills in productivity studies, and in particular, the impact of skills shortages. Section 3 contains details of the data merging process that was carried out in order to undertake the present analysis; it highlights problems with data matching and the differences that are likely to occur because of matching at different levels. Section 4 contains analysis of the matched data for manufacturing in 2001. The model employs a standard cross-sectional Cobb-Douglas production function to estimate productivity for plants in manufacturing, including a number of variables that aim to address the

[2] The merged and individual datasets are available for analysis on-site at the ONS, London. For further information contact the Business Data Linking group at Business.Data.Linking@ons.gsi.gov.uk

impact of skills shortages, and labour quality more generally. Finally, Section 5 highlights the contribution this work makes to the existing literature, and raises issues for future research.

2. The importance of skills in production

It has long been a priority for research to understand the role of skills within the production process (ESRC, 2005; Skills Strategy White Paper, 2005). Much of the labour economics skills literature considers the returns to the worker, and thus wage differentials, which, at least in part, are indicative of productivity differences (e.g. efficiency-wage models). This paper considers the other side of the efficiency-wage relationship in that it is specifically concerned with the direct productivity impact of heterogeneous labour (shortages).

At the national level, literature that looks to explain the existing productivity gap between the UK and its major competitors (France, Germany, US) attributes some of the differential to skill shortages in the UK and a continued high proportion of adults with poor basic skills (DTI, 2005). Compared to its European counterparts, particularly Germany, the UK has been seen to be lacking intermediate skills, stemming from less vocational training, etc. With the US, the skills differential is particularly noticeable in the graduate proportion of the workforce.

Another body of literature has concentrated on poor UK management as a key factor in lower levels of productivity in the UK, particularly in contrast with the US (Porter and Ketels, 2003; McKinsey, 1998). Porter and Ketels (*op cit*) identify this as a problem mainly with middle management rather than senior managers. In many respects however, the importance of management skills relates more to the organisational structure of the enterprise rather than skills in the workplace *per se* and their contribution to productivity growth.

Whilst skills may be broadly defined as high, intermediate and low, there are certain occupational groups that are likely to be more important to a firms' performance than others. There is an increasing trend to identify areas of skills deficiencies that contribute significantly to productivity differences, most notably, the important contribution of ICT skills (Forth and Mason, 2003). Forth and Mason (op cit) use Dun and Bradstreet financial data, matched into the ICT Professional Survey (carried out on behalf of the DTI). Their analysis finds a negative relationship between performance and skills gaps, and evidence of a link between sales performance and the provision of ICT training.

There is also a significantly developed area of literature that considers the skill biased nature of technology, which examines how the demand for labour is affected by innovation in light of technological changes (O'Mahony et al, 2005) and in a more recent strand of literature, organisational changes, and the complementarity between them.[3] (Berman et al., 1994; Lindbeck & Snower, 1996; Doms et al., 1997; Siegel, 1998; Greenan, 2003; Falk & Heobel, 2004) This is tangential to the relationship between productivity and skills, but is nonetheless relevant.

At the micro level, Haskel and Galindo-Rueda (2005) have recently also matched the ESS and ARD datasets. Their analysis differs to that presented here since it matches plant level ESS data into reporting unit level ARD data, although overall there are important similarities to the approach adopted here. In addition, they match these data to the population census for 2001, to include qualifications at the local authority level. With this combined data set, they are able to consider any spillovers from a highly skilled area. Their findings indicate that generally, reporting units that employ high skilled, male, full time workers are more productive than those that employ low skilled, female, part time workers. This finding varies in intensity between industries. Haskel and Galindo-Rueda (*op cit*) also find, for their sample of firms, evidence of spillovers to firms located in comparatively higher educated areas. This conclusion does suggest that investment in upskilling an area is linked to an overall rise in productivity for those firms co-located in such areas.

