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THE CHARACTERISTICS OF ENERGY EMPLOYMENT IN A SYSTEM-WIDE CONTEXT

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GRANT ALLAN AND ANDREW ROSS

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The characteristics of energy employment in a system-wide context

Grant J. Allan[†] *

Andrew G. Ross[†]

[†]Fraser of Allander Institute and Department of Economics, Strathclyde Business School, University of Strathclyde

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Abstract

Anticipated changes in energy provision over the next decades will likely have major implications on employment within energy activities. To understand the possible consequences, many studies have considered the level and types of employment in existing energy technologies. Using the hypothetical extraction approach for the UK, we explore the employment in and supported by energy activities – including across occupations and skills categories. We show that the impact on occupation and skills across the whole economy is more evenly spread than the employment in individual sectors. From the empirical results presented here, it is evident that the system-wide demands for skills – including not only the direct, but also knock-on effects across the economy – can change the pattern of labour market needs, which have implications for labour market planning in the low carbon transition.

Keywords: Skills, energy, low carbon transition, occupations
JEL code: C67, J21, Q43

*Corresponding author. Address: Department of Economics, University of Strathclyde, Sir William Duncan Building, 130 Rottenrow, Glasgow G4 0GE, Scotland, UK; Phone: +44 (0) 141 548 3838, grant.j.allan@strath.ac.uk

1 Introduction

The global energy mix is changing at a quickening pace. The last decade has seen unprecedented policy action - both internationally and at national and sub-national levels – as well as developments of new technologies and innovations. Taken together, these are likely to set the world on a path to a low carbon energy future. This transition is also expected to see a falling contribution to the global energy mix from fossil technologies. This significant change in the delivery of energy is likely to have major implications for employment, changing not only the scale of employment in energy activities, but also the mix of energy technologies at all spatial scales: the US Department of Energy estimates that in 2016, 6.4 million Americans were employed in the “Traditional Energy and Energy Efficiency” sectors. Within this, employment in Electric Power Generation rose by 13% in the last year, with majority that growth from the installation and construction of new renewable technologies ([US Department of Energy, 2017](#)). Some 181,000 people in the UK are currently employed in the energy sector ([UK Government, 2018](#))¹.

There is a growing literature exploring the employment consequences of the transition to a low carbon future. In this paper we seek to contribute to this field from both theoretical and practical perspectives. First, there is a well established literature on estimates of current employment in energy activities. Much work has been undertaken, for instance, on measures of “green jobs”, or employment in low carbon technologies or similar. Such studies, however, typically focus on employment in only part of the energy system, e.g. that which is focusing on “green” activities will omit employment in fossil technologies, for instance. A full understanding of the employment consequences of future energy scenarios should be informed by an evidence base which includes all energy activities.

Taking the specific example of oil and gas extraction activities in the UK: fossil fuels accounts for 81.5% of UK primary energy supply, while in 2016, the UK imported 34% and 47% of oil and gas respectively. A shift towards renewable energy, perhaps alongside increasing import dependence, will therefore have major impli-

¹This is defined using Standard Industrial Classifications and jobs in “Solid fuels production”, “Oil and gas extraction”, “Refining”, “Nuclear fuel processing”, “Electricity” and “Gas”.

cations for employment in energy. Second, much of this same literature focuses on direct employment, i.e. jobs involved in energy production activities, and not all jobs supported throughout the economy by energy activities (e.g. [UK Government, 2010, 2011](#)). Different energy technologies are likely to have quite different interconnectedness to the economy, so that the energy mix will matter for the scale of employment in energy activities.

Third, in addition to the *level* of employment sustained by energy activities, there is major interest in planning for the skills required in the future labour market. Whether “green jobs” are also high-skilled jobs has previously been analysed (e.g. [Consoli et al., 2016](#)). However, planning for future energy scenarios requires an assessment of the skill requirements not only in energy roles, but elsewhere in the economy – not only the supply chains for energy supplies but also for the labour requirements². Further details on the link between climate policy and skills issues are given in [Jagger et al. \(2013\)](#). They identify a distinction between “light-green” and “deep-green” jobs, where the latter covers “those directly involved in manufacturing, installing, and operating the many low carbon technologies involved in the transition”.

The UK’s recent *Clean Growth Strategy* (CGS) for instance, introduced reforms to technical education to “provide businesses with the skilled professionals they need to thrive in the clean energy economy”. A key theme of CGS is to “maximise the social and economic benefits for the UK from this transition [to a low carbon economy]” and to “shape new commercial opportunities for the UK that can help improve skills and create good jobs” ([UK Government, 2017a](#), p.47). Further, [House of Lords \(2018\)](#) examined the potential impacts on energy security of the UK leaving the EU. It notes that UK energy sectors rely heavily on specialist labour from other EU countries ³.

²In the specific case of the nuclear power, ([Hoggett, 2014](#), p.300) notes that skills are a “significant bottleneck”: “the lack of skilled nuclear workers is also recognised as a significant bottleneck by government and industry . It is expected that many of those currently working within the domestic supply chain are now over the age of 50 and likely to be retiring within the next decade, with implications for the delivery of new build, given that their knowledge and experience could be vital for managing construction and safety risk within the UK. The availability of skilled workers could also be exacerbated by strong competition between countries with new nuclear build programmes; as well as competition for similar skills sets needed for both new build and decommissioning”.

³Similar reports are published for Scotland, in which access to skilled workers is cited as a key concern

We propose that all three points noted above can be analysed using Input-Output (IO) analysis, with an appropriately disaggregated focus on the occupation and skill component of employment ⁴. The IO approach has been used widely to analyse the economic contributions of individual elements in an economy, and is widely applied to energy issues. IO analysis employ a set of inter-industry economic accounts, classified using Standard Industrial Classifications (SIC), permitting the definition of all activities including energy, and explicitly show each sector's interactions and embeddedness with other sectors in the economy. The Hypothetical Extraction Method (HEM) approach has been applied to understand the contributions of sectors to occupations previously (Wan et al., 2013) however our application to the energy sectors and skills is novel to the best of our knowledge.

In this paper, we use a recent set of IO tables for the UK (Ross, 2017a). By "extracting" energy activities using the widely applied HEM (e.g. Cella, 1984) we can identify the economic contribution made by an energy sector to the economy as a whole, explicitly capturing inter-sectoral knock-on effects. We focus on employment supported by three elements of existing energy activities - specifically, "Oil and Gas extraction", "Electricity", and "Gas" – and use a unique extension of labour market accounts showing employment by sector, which capture the occupation and educational qualifications. We can thus identify the level and the types of occupations and skills supported in the whole economy by each specific economic activity. Currently, a lack of data on renewable energy (including electricity) prevents a full comparison of all energy technologies on the same basis; a point we return to in Section 5.

We analyse the skill composition of these energy sectors in two distinctive ways. First, we consider workers' skills in terms Standard Occupation Classifications. This includes nine major occupation groups ranging from Managers, directors and senior officials to Elementary occupations. Second, we consider workers' skills in terms of their highest qualifications attained. These two main approaches to categorise skills are employed widely within the labour market literature (e.g. Blanchflower

for the energy sector (Scottish Parliament, 2018; ClimateXChange, 2018).

⁴The usefulness of IO approach has also been noted by (Fankhaeser et al., 2008, p.424) who noted, "The economy-wide effects of climate policy have to be studied in an input-output framework that traces the effects of a policy through the supply chain."

and Oswald, 1994; Layard et al., 2005).

To further illustrate the importance of identifying wider “knock-on” effects through the supply chain across the rest of the economy, we also extract a number of non-energy production sectors in our analysis for comparison. These sectors are: “Manufacture of Motor Vehicles”, “Construction”, “Financial Service Activities”, and “Scientific Research & Development”. More importantly, however, these sectors are also selected as they are specifically highlighted within the current UK Industrial (2017b) and Clean Growth Strategies (2017a) and are thereby of significant policy relevance.

The paper proceeds as follows: Section 2 discusses the key literature for our study, covering the definitions of employment in energy activities, and the need for a system-wide perspective on employment supported by energy activities. Section 3 discusses the HEM and the data use, while Section 4 provides the results of our analysis across occupation and educational qualification measures. Section 5 summarises our results and discusses these findings with particular relevance to the limitations of our analysis and the challenge of comparable data for other energy technologies.

2 Literature review

A comprehensive review of studies linking employment and energy technologies is provided by Lambert and Silva (2012). This concludes that – while there is in some cases evidence of positive employment estimates for renewable compared to fossil technologies there are many factors involved in this holding true. These include the modelling approach, while they also make the point that it is problematic to generalise from specific regions or nations to other areas: “A critical evaluation of the literature reveals factors that should be considered when completing a study about renewable energy and employment: labour intensity of renewables; cost increases and availability of investments; counting job losses; job quality and skills, model assumptions and sources of information.” (Lambert and Silva, 2012, p.4667).

A number of studies have identified the scale of employment in existing energy-

related activities. There has been many studies of the definition and measurement of issues such as “green jobs” (e.g. [Furchtgott-Roth, 2012](#); [Allan et al., 2017](#); [Connolly et al., 2016](#)) and the considerable policy interest in the promotion of low carbon policies for employment benefits (e.g. [Blyth et al., 2014](#)). As acknowledged in several studies there are typically two ways to estimate such. The first undertakes surveys of companies to solicit the scale of employment in specific activities which are pre-determined as having “green” characteristics - e.g. ([US Bureau of Labor Statistics, 2013](#)). The second is to identify specific activities from conventional economic statistics as having these same characteristics, and using existing sectoral definitions.

Some examples from the Scotland demonstrate this typical split. Starting with the latter, the latest Scottish Government’s ([2015](#)) Economic Strategy identifies growth sectors, that is sectors which are expected to benefit from a particular focus of government policy. One such sector is “Energy (including renewables)” sector, which – like other Growth Sectors – is identified using a specific collection of SIC⁵. This has advantages of transparency – it is consistent with existing classifications of economic activity – and is regularly updated with each new issue of economic indicators on wages, GVA, employment, etc.

Two major drawbacks exist however. First, this assumption that the aggregate SIC classification identifies activities which are sufficiently homogeneous that changes in each element and the activities jointly demonstrate success in the activities in the growth sector. An increase in employment in one area with a corresponding decrease in another category would suggest that the level of employment in the growth sector was unchanged. Second that the activities within the industries identified relate to the intended area of policy. This is problematic in practice - the Scottish Government’s measured “Energy (including renewables)” includes activities in the operation of coal and nuclear power stations, and neglects manufacturing of

⁵Specifically, these are SIC2007 categories of “SIC 5: Mining of Coal and Lignite”, “SIC 6: Extraction of crude petroleum and natural gas”, “9: Mining support service activities”, “SIC 19: Manufacture of coke and refined petroleum products”, “SIC 20.14: Manufacture of other organic based chemicals”, “SIC 35: Electricity, gas, steam and air conditioning supply”, “SIC 36: Water collection, treatment and supply”, “SIC 38.22: Treatment and disposal of hazardous waste”, “SIC 71.12/2 Engineering related scientific and technical consulting activities”, and “SIC 74.90/1 Environmental consulting activities”.

wind turbines, for instance, despite being used as short-hand for success of renewable policies.

Surveys on the other hand offers a neater approach in a number of dimensions. They can acknowledge that employment in green or low carbon activities exist across a wider range of sectors – in principal, many economic activities could be serving low carbon activities. Firms undertaking business in activities as diverse as manufacturing, legal and financial activities might have a portion of activity which (while perhaps small) would typically be omitted from definitions using sectoral approaches. This approach is used in the UK in the estimation of jobs related to low carbon economy ([Office for National Statistics, 2018](#)).

Skills in the low carbon transition have been the subject of some discursive analysis (e.g. [Jagger et al. 2013](#); [Hoggett 2014](#)), as well as the focus of recent UK industrial policy. There are a small number of empirical studies examine the existing features of employment in low carbon or green activities, and the properties of such jobs. [Louie and Pearce \(2016\)](#) examines the potential losses from a reduction in activity (and employment) in coal, and the possibility for a “smooth transition” to a rapidly growing energy technology, namely solar. They use detailed occupation-position information to identify the comparable employment in solar of existing employment related to coal, and calculate the cost of retraining existing employees in the former to accommodate with a growing demand for capacity in the latter. [Consoli et al. \(2016\)](#) find that “green jobs” typically have less routine activities and require a greater range of skills than “non-green” jobs, where both are defined by a specific definition of industry and occupation activities.

A separate set of studies use empirical and modelling techniques to estimate the employment consequences of the transitions to a low carbon economy. The work of [Kammen et al. \(2004\)](#) reviews a broad range of studies and concludes that renewable energy technologies could be positive for overall employment. This approach compares jobs per installed megawatt (MW), as well as jobs in different elements of the technology lifecycle, e.g. construction, installation, operation. [Barros et al. \(2017\)](#) for instance, propose a method to permit comparable estimates of the direct

employment supported by different power plants through their lifetime ⁶. In a similar vein, [Sooriyaarachchi et al. \(2015\)](#) explore employment in the supply chain for a number of renewable technologies - namely PV, Concentrating Solar Power, wind and waste-to-energy. They identify the value chain for each technology, and examine "employment-factors" at each stage to quantify the potential scale of employment related to each technology.

[Fankhaeser et al. \(2008\)](#), for instance, discuss two elements of job change. First, the "short-term" effect of switching direct employment from fossil fuel to low carbon energy activities, such as when coal-fired power plants are decommissioned and might be offset by new jobs in running a wind farm. They note that there are "only a few studies on the employment aspects of concreted climate change policies", but acknowledge a larger literature on the employment effect of renewable energy, e.g. [Kammen et al. \(2004\)](#). Importantly for our analysis, they note ([Fankhaeser et al., 2008](#), p.424) "The economy-wide effects of climate policy have to be studied in an input-output framework that traces the effects of a policy through the supply chain.". [Fankhaeser et al. \(2008\)](#) refer to these as "medium-term" impacts, with the notion that changes in the profile of energy production will create roles (and jobs) in firms supplying new technologies.

As noted earlier, IO analysis explicitly identifies the interconnectedness of specific economic activities. These frameworks provide a standardised approach to assessing the contribution of specific activities, based around a set of economic accounts. In the case of employment supported by energy, while the IO approach provides a way of assessing *all* energy technologies ([Allan et al., 2017](#)), studies using IO to date have typically focused on electricity generation (e.g. [Bryan et al., 2017](#); [Allan et al., 2007](#)).

The IO approach allows the user to distinguish between direct and indirect/induced employment (e.g. [Lambert and Silva, 2012](#)). The former refer to those jobs in the operation of the energy technology – e.g. the plant operator – while the latter relate to jobs supported elsewhere through linkages between the energy technology and

⁶In this context, direct is defined as "jobs created in building, manufacturing, installing, operating, maintaining and eventually decommissioning the components of the power plant under consideration" ([Barros et al., 2017](#), p.544), and so is not directly comparable to estimates of direct employment in specific industry calculated from an annual IO table.

firms in the rest of the economy – the worker producing parts, or the provider of monitoring services to the facility. [Bryan et al. \(2017\)](#) note that one major interest of policy around the low carbon energy transition concerns not only the amount of (however defined) jobs, but also the nature of these. They note that choices about energy mixes, “could lead to questions about the quality of jobs offered and training and skills needs, and whether green transitions related to electricity production are a means of a ‘high road’ or ‘low road’ green transition in terms of ‘decent’ jobs” ([Bryan et al., 2017](#), p.416). It is this precise issue that our use of IO methods to energy sectors, with a focus on skills and occupations permits, and we describe our approach and data in the following section.

3 Method and data

3.1 Method

We undertake the Hypothetical Extraction Method (HEM) using IO tables for the UK to calculate the level of employment, plus the occupation and skill characteristics, which is supported by existing energy activities, as well as other important industrial sectors for comparability. The HEM approach uses the interconnectedness between sectors of the economy – as explicitly provided in a set of inter-industry economic accounts such as Input-Output tables [Miller and Blair \(2009\)](#) – to quantify the economic importance of individual sectors, groups of sectors or regions, to supporting activity throughout the economy ([Schultz, 1977](#); [Cella, 1984](#); [Dietzenbacher et al., 1993](#); [Temurshoev, 2010](#); [Wan et al., 2013](#))⁷. We extend this with a matrices of sectoral occupation and qualification detail, to explore the consequences not simply on total employment but its characteristics.

HEM evaluates the extent which individual economic sectors are “key” to economic activity. Usually applied, HEM specifically refers to the extraction of all purchases and sales made by one sector, or a group of sectors, from and to other sectors in the economy. The “hypothetical” gross output of the economy after that

⁷See [Miller and Blair \(2009\)](#) and [Cai and Leung \(2004\)](#) for details of the variety of linkage measures which can be calculated from IO accounts.

sector(s) removal will be smaller than the initial economy due to the loss of the extracted sector, its purchases or sales to the non-extracted sectors, and the loss of forward and backward linkages, as captured in the IO table ⁸. Simply put, for two sectors of otherwise identical economic characteristics, the sector which has “lower” connectedness to the economy – as measured through its backward linkages – would thus generate smaller knock-on effects from its extraction. It is assumed that the loss of inputs or sales to the extracted sector is not compensated by substitution from other (non-extracted) sectors (Wan et al., 2013).