Thus, it can be seen that the impact of skills on productivity is likely to be significant, and there are likely to be additional spillover effects in different spatial areas. However, much of the micro economic research that has looked at productivity in

---

[3] See Pianta (2004) for a theoretical survey on the effects of innovation on labour demand, and Piva et al. (2005) for a survey of literature on the 'Skill Biased Technological Change' (SBTC) and 'Skill Biased Organisational Change' (SBOC) hypotheses.

recent years based on the Annual Respondents Database (ARD), has not focussed on skills availability or shortages because of data limitations associated with the ARD. In addition, much of the literature on skills and skill shortages has not collected firm-level financial data from which to derive productivity measures. This has meant that much of the recent micro-level research in the UK has not fully taken into account the productivity impact of the quality of the labour force, or the impact of skills shortages. A major exception to this is the work of Haskel et al (Haskel and Pereira, 2002; Haskel et al, 2003; Haskel and Galindo-Rueda, 2005), as discussed above.

The purpose in this paper is to extend this work by matching at the plant level, thereby enhancing the 'representativeness' of the sample. This paper also focuses on the demand for skills, in that it considers the perceived importance of skills gaps, as reported by plants.

3. Data merging

The ESS is obtained from sampling plants (i.e. local units)[4], so a large multi-plant company included in the ESS is very likely to have only some of its plants included. The ARD contains information at three major levels of aggregation: the enterprise (covering all plants in the organisation); the reporting unit level (these are accounting units which firms use to report back to the ONS and they can cover any number of plants in a multi-plant organisation); and the plant (or local unit). Harris (2002, 2005a, 2005b) provides a discussion on the strengths and weaknesses of using the different levels within the ARD, arguing that for most types of analysis the plant (or enterprise, in the case of single plant enterprises) is the appropriate unit of analysis, and not reporting units (when these belong to multi-plant enterprises).

Since the ESS is based on plant-level data, it can be argued that the ESS needs to be matched to plant-level ARD information. In this way, problems of skill levels (and other aspects of human capital) at the plant level being wrongly matched to productivity information at the reporting unit or enterprise level may be avoided. Unless it is assumed that all plants in an organisation have the same human capital

[4] Details on the sample frame used are provided in the documentation for the version of the dataset lodged at the ESRC Data Archive, University of Essex, accessible at http://www.data_archive.ac.uk

characteristics (as represented by just those plants included in the ESS), merging ESS plant level data at any other level of aggregation could lead to potentially biased outcomes.

The match between the ESS and the ARD undertaken for this paper should be more representative of the population of plants operating in the UK economy than earlier attempts, since by matching at the plant level we include multi-plant enterprises (and not just single-plant enterprises) who contribute proportionately a larger amount to UK GDP and make up a significant proportion of the 'selected' files which contain financial data in the ABI.

An early attempt to match the ESS with the ARD was made by Hawkes (2002). The approach used was to match the ARD and the ESS using the IDBR codes matched at the enterprise level. Consequently, only some 2,313 matches out of 17,110 were obtained comprising single-plant enterprises with financial and employment information (according to Hawkes, *op. cit.*, Table 5, a further 546 reporting units were matched but these comprised data from the ARD covering more than one local unit[5]). Of these, some 834 were reported to belong to the manufacturing sector[6].

The approach to matching used here builds on the earlier work by Hawkes by taking the original 17,110 ESS/IDBR matches for 2001 found by the ONS (at enterprise level), and attempting to locate the actual plant in the ARD that matched the ESS plant that was surveyed. To do this, the first step was to take those 17,110 plants[7] in the ESS that had IDBR enterprise reference codes and then for each enterprise match the industry SIC (at the 5-digit level) and postcode information in the ESS to the industry SIC and postcode information at plant level available in the 2000 ARD[8]. This produced 9,382 unique plant level matches between the ESS and ARD.

---

[5] That is, 2,859 matches were found but only 2,313 comprised single-plant reporting units (or enterprises) for the 2001 ESS.

[6] Note, it is not clear why the study by Haskel *et. al.* (2003, Table 1), which uses the merged data produced by Hawkes, only has 319 matches in manufacturing comprising single-plant enterprises (and a further 340 matches comprising reporting units covering more than one plant in each RU).

[7] Although, note, we could only find 16,949 matches where the enterprise reference code and postcode in the ARD were uniquely matched to the ESS sample with IDBR code at enterprise level. That is, 161 'matches' comprised enterprises which featured in the ARD more than once at different postcode addresses.