The conventional IO approach begins with the economic system as a set of equations relating output X for sector i as the sum of sales to, in turn, itself (X_{ii}), to sector j (X_{ij}) and to final demand f_i :

$$X_i = X_{ii} + X_{ij} + f_i \quad (1)$$

With N sectors, the output of all sectors can similarly be specified:

$$\begin{aligned} x_1 &= X_{11} + X_{12} + \dots + X_{1N} + f_1 \\ x_2 &= X_{21} + X_{22} + \dots + X_{2n} + f_2 \\ &\vdots \\ x_N &= X_{N1} + X_{N2} + \dots + X_{NN} + f_N \end{aligned} \quad (2)$$

The IO table provides the expenditure flows between sectors, X_{ij} , which is used to construct a square, A , matrix of “technical production coefficients” with elements a_{ij} , where:

$$a_{ij} = X_{ij}/X_j \quad (3)$$

We can then restate equation 2 above and rearranging, we get:

$$(I - A)x = f \quad (4)$$

⁸As Dietzenbacher and Lahr (2013, p.345) put it, “To find the importance of a phenomenon that can be measured in terms of a transaction or set of transactions, one need to only remove those related transactions from the I–O table and/or model, re-run the model, and find the difference between the two sets of computations.” while Schultz (1977, p.85) notes hypothetical extraction is “a calculation of the impact of a hypothetical production shut-down in each sector to determine that sector’s economic importance in inter sectoral flows

where I is an $N \times N$ identity matrix.

Restating in terms of gross output (X), gross output is found by the product of the Leontief inverse matrix (L), $(I - A)^{-1}$, and the level of final demand. With a vector of sectoral employment-output coefficients, m , we can thus solve for the initial level of employment (e) as:

$$e = m(I - A)^{-1}f \quad (5)$$

Extraction of a sector(s) thus requires the calculation of a system with and without the extracted element. If we note the extracted and non-extracted sectors by r and nr respectively, the difference in the level of employment with (e^*) and without extraction e can be estimated as:

$$\begin{aligned} \begin{bmatrix} e_{nr} - e_{nr}^* \\ e_r - e_r^* \end{bmatrix} &= \begin{bmatrix} m_{nr} \\ m_r \end{bmatrix} \begin{bmatrix} (L_{nr,nr})^{-1} & (L_{nr,r})^{-1} \\ (L_{r,nr})^{-1} & (L_{r,r})^{-1} \end{bmatrix} \begin{bmatrix} f_{nr} \\ f_r \end{bmatrix} \\ &\quad - \begin{bmatrix} m_{nr} \\ m_r \end{bmatrix} \begin{bmatrix} (L_{nr,nr})^{-1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} f_{nr} \\ 0 \end{bmatrix} \quad (6) \end{aligned}$$

As noted in (Dietzenbacher and Lahr, 2013, p.344), conventional HEM methods have focused on changes in economic output, which "is not a very useful measure for many reasons". Rather than economic output - and given the focus of this paper - we are primarily concerned with the employment and in particular the impact on different skill- and occupation types.

With additional employment matrices showing occupations per unit output of industry and qualifications per unit output of industry, we can examine the impact of extraction of individual sectors on these measures, in addition to aggregate employment. Other studies have used the HEM approach to explore other variables in addition to output. Guerra and Sancho (2010) extends the HEM approach with a novel treatment of energy efficiency improvements in an IO setting to explore the economy-wide (including impacts on non-energy sectors) of the extraction of energy sectors, while Ali (2015) applied a number of linkage methods to an IO table

extended with sectoral CO^2 emissions to identify sectors and demands which are critical for emissions in Italy.

As we are interested in both employment and occupations and skills, our application is most similar to [Wan et al. \(2013\)](#) which analysed the occupation-industry impacts of extraction of all sectors in the Illinois economy. They show differences between the “direct” occupations lost from the loss (extraction) of each sector in turn, and the “indirect” occupations - termed “non-self-induced effects” which occur in other sectors due to links of the extracted sectors. They reveal which industries are particularly important for the 22 occupations of their analysis, and (for example) the critical role that the manufacturing sector plays in indirect effects on occupation types throughout the spectrum of job roles.

3.2 Data

For our analysis we use an IO Table for the UK as compiled by [Ross \(2017a\)](#). The IO table is a symmetric Industry by Industry (IxI) IO table with 30 industries defined at the SIC07, for the year 2010. [Table 1](#) gives an overview of the sectors, abbreviations, and sector numbers. The IxI table presentation allows the interdependence of industries to be formally examined as each industry is shown as intermediate purchasers of their own and other industries’ output.

The IxI table gives the destination of industry output, for example primary manufacturing products. The columns of the IxI Table show purchases made by industries and final demand from each UK industry’s output arising from both principal production and intermediate demand. Conversely, the rows provide a breakdown of industry receipts by origin. The IO table thereby provides an internally consistent accounting framework. This data on industry linkages can be used in conventional multiplier analysis to estimate knock-on effects throughout the UK economy of a change in final demand.

[Table 2](#) summarises sector characteristics by income and expenditure components, and employment figures in terms of full-time equivalent (FTE) employment. All sectoral interactions, including private, public and voluntary sector production and consumption activities, are aggregated here into ‘Activities’ for illustration

purposes. This table is called to mind when analysing our results as these sectoral characteristics play a significant role in determining aggregate and also skill-specific labour market outcomes.

We outline some of the key characteristics of the sectors we directly extract – sectors 2,3,4,5,12,13,14,16,23, and 26 – as they differ significantly in their income and expenditure characteristics.

The share of costs on domestic activities given in the first column varies between 26% and 67% across the key sectors we directly consider in our analysis. The higher this figures the greater the domestic consumption linkages to other production sectors. The ELE and GAS sectors are leading here with %67 and 57% respectively.

The RND sector has a relatively small share of costs on domestic activities with 37%, but has by far the highest share of labour costs - a reflection of the large share of highly skilled workers in that sector. Similarly, the EXT also has a relative small share of costs through activities, but has by far the largest proportion of OVA with 61%. Across the sectors we consider, the reliance on imported goods & services is proportionately the highest in the MOT sector with 23% of total expenditures.

A similarly diverse picture can be seen when considering incomes. The MIN and the MSS sectors receive 97% and 82% of their total incomes from domestic activities. The MIN, ELE and GAS sectors display strong domestic demand linkages with a large proportion of their incomes coming from both domestic activities and domestic households. In contrast, the MOT and the OMI sectors mainly serve export markets. The CON sector receives 52% of total incomes from providing investment goods. This is by far the largest capital share of output across all sector.

The IO table given by [Ross \(2017a\)](#), however, also provides internally consistent wage and employment differentials by worker type and industry. A detailed methodology on the skill-disaggregation is given in [Ross \(2017b\)](#).

The skill-disaggregated data distinguish different worker types in terms of their Standard Occupational Classification (SOC2010). The nine major occupation groups included in our analysis are: 1. Managers, directors and senior officials, 2. Professional occupations, 3. Associate professional and technical occupations, 4. Administrative and secretarial occupations, 5. Skilled trades occupations, 6. Caring,

leisure and other service occupations, 7. Sales and customer service occupations, 8. Process, plant and machine operatives, and 9. Elementary occupations.

To provide an additional skill dimension to our analysis we also briefly touch upon the sectoral skill composition where workers are distinguished by their highest qualification attained ranging across 50 educational attainment categories from: higher degree, different NVQ levels, to entry level qualifications (as defined by the Labour Force Survey).

We do not describe the skills data in this section any further, as these are described in detail in the results section where we show the ‘direct’ employment effects across sectors - essentially the sectoral skill characteristics as given in the IO Table.

4 Results

We report our results in four main sections. First we focus on supported employment on the aggregate level. We then discuss supported employment at sector level, individual occupation, and last we consider briefly supported employment by individual education qualification.

4.1 Supported employment: Aggregate level

Table 3 gives the number of FTE employment jobs supported by the extracted sectors, broken down by “direct”, “direct plus indirect”, and the “direct, indirect plus induced” employment effects. The ‘direct’ FTE employment figures give the employment in that sector (as also detailed in Table 2). For example, the direct employment supported by EXT is 11,281 jobs.

All products are made using – to differing degrees – intermediate inputs from other sectors of the economy, with that production requiring the employment of workers in sectors producing these goods. Additionally, sectors will sell their outputs to households, and so be negatively impacted by reductions in household income. The scale of the employment impacts of these two effects are captured in

Table 1: Sectors, codes, and abbreviations

1. AGR	Agriculture, forestry and fishing
2. MIN	Mining Of Coal And Lignite
3. EXT	Extraction Of Crude Petroleum And Natural Gas & Mining Of Metal Ores
4. OMI	Other Mining And Quarrying
5. MSS	Mining Support Service Activities

6. FAD	Food & Drink (and Tobacco)
7. TEX	Textile, Leather, Wood, Paper, Printing
8. COK	Coke and refined petroleum products
9. CHE	Chemicals & Pharmaceuticals
10. RUB	Rubber, Cement, Glass, Metals

11. MEL	Electrical, Mechanical, and other Manufacturing (incl Repair)
12. MOT	Manufacture Of Motor Vehicles, Trailers And Semi-Trailers
13. ELE	Electric power generation, transmission and distribution
14. GAS	Manufacture of gas; distribution of gaseous fuels through mains; steam and aircon supply
15. WTR	Water, sewerage and Waste

16. CON	Construction
17. WHO	Wholesale and Retail Trade
18. TRW	Water transport
19. TRA	Air transport
20. TRL	Land transportation and Storage

21. ACC	Accommodation and Food Service Activities
22. ICT	Information and Communication
23. FIN	Financial Service Activities, Except Insurance And Pension Funding
24. INS	Insurance & Pensions & Service auxiliary + Real Estate Activities
25. PRO	Professional, Scientific and Technical Activities

26. RND	Scientific Research And Development
27. ADM	Administrative and Support Service Activities
28. PUB	Public Administration And Defence; Compulsory Social Security
29. EDU	Education, Health & Care
30. OTR	Other Service Activities (incl Households) + Arts, Entertainment and Recreation

Table 2: Sector characteristics by key income and expenditure components from UK Industry by Industry Table for 2010

	% share of costs					% share of incomes						FTE Employment
	Activities	Labour	OVA	Taxes on expenditures	ROW Imports	Activities	Households	Government	Capital formation	Stock	ROW exports	
1. AGR	47	17	31	- 9	14	54	32	-	4	0	10	116,743
2. MIN	47	28	7	5	13	97	30	-	0	- 36	8	5,911
3. EXT	26	7	61	1	5	46	4	-	1	- 1	49	11,281
4. OMI	30	29	18	3	19	25	8	2	1	0	63	17,895
5. MSS	36	6	54	1	3	82	6	-	1	0	12	20,341
6. FAD	57	22	6	1	14	50	33	1	0	1	16	373,856
7. TEX	36	28	10	1	24	64	14	1	3	0	17	357,701
8. COK	21	10	3	5	62	34	25	0	0	- 0	41	9,903
9. CHE	38	14	7	2	38	35	4	0	1	- 0	60	99,967
10. RUB	34	22	15	2	27	50	2	0	1	1	47	320,469
11. MEL	42	30	8	1	19	45	5	0	9	1	39	1,051,995
12. MOT	53	18	5	1	23	24	13	0	2	1	60	127,349
13. ELE	67	6	11	2	14	67	30	1	1	0	2	66,949
14. GAS	57	10	12	3	18	56	44	-	0	0	0	42,730
15. WTR	42	21	26	6	5	35	35	15	1	- 0	13	181,602
16. CON	49	22	19	3	7	47	1	0	52	- 1	1	1,593,474
17. WHO	39	35	15	4	7	24	57	1	3	- 0	16	3,704,615
18. TRW	55	24	4	1	15	22	32	1	1	0	44	15,212
19. TRA	38	22	12	5	22	2	72	0	0	0	26	62,239
20. TRL	44	36	9	3	7	70	22	1	1	- 0	6	975,157
21. ACC	35	32	12	8	13	13	72	1	2	- 0	12	1,347,877
22. ICT	32	33	21	1	12	46	27	2	13	0	12	1,035,675
23. FIN	31	27	30	4	7	60	22	-	-	0	18	326,098
24. INS	37	11	47	2	3	16	68	0	3	- 0	12	804,054
25. PRO	35	36	22	1	5	76	5	1	6	0	12	1,513,188
26. RND	37	59	- 0	- 11	16	39	8	1	1	1	51	101,019
27. ADM	36	33	20	2	9	62	13	1	2	0	22	2,187,422
28. PUB	31	42	7	6	14	9	3	85	2	-	1	1,831,211
29. EDU	29	52	6	4	10	19	19	61	0	- 0	1	5,460,386
30. OTR	29	37	22	5	7	32	46	5	6	0	11	1,168,254

Adapted from [Ross \(2017a\)](#)

Table 3: Direct, indirect, and induced full-time equivalent employment

	Direct	Direct, plus indirect	Direct, indirect, plus induced	(A/B)	(B/C)
	(A)	(B)	(C)		
S2. MIN	5,911	10,355	19,625	1.75	3.32
S3. EXT	11,281	118,614	248,188	10.51	22.00
S4. OMI	17,895	33,868	75,984	1.89	4.25
S5. MSS	20,341	38,013	57,452	1.87	2.82
S12. MOT	127,349	337,505	649,258	2.65	5.10
S13. ELE	66,949	273,717	524,196	4.09	7.83
S14. GAS	42,730	113,448	219,621	2.65	5.14
S16. CON	1,593,474	2,419,774	3,843,896	1.52	2.41
S23. FIN	326,098	1,083,441	2,260,994	3.32	6.93
S26. RND	101,019	157,009	301,603	1.55	2.99

the “indirect” and “induced” effects, respectively. The “indirect” employment figures detail the total employment which is supported by the output of the specified sector i.e. employment in other sectors which are in the supply chain of the sector, to which the row relates. Taking the example of the MIN sector, the indirect employment of 4,444 (10,355 minus 5,911) supported by that sector is almost 75% of direct employment in that sector.

In addition to supply chain links for intermediate inputs, production of the output of any sector requires the payment of income to workers employed in that sector and in the sectors where indirect employment is supported. Receiving income, households then, in turn, purchase goods and services across the economy as a whole. The extracted sector, therefore see not only income fall across the sector, but also those sectors where outputs were previously produced for consumption in the extracted sector, and in sectors where household income was previously spent. This has a knock-on effect reducing demand in the economy and employment. The employment supported by incomes is termed “induced” employment. The direct, indirect, plus induced of the MIN sector is just above three times larger (19,625 vs 5,911) than the direct employment of that sector.

The ratios between the direct FTE employment to the direct plus indirect, and

the direct to the direct, indirect and induced FTE employment are identified in the fourth and final column of Table 3 respectively. Recall that when each sector (given by the row in Table 3) is extracted, the economy is smaller – and employment lower – due to the removal of the purchases and sales made by these sectors, and (in the induced effect) the purchases made by the incomes supported by each sector. For these selected sectors, we can see that these ratios for the direct to the direct and indirect are generally around 2. We see higher ratios for the ELE sector (4) and the EXT sector (11). This demonstrates the strong connections of the EXT sector with the rest of the UK economy⁹. We will return to the reasons for this major connectedness when we note the sectoral pattern of impacts. Including the induced effect, we see (in the third and final columns of Table 3) that each sector sees all figures increase, as we would expect as the incomes and spending previously supported by these sector is now removed from the economy as well. We again see the major number of jobs supported by our three energy sectors – ELE, EXT and GAS – which roughly double when the induced effects are included.

4.2 Supported employment: Sectoral level

We illustrated above that in aggregate the energy sectors – EXT, ELE and GAS – support many more times their direct employment across the rest of the UK economy. We now turn to the sectoral incidences of these effects, which help to understand the scale of each of the sectors’ aggregate effects.

IO analysis assumes that all sectoral variables respond linearly with changes in sectoral output, therefore we can analyse changes in the latter to show the change in employment, by sector. Figure 1 detail the percentage difference between the actual Gross Output (from the IO table) and the estimated Gross Output (post extraction), at individual sector level, so that the extracted sector is given as -100%. In order to show this graphically, the extracted sectors are set to zero (instead of -100), and highlighted accordingly. Appendices A & B give a detailed set of results.