[8] The 2000 ARD was used as the ESS sample was drawn based on the 2000 (and not the 2001) IDBR.

Thus there were some 7,550 observations with potential matches at the enterprise level between the ESS and ARD, but for which no unique match could be found when using (5-digit) industry SIC and (8-element) postcode data. Thus, using employment information from both datasets, plus the industry SIC and postcode information, a manual checking exercise was undertaken to locate more matches between the ARD and ESS. This produced a further 1,068 observations that had not been uniquely computer matched using industry SIC and postcode information but which we are fairly certain are unique matches. Usually the industry SIC matched perfectly, but postcodes were only correct for the first 4 or more elements (with employment information from both datasets being used to verify that the correct plant was being matched). In total then, we were able to match some 10,450 observations from the ESS uniquely into the ARD at the plant level. It should be noted that this approach is unlikely to be as good as that which could be obtained by the ONS if they were to match the ESS (using names and addresses) to the IDBR *at the local unit level*. But the ONS did not match at this level for Hawkes, resulting in our having to use what information is available in the ESS and the ARD to try to match at the plant level.

Of the 10,450 matched ESS/ARD plant level observations, 3,417 comprised of plants that had been selected for inclusion in the ABI(2) and thus have financial and employment information with which to undertake productivity analyses. Of these, some 840 are in manufacturing.

When compared to Hawkes (2002, Table 5), it might seem that we have not managed to obtain many more matches; however, as will be shown in the next section, the matched ESS/ARD database presented in this paper comprises mostly plants that belong to multi-plant enterprises, which suggests a much more representative sample compared to that used by Hawkes (2002) and in subsequent work by CeRiBA (cf. Haskel, *et. al.*, 2003)[9].

[9] That is, of the 17,110 ESS plants matched at the enterprise level that both Hawkes and this project started out with, our 3,417 matches at plant level with financial data are likely to be a different sub-set of the ARD compared to the 2,859 matches at reporting unit level obtained by Hawkes.

Moreover, weights have been calculated for this matched sample, which ensures that it is representative of the population of English plants covered by the ARD[10]. The importance and implications of weighting data for merged datasets is discussed in greater detail in Cheshire and Neisham (2004). The weights used in this dataset have been calculated using the following method: based on employment data at the 2-digit SIC level, the total employment of the population of plants for each industry is calculated, and separately the total employment covered by those plants that are both included in the selected ARD sample (with financial data – hereafter denoted ABI(2)) and in the ESS. The ratio of total population to sample employment for each industry provides a population weight with which to gross up the matched ESS/ARD sample to ensure it represents all the plants in each industry. Therefore, analysis based on weighted data can be regarded as representative of the distribution of plants in England.

In order to give some indications of how the 3,417 plants are distributed across certain key variables (such as whether they are single-plant enterprises, by region and by industry), some basic descriptions of the merged dataset comprising ABI(2) information are presented in Table 1,. Note the data in Table 1 have been weighted, based on the weighting procedure described above.

Given that the average size of plants, covered in the matched ESS/ARD dataset with financial information from the ABI(2), is around 135 employees and £15.2m real gross output overall, this dataset covers larger plants than would typically be found in the full ABI(2) dataset within the ARD. Part of the reason is because (as seen in Table 1) the merged dataset covers a higher proportion of multi-plant enterprises than would be typical of the plants included in the much larger ARD.

As expected, foreign-owned plants are on average larger with much higher levels of labour productivity (obtained when dividing real gross output by employees). The latter is highest in the West Midlands, followed by London and the South East. While this merged dataset has good coverage of the English regions and includes a

[10] For a more detailed discussion of the need for weighting see Harris (2002).

representative sample of the industries included in the ARD, the above point that it is biased towards larger plants (and enterprises) needs to be kept in mind when undertaking any analysis with the data.