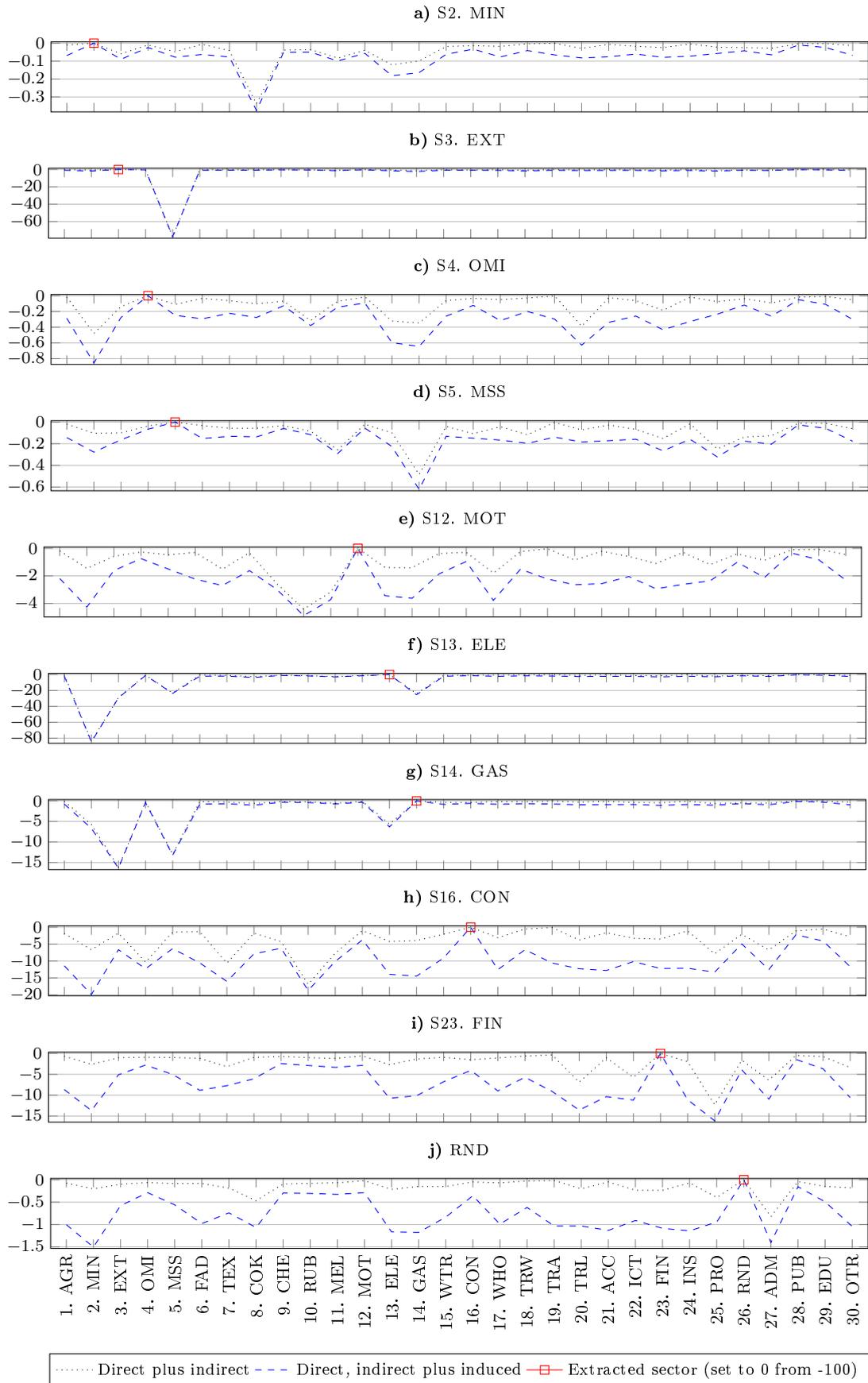
We can identify a number of interesting features from the results shown in Figure

⁹We will see that these aggregate numbers are explained when we consider the sectors indirectly connected to the extracted sectors.

1. First, noting the different values on the y-axis, we can see that the extraction of some sectors have major impacts on a small number of other industries, whereas for others, the incidence of economic impacts are more evenly spread. For instance, considering the OMI sector (sector 4) we see that when taking the induced effect into account, the change in output of each sector – apart from the extracted sector – is between -0.1% and -0.8%. Similar small and evenly distributed effects are seen for the extraction of the MIN sector.

Second, we can see cases where the losses in output following its extraction are spread across a large number of sectors. However, there are significant reductions in some sectors more than others. For instance, the MOT, CON and FIN sectors fall into this category. A final category of sectors – including the three energy sectors (EXT, ELE and GAS) – impact upon a small number of sectors with large reductions. The extraction of the ELE sector – 67% of its costs from intermediates as given in Table 2 – impacts principally on output of three sectors, MIN, EXT, MSS and GAS, which fall by 83.83%, 28.89%, 23.20% and 23.89%. We posit that the links to the MIN and GAS sectors are principally for the fuel inputs to fossil-fuel electricity generation technologies. From Figure 1 panel b) we can see that EXT is principally connected to the MSS sector, demonstrated by the reduction of almost 80% in the output of this sector when EXT is removed. In effect, therefore, removing the EXT sector causes the output of the MSS sector to contract by almost four-fifths. Thus, through the multiplier process, the extraction of the EXT sector will impact upon not only its direct employment, but also in those sectors indirectly connected, including MSS.

Figure 1: Change in output at sectoral level with extraction of individual sectors



4.3 Supported employment: Occupations

Using our detailed database we can also examine the skills composition within the supply chains for the each sector. We are primarily interested in the distribution of the employment supported by each sector across occupation types and educational qualifications held by FTE employees. Here we focus on nine occupation types while in Section 4.4 we show the results across educational qualifications. We show our occupation results initially for one sector (EXT) in Figure 2 before repeating the analysis in Figures 3 and 4 for the extracted other sectors.

First, Figure 2a gives the proportion of each occupation of total direct employment relative to overall UK employment as a whole. For example, in the EXT sector the proportion of people employed in Manager & Senior occupations is 8% greater in that sector as compared to the UK.

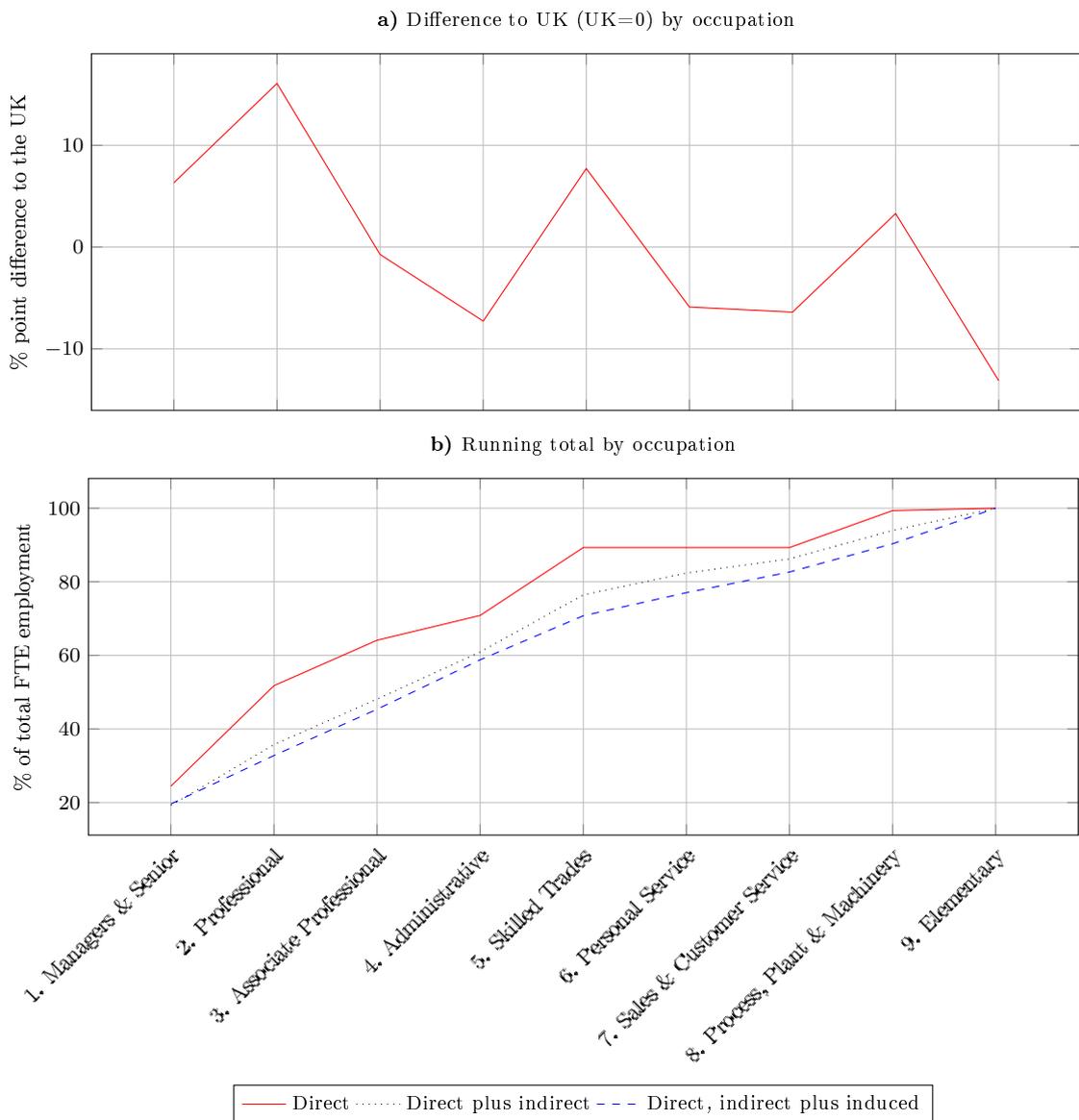
First, Figure 2b gives a running total, summing up the shares of total supported employment, i.e, that which is lost by the extraction of the sector, in total direct (i.e. the sector itself) and direct + indirect, and direct + indirect plus induced employment. For example, the graph shows that around 50% of total direct employment is covered by the first two occupation types - Managers & senior, and Professional occupations. Similarly, around 90% of total direct employment is covered by the first five occupations including Skilled Trade occupations (occupation category 5).

We can identify several key results from Figure 2a. First, note and can quantify precisely – from the “direct” information – that employment in the sector is more intensive in four occupations than the UK economy on average; both in “Managers and Senior” and “Professional” roles, as might be expected, but also in “Skilled Trades” and “Process, Plant and Machinery” positions. This detail of the multi-modal distribution of occupation types within one sector of the economy is an important insight to bring to the discussion of ‘skill intensity’ of sectors.

Second, looking at Figure 2b we can see that capturing the indirect effect of occupations types serves to move the profile of the line to the right. This reflect that the occupation types supported outside the EXT sector are less heavily skewed to higher occupation types. Additionally, adding in those jobs supported through the induced channel, we see the line continue its move towards the 45 degree line.

Moving from the direct, to the direct, indirect and induced lines we can see how the occupational distribution of supported employment changes when the impacts on the whole economy is captured. Whereas under the direct measure, over 50% of EXT employment is in occupations 1 and 2, less than 40% of the total employment supported by the EXT sector is in these occupations. While almost 90% of the direct employment is in occupations 1 to 5, 90% of the total supported employment is captured in occupations 1 to 8.

Figure 2: Direct, indirect, and induced employment by occupation for the EXT sector



Figures 3 and 4 detail the same set of results as in Figure 2 but for all of the sectors included in our analysis. We can identify those sectors where direct occupations are more heavily skewed towards “Managers and Seniors” or to “Elementary” activities, and then how taking into account indirect and induced employment moves this running total line towards the right and left respectively.

As with the EXT example given above, we see a similar profile to direct occupation types in the MSS, ELE, FIN and RND sectors. We see from Figure 4 that the direct occupations relative to the UK average is very similar between EXT and MSS, and ELE. The occupation profile within the FIN and RND sectors are more dominated by the occupation types “Managers and Senior” and “Professional” with close to UK averages across remaining occupation categories. In all these sectors case, adding the indirect and induced employment supported serves to flatten the distribution across a more broad range of occupation types, making the share of employment supported more like the UK average distribution.

Some sectors however have quite different profiles of occupation types, particularly MIN, OMI and CON. In the first two of these, direct employment is particularly strong in “Processing, Plant and Machinery”, while in the CON sector, direct employment is 40% above the UK average share in “Skilled trades”. Note that the CON sector employs 30.25% of total skilled trade FTE’s (809,415 of the 2,675,883 total FTE’s) and is the single largest sector in terms of FTE employment of skilled trades. Taking account of the indirect and induced employment supported by these sectors moves the total distribution to the left. We can see, for instance, that 36% of total employment supported by the CON sector is across occupation types 1 to 3, despite only 26% of direct employment in that sector in those types.

Figure 3: Direct, indirect, and induced employment by occupation: running total

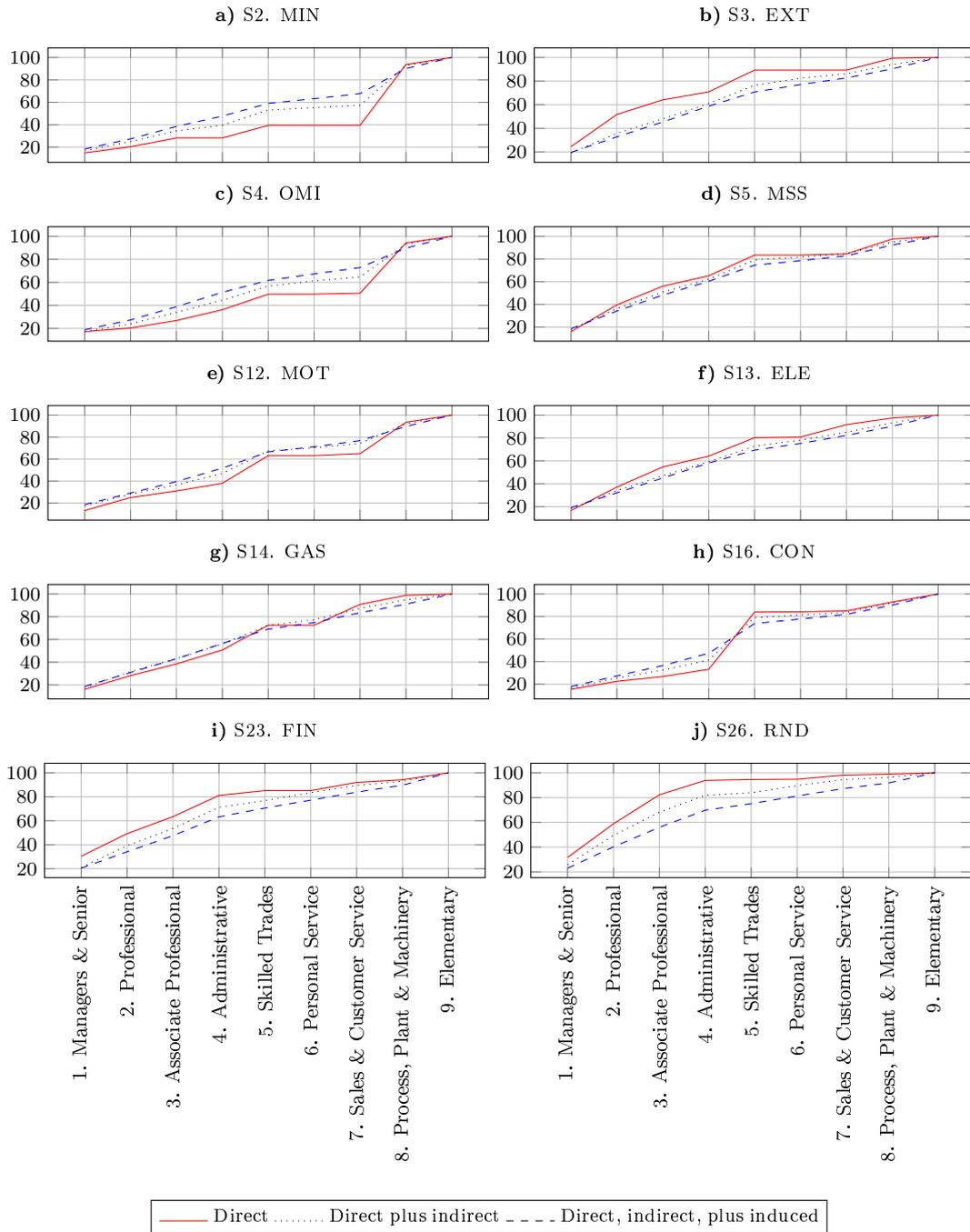
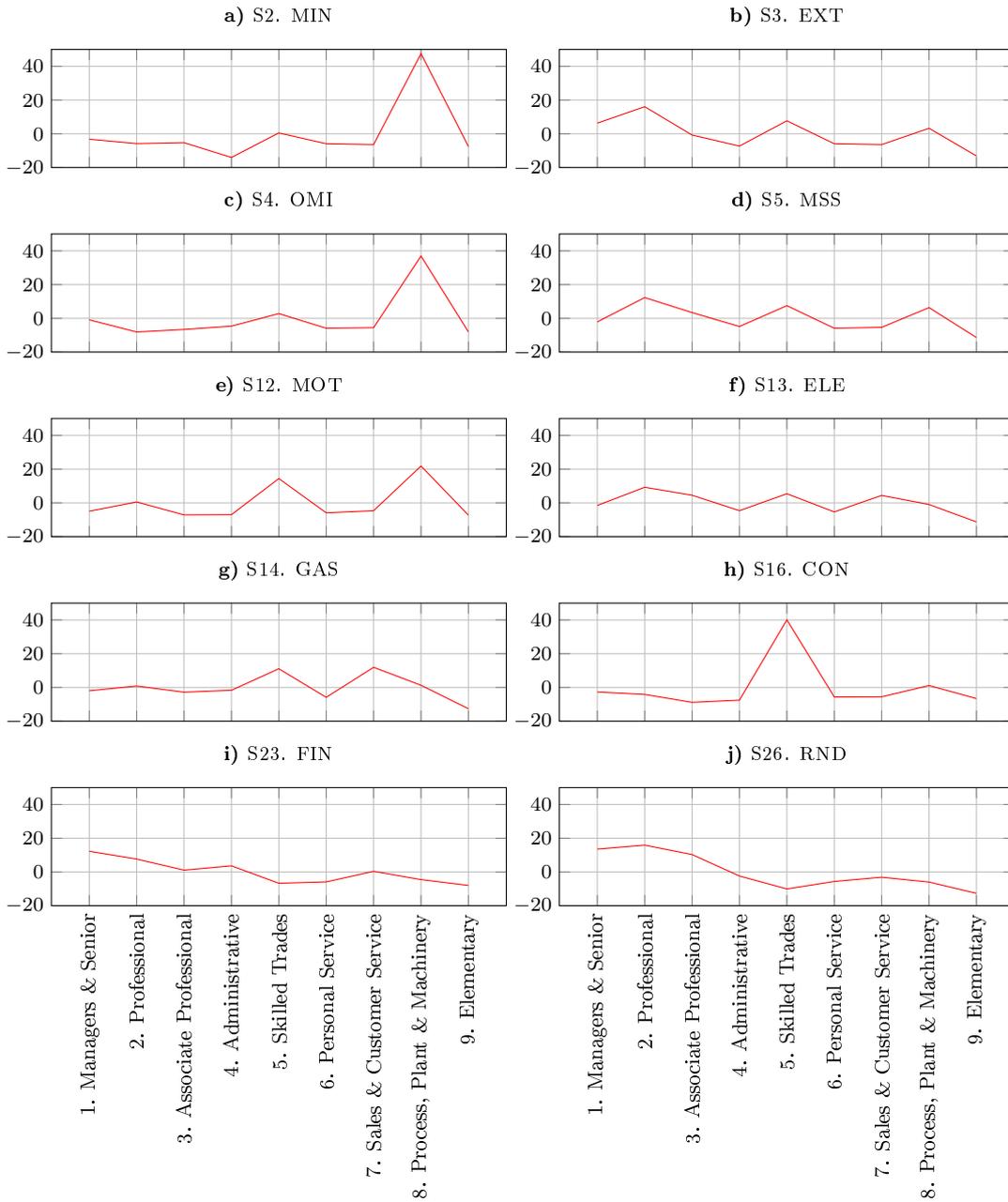