Table 1 about here

4. Productivity model

A preliminary productivity model of the manufacturing sector sub-set of the merged ESS/ARD dataset has been estimated. The analysis is limited to manufacturing because capital stock estimates (taken from Harris, 2005b) are only available for this sector. Initially the following simple Cobb-Douglas production function was estimated, using the weighted data in the ESS/ARD for manufacturing:

$$y = \alpha_0 + \alpha_E e + \alpha_K k + \alpha_{AGE} age + \alpha_{US} US + \alpha_{FO} FO + \sum_{i=1}^{20} \beta_i SIC_i \qquad (1)$$

Table 2 about here

The results for the standard model are as expected, with slightly increasing returns to scale ($\alpha_E + \alpha_K > 1$). For older plants, *cet. par.*, doubling the age of a plant results in nearly an 18 per cent decrease in output (and thus TFP). US-owned plants are nearly 15 per cent more productive, while other foreign-owned are some 14 per cent more productive than UK owned plants. Only one industry dummy proved to be significant in this basic model, and then at only the 10 per cent level. Note, we did introduce a dummy variable to take account of whether the plant was a single plant enterprise or not, but found this was not significant in any of the models we estimated.

Next the basic model was augmented to include variables drawn from the ESS. Specifically, we calculated a variable to measure whether a plant experienced a (broad) skill gap, based on the question in the ESS on whether all workers in 9 occupation groups had the relevant skills to do the job. Coding responses as 1 if the respondent said there was a gap for any occupation, and then weighting the 9 occupation figures by the proportion of the workforce in each occupation group, gave an overall skill-gap figure (denoted by SKILL).[11] The QUAL variable used is constructed in a similar way; for each occupation group respondents gave information on the most common qualification available (which we coded from 0 = none to 6 = highest level qualifications – i.e. postgraduate or equivalent level), and these were weighted by the proportion of the workforce in each occupation group to obtain an overall figure. Four other variables from the ESS were also included as potentially relevant: premium (coded 1 for plants producing quality products or services), underload (coded 1 if operating at considerably less than full capacity), import (coded 1 if main supplier is from overseas) and innovate (coded 1 if plant leads in product and process innovation).

The results for the augmented model are presented in the column headed model (2) in Table 2, showing that as expected skill gaps had a significant negative impact on productivity, while a better qualified workforce has a significant (although much smaller) positive effect on production. Plants operating considerably below full capacity are some 19 per cent less productive, while those that produce a quality product/service and/or lead with new innovations are between 12 and 15 per cent more productive, respectively. Note, the statistically significant foreign-ownership effects in the basic model are now absent, while many more industry differences now become important in the extended model.

The final model estimated links the SKILL and QUAL variables with the variables covering industry sector and those available from the ESS. Other composite variable combinations involving SKILL and QUAL could have been tried, and future work can undertake these additional calculations. The results from the current exercise are reported in the column headed model (3) in Table 2.

The results of model (3), associated with the model including composite dummy variables involving the skill and qualification variables, show that skill gaps have a more important negative impact in certain industries but that higher levels of qualifications do not always result in positive impacts for some industries. However,

[11] This variable ranged between 0 and 1, since the 0,1 responses for each occupation group are weighted by their share of total plant employment.

innovative plants appear to benefit from better qualified workforces, with productivity some 5 per cent higher in this instance.

5. Conclusions

This paper considers the impact of skills and perceived skills gaps on the productivity of plants in England, 2001. Overall, the results indicate, in line with expectations, the higher the skill of the average employee, the higher the productivity performance. This is consistent with findings from a similar study for English reporting units (Galindo-Rueda and Haskel, 2005). In the initial augmented model, which includes the skills and workplace characteristic variables, we find that qualifications are only weakly significant. Taking an active part in innovation and producing a quality product or service seem to have a more significant and larger impact on productivity.

When composite dummy variables are included in the model, we see that the industry effects, combined with skills gaps and qualification measures, become significant. These effects are generally negative. However, innovative firms with a higher qualified workforce are around 5 per cent more productive. The region in which a plant is based does not appear to have a significant impact on productivity, although as an extension of this work, interacting regions with skills variables might shed light on regional labour markets. Particularly we see that skills gaps are more important in a number of industries, including fabricated metal products, motor vehicles and scientific instruments, as well as in more traditional, lower technology industries such as wood products and wearing apparel. These results highlight the importance of changes in the demand for different types of labour. From a policy perspective, these results provide some evidence to suggest that government investment that addresses identified skills gaps has the potential to raise productivity.