Figure 4: Direct employment by occupation: difference to UK



4.4 Supported employment: Educational qualifications

In the results sections to now, we have used the links between sectoral activity and occupation types. However, we can also use the HEM approach to examine the employment supported by each sector by educational qualifications, rather than occupation types. As outlined in Section 3.2, in addition to occupations, FTE employment at individual sector level is also broken down by the highest educational qualification level held by each worker.

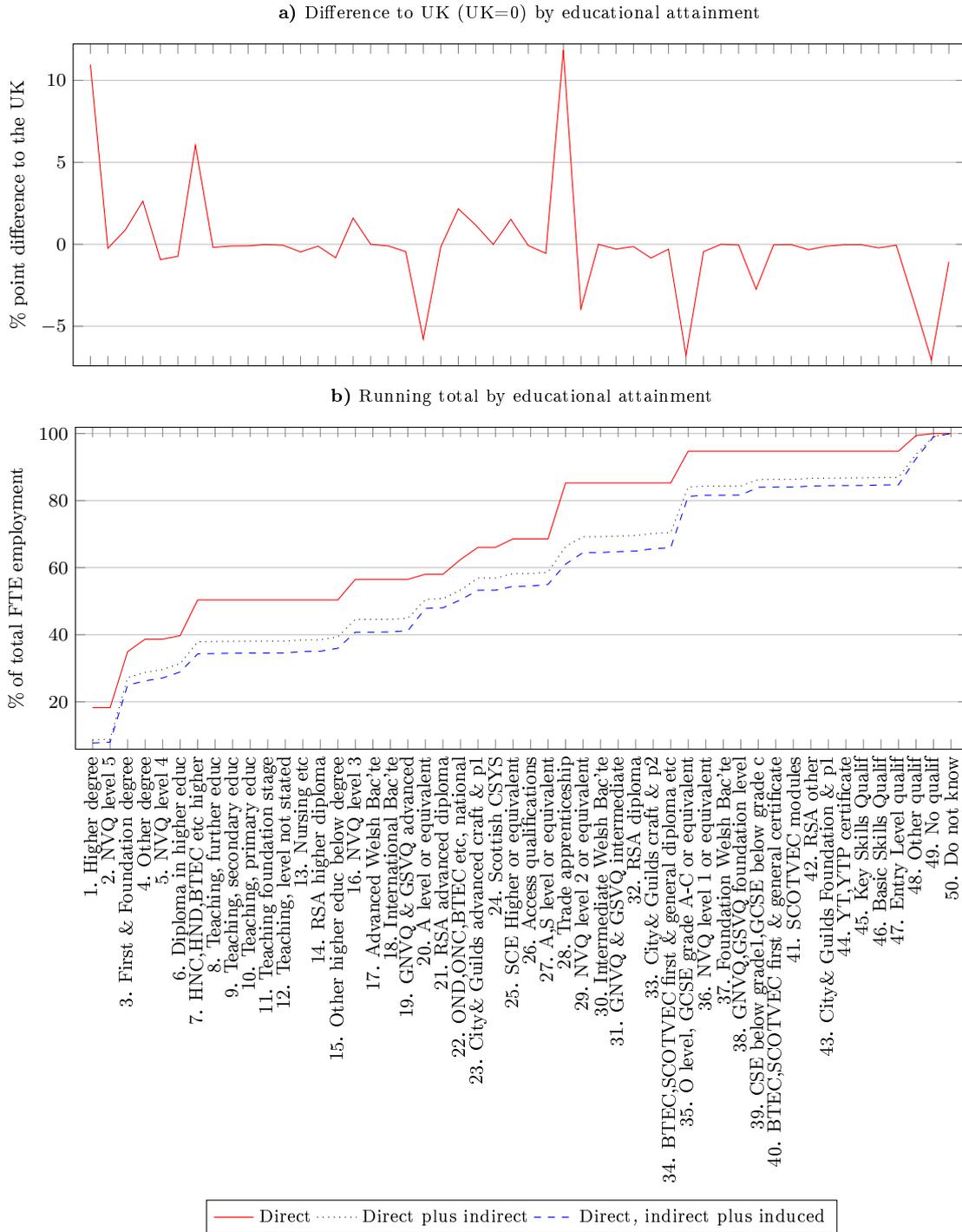
Figure 5a shows the direct incidence of employment by educational qualification in the EXT sector, while Figure 5b shows the cumulative total of direct, direct plus indirect and direct, indirect and induced employment supported by this sector. Appendices C and D give a full set of results for each of the extracted sectors.

We saw previously (Figure 2a) that the EXT sector had a higher than average share of its direct employment in the “Managers and Senior” and “Professional” occupation types, as well as in “Skilled trades”. It is not a surprise therefore to see that in terms of highest qualifications, there is a large proportion of workers in this sector with a “Higher degree” (including University Degree and Postgraduate qualifications). The high share of skilled trades in direct employment is again evident in from Figure 5a with a “Trade apprenticeship”.

Figure 5b similarly reveals the cumulative employment in and supported by the EXT sector, disaggregated by workers highest qualifications. As seen previously, including indirect, and the induced, employment, the distribution of employment flattens across the qualifications spectrum.

With such a high share of employment in the EXR sector with a “Higher degree”, the gaps remains fairly stable across qualifications types, narrowing particularly at qualifications types between 20 and 30, where a significant share of direct employment is concentrated in consumer-facing sectors, including these in wholesale and retail trade (WHO).

Figure 5: Direct, indirect, and induced employment by educational attainment for the EXT sector



5 Conclusions

In this paper, we have examined the scale and skills components of employment related to energy activities in the UK economy. We employ the widely used Hypothetical Extraction Method approach to evaluate the level of employment directly in three energy activities – Oil and Gas Extraction, Electricity and Gas – as well as employment supported by activity in each of these sectors in turn in the rest of the economy. Our particular novelty is to complement the IO analysis with a detailed dataset mapping sectoral employment to occupation types and educational qualifications. This lets us also examine the occupation and skills characteristics of jobs in (and supported by) existing energy activities in the UK.

To further illustrate the importance of identifying wider “knock-on” effects through the supply chain across the rest of the economy, we also extract a number of non-energy production sectors in our analysis for comparison. These sectors are of policy interest as they are specifically highlighted within the current UK Industrial (2017b) and Clean Growth Strategies (2017a).

We make a number of important observations. First, employment in the three identified energy activities is relatively small with regards to the scale of the UK economy, however the number of jobs supported throughout the economy by these sectors is a significant multiple of their direct employment. For the Electric power generation, transmission and distribution sector, almost 7 jobs in the wider economy (indirect and induced) are supported by each 1 in that sector, with this ratio higher for the Extraction Of Crude Petroleum And Natural Gas & Mining Of Metal Ores sector - in part due to that sectors strong connections to the Mining Support Service Activities sector. This reinforces the important economic role played by energy activities in the UK, due to their embeddedness in the UK economy through highly developed supply chains.