Overall, it can be seen that the inclusion of skills measures and estimates of skills gaps in the econometric estimation of productivity offer considerable insight into the role that the quality of labour plays in the production process. In addition, this work highlights the usefulness of combining micro datasets in exploring workplace characteristics and their impact on productivity.

References

Chesher, A. and L. Nesheim (2004) 'A Review of the Literature on the Statistical Properties of Linked Datasets', Report to the DTI.

Doms, M., T. Dunne, and K. Troske (1997) 'Workers, Wagers and Technology', *Quarterly Journal of Economics*, **112,** 253-290.

DTI (2005) UK Productivity and Competitiveness indicators 2003, available at: http://www.dti.gov.uk/competitiveness/pdf/indicators2003.pdf

Falk, M., B.M. Koebel (2004) 'The Impact of Office Machinery and Computer Capital on the Demand for Heterogeneous Labour'. Labour Economics, 11, 99-117.

Forth, J. and G. Mason (2003) ICT Investments, Workforce Skills and Company-level Performance: Recent Evidence for the UK. NIESR Discussion Paper 236.

Galindo-Rueda, F. and J. Haskel (2005) Skills, workforce characteristics and firm-level productivity: Evidence from the matched ABI/Employer Skills Survey, IZA Discussion Paper, 1542.

Greenan, N. (2003) 'Organisational Change, Technology, Employment and Skills: An Empirical Study of French Manufacturing', *Cambridge Journal of Economics,* **27,** 287-316.

Haskel, J., D. Hawkes and S. Pereira (2003) 'Skills and productivity in the UK using matched establishment, worker and workforce data', CeRiBA working paper

Harris, R. I. D. (2002) 'Foreign Ownership and Productivity in the United Kingdom - Some Issues When Using the ARD Establishment Level Data', *Scottish Journal of Political Economy*, **49**, 318-335.

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

Harris, R. I. D. (2005b) Economics of the Workplace: Special Issue, *Scottish Journal of Political Economy*, **52**, 323-343

Hawkes, D., (2002) 'Report on Matching the Annual Business Inquiry to Learning and Training at Work Survey and Employers Skills Survey', CeRiBA working paper.

Lindbeck, A., D. Snower (1996) 'Reorganisation of Firms and Labour-market Inequality', *American Economic Review*, **86,** 315-321.

Mason, G. and R. Wilson (2003) *Employers Skill Survey: New Analyses and Lessons Learned.*

McKinsey (1998) *Driving Productivity and Growth in the UK Economy*, available at http://www.mckinsey.com/mgi/publications/uk.asp accessed 28/07/05.

O'Mahony, M, C. Robinson and M. Vecchi (2005) 'The Impact of ICT on the Demand for Skilled Labour: A cross-country comparison', paper presented at the *Economic impact of ICT: firms, industries and the macro economy* conference, London Business School, 1st July, 2005.

Pianta, M. (2004) ' Innovation and Employment'. In: Fagerberg, L., Mowery, D., R.R. Nelson. (Eds), *The Oxford Handbook of Innovation.* Oxford University Press, Oxford, Chapter 21.

Piva, M., E. Santarelli, an d M. Vivarelli (2005) 'The Skill Bias Effect of Technological and Organisational Change: Evidence and Policy Implications', *Research Policy*, **34**(2), 141-157.

Porter, M. E. and C. H. M. Ketels (2003) UK Competitiveness: Moving to the next stage, DTI Economics Paper No3.

Siegel, D.S. (1998) 'The Impact of Technological change on Employment: Evidence from a Firm-level Survey of Long Island Manufacturers.' *Economics of Innovation and New Technology* **5,** 227-246.

Table 1 Weighted mean values of the merged ESS/ARD plant level dataset

Variable	Plant level Employment	Real gross output (£'000 1990 prices)	n
Multi-plant enterprise	129	15502	2590
Single-plant enterprise	153	14387	837
North East	90	9029	225
Yorkshire-Humberside	135	13141	327
North West	140	14291	391
West Midlands	166	24169	406
East Midlands	127	10573	329
South West	137	13328	368
South East	129	16730	543
Eastern	128	11826	359
London	141	18327	475
UK-owned	127	11748	3131
US-owned	292	70604	96
Other foreign-owned	186	43012	200
Industry 1992SIC			
14	37	4651	10
15	304	37195	113
16	173	24948	25
18	99	5430	11
21	136	21252	28
22	166	22409	62
24	190	36416	62
25	132	11578	56
26	138	10270	48
27	185	32461	35
28	79	6177	79
29	204	21994	85
30	404	142967	10
31	168	11404	43
32	225	25635	20
33	151	12641	35
34	387	102592	40
35	361	40295	25
36	213	17906	34
45	91	13453	160
50	58	12157	66
51	108	32686	212
52	126	13094	537
55	54	2866	481
60	163	11433	72
63	135	18523	72
64	120	6345	122
70	66	6427	59
71	64	7545	45
72	207	21875	29
74	120	9598	277
75	112	Na	11
80	328	3488	150
85	89	2055	104
90	148	13749	10
91	75	4029	22
92	85	6305	97
93	55	2740	17

Table 2 Weighted OLS regressions using the ESS/ARD dataset

RHS variables[a]	Standard model (1)	Model (1) + ESS variables (2)	Model (2) + interaction Skill variables (3)
ln capital	0.236 (0.052)***	0.236 (0.047)***	0.246 (0.053)***
ln labour	0.779 (0.073)***	0.779 (0.067)***	0.761 (0.073)***
ln age	-0.175 (0.050)***	-0.167 (0.044)***	-0.173 (0.051)***
SIC22	0.301 (0.112)***	0.326 (0.113)***	
US-owned	0.143 (0.090)		
Other foreign-owned	0.135 (0.089)		
SIC16	-0.295 (0.166)*	-0.256 (0.166)	
Premium		0.139 (0.050)***	0.215 (0.063)***
Qual		0.030 (0.016)*	0.045 (0.020)**
Innovate		0.129 (0.047)***	
Underload		-0.186 (0.111)*	
SIC29		0.159 (0.076)**	
SIC28		0.168 (0.086)*	
SIC21		0.326 (0.186)*	
Premium x Skill			-0.228 (0.098)**
SIC19 x Skill			-0.395 (0.168)**
SIC18 x Qual			0.102 (0.057)*
SIC28 x Skill			-0.367 (0.142)***
Underload x Skill			-0.510 (0.194)***
SIC20 x Qual			0.137 (0.076)*
SIC28 x Qual			-0.091 (0.035)***
SIC24			-0.264 (0.121)**
SIC34 x Qual			-0.081 (0.037)**
SIC31			-0.238 (0.092)***
NW region			-0.102 (0.066)
SIC29 x Skill			-0.499 (0.164)***
SIC19 x Qual			-0.207 (0.042)***

RHS variables[a]	Standard model (1)	Model (1) + ESS variables (2)	Model (2) + interaction Skill variables (3)
SIC32			-0.307
			(0.162)*
SIC33			-0.497
			(0.214)**
SIC30 x Skill			-0.275
			(0.106)***
Innovate x Qual			0.049
			(0.015)***
SIC15			-0.196
			(0.080)**
SIC25 x Skill			-0.386
			(0.131)***
SIC29 x Qual			-0.097
			(0.030)***
SIC19			0.526
			(0.178)***
SIC20			-0.337
			(0.175)*
SIC16 x Qual			-0.160
			(0.054)***
SIC26			-0.226
			(0.106)**
N	820	820	820
R^2	0.76	0.77	0.78

Robust standard errors in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%)

[a] Definitions

Qual = most common Qualification for entire workforce ranging 0=none to 6=higher level
Skill = broad skill gap for entire workforce ranging 0=none to 1=all
Premium = coded 1 if quality product/service produced
Innovate = coded 1 if plant leads in developing products, processes in industry
Underload = coded 1 if plant working considerably below full capacity
Import = coded 0 if main supplier in UK and 1 if main supplier overseas