Second, our results show that within each sector, there is a unique spectrum of occupation types and qualification levels. Our detailed mapping of occupation types being matched to the economic accounts permits this level of analysis. We can see for instance how the Extraction Of Crude Petroleum And Natural Gas & Mining Of Metal Ores sector has a significant share of direct employment at higher

occupation categories - and indeed in both occupation types and qualifications at a higher degree or above – the sector also has a higher share of employment in “Skilled trades” and in “Process, Plant and Machinery” categories than the UK average. Similar results for other sectors suggest that a more nuanced message around the skills classification of particular sectors would be more meaningful.

Third, and perhaps our strongest theoretical contribution is our identification of the occupation and educational qualifications supported elsewhere in the economy by individual sectors. We demonstrate how the Hypothetical Extraction Method approach can be used to link supported employment to skills issues. Critically, we show that there are significant impacts on occupations and educational qualifications outside of each sector, and these move the aggregate ‘skills’ impact of changes in each sector closer to the national average ‘skills’ level. We demonstrate, for instance, that the extraction of sectors with higher representation at upper and lower occupation categories leads to changes across all occupation types once the indirect and induced effects of sectors extraction are captured.

An important policy recommendation follows from this point. Changes in the level of activity in energy activities will have important consequences for the demand for labour throughout the economy. Our analysis also suggests that there will be important links between the level of labour demand and the need for occupations and skill levels. From the empirical results presented here, it is evident that the system-wide demands for skills – including not only the direct, but also knock-on effects across the economy – can change the pattern of labour market needs, which have implications for labour market planning in the low carbon transition.

We do however note some caveats are in order for our results. First, in our extraction of each sector in turn we are essentially taking a “worst-case” scenario of the wider impacts of that sectors change. This is a useful framework, that it shows the knock-on consequences of existing activities, including those in energy. A critical point is that our Hypothetical Extraction Method technique assumes that the freed-up resources in the economy are not taken up by other sectors. There is explicitly assumed to be no additional demand for sectors output to compensate - in part or entirely - the effect of extraction activities. The true economic cost of changes

in energy activities should also include the increase in other energy activities, for instance, those related to low carbon energy (we return to this point below).

Finally, having seen the usefulness of an appropriately extended economic and labour market dataset, we note that this analysis has been carried out at fairly high level of sectoral analysis, for instance, the electricity sector is considered as one industry. We know that the electricity sector itself is composed of many different generation technologies, and activities related to transmission, distribution and supply which are *not* related to the generation mix in the UK. Previous analysis has shown that generation technologies can have quite different linkages to the rest of the economy (e.g. [Allan et al., 2007](#)). The approach outlined here performed at a more disaggregated level of energy technology would be a useful way not only to understand the skills consequences of existing energy technologies, but also to explore how changes in the UK's energy mix would impact on the wider economy and labour market.

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Disclosure statement

The authors have no financial interests or benefits arising from the direct applications of this research.

Appendices

Appendix A: Change in output at sectoral level (rows) with extraction of individual sectors (column), Type 1

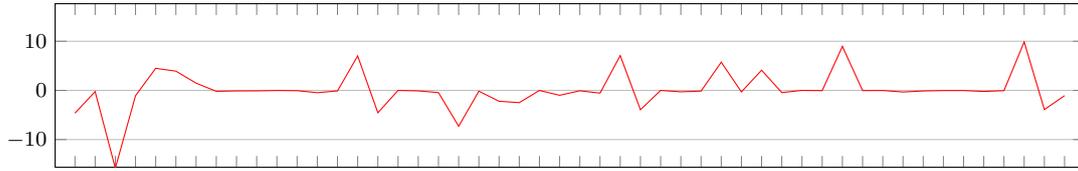
	2. MIN	3. EXT	4. OMI	5. MSS	12. MOT	13. ELE	14. GAS	16. CON	23. FIN	26. RND
1. AGR	- 0.01	- 0.09	- 0.02	- 0.02	- 0.18	- 0.26	- 0.08	- 1.85	- 0.65	- 0.08
2. MIN	- 100	- 0.52	- 0.48	- 0.10	- 1.45	- 83.83	- 5.76	- 6.66	- 2.61	- 0.20
3. EXT	- 0.06	- 100	- 0.14	- 0.10	- 0.58	- 28.89	- 16.15	- 1.75	- 1.02	- 0.10
4. OMI	- 0.01	- 0.17	- 100	- 0.04	- 0.27	- 0.65	- 0.24	- 10.31	- 0.90	- 0.06
5. MSS	- 0.05	- 77.52	- 0.11	- 100	- 0.47	- 23.20	- 12.97	- 1.45	- 0.97	- 0.08
6. FAD	- 0.01	- 0.16	- 0.03	- 0.03	- 0.30	- 0.42	- 0.14	- 1.34	- 1.16	- 0.08
7. TEX	- 0.04	- 0.29	- 0.06	- 0.06	- 1.51	- 0.97	- 0.28	- 10.62	- 3.15	- 0.19
8. COK	- 0.34	- 0.28	- 0.10	- 0.06	- 0.33	- 2.56	- 0.61	- 1.75	- 0.94	- 0.47
9. CHE	- 0.04	- 0.17	- 0.07	- 0.03	- 2.54	- 0.68	- 0.16	- 4.28	- 0.71	- 0.10
10. RUB	- 0.04	- 0.35	- 0.31	- 0.09	- 4.42	- 1.28	- 0.23	- 16.87	- 1.00	- 0.08
11. MEL	- 0.08	- 1.05	- 0.07	- 0.26	- 3.17	- 2.48	- 0.55	- 7.68	- 1.18	- 0.07
12. MOT	- 0.04	- 0.08	- 0.01	- 0.02	- 100	- 0.98	- 0.12	- 1.03	- 0.59	- 0.02
13. ELE	- 0.12	- 0.52	- 0.32	- 0.10	- 1.39	- 100	- 5.66	- 4.22	- 2.69	- 0.21
14. GAS	- 0.10	- 1.42	- 0.35	- 0.48	- 1.41	- 23.89	- 100	- 3.95	- 1.32	- 0.15
15. WTR	- 0.02	- 0.21	- 0.06	- 0.04	- 0.38	- 0.89	- 0.35	- 2.09	- 0.92	- 0.15
16. CON	- 0.01	- 0.62	- 0.03	- 0.11	- 0.29	- 0.74	- 0.37	- 100	- 1.50	- 0.05
17. WHO	- 0.02	- 0.19	- 0.05	- 0.04	- 1.79	- 0.58	- 0.16	- 3.11	- 1.06	- 0.07
18. TRW	- 0.00	- 1.06	- 0.03	- 0.12	- 0.24	- 0.47	- 0.23	- 0.54	- 0.62	- 0.03
19. TRA	- 0.00	- 0.03	- 0.00	- 0.00	- 0.03	- 0.04	- 0.01	- 0.10	- 0.33	- 0.02
20. TRL	- 0.03	- 0.43	- 0.39	- 0.07	- 0.85	- 0.92	- 0.32	- 3.81	- 6.88	- 0.20
21. ACC	- 0.01	- 0.12	- 0.02	- 0.03	- 0.22	- 0.28	- 0.10	- 1.64	- 1.03	- 0.05
22. ICT	- 0.02	- 0.39	- 0.06	- 0.07	- 0.59	- 1.06	- 0.37	- 3.28	- 5.74	- 0.23
23. FIN	- 0.02	- 0.81	- 0.19	- 0.15	- 1.10	- 1.40	- 0.46	- 3.51	- 100	- 0.23
24. INS	- 0.00	- 0.08	- 0.02	- 0.02	- 0.30	- 0.19	- 0.08	- 1.09	- 1.94	- 0.07
25. PRO	- 0.02	- 1.34	- 0.08	- 0.25	- 1.18	- 1.84	- 0.64	- 7.87	- 12.30	- 0.40
26. RND	- 0.02	- 0.61	- 0.04	- 0.14	- 0.40	- 0.99	- 0.45	- 2.12	- 1.62	- 100
27. ADM	- 0.03	- 0.65	- 0.09	- 0.13	- 0.87	- 1.28	- 0.52	- 6.74	- 6.40	- 0.83
28. PUB	- 0.00	- 0.06	- 0.02	- 0.01	- 0.10	- 0.13	- 0.04	- 1.10	- 0.47	- 0.04
29. EDU	- 0.00	- 0.06	- 0.01	- 0.01	- 0.07	- 0.13	- 0.04	- 0.55	- 0.75	- 0.15
30. OTR	- 0.01	- 0.31	- 0.05	- 0.06	- 0.44	- 0.85	- 0.31	- 2.86	- 3.37	- 0.18

Appendix B: Change in output at sectoral level (rows) with extraction of individual sectors (column), Type 2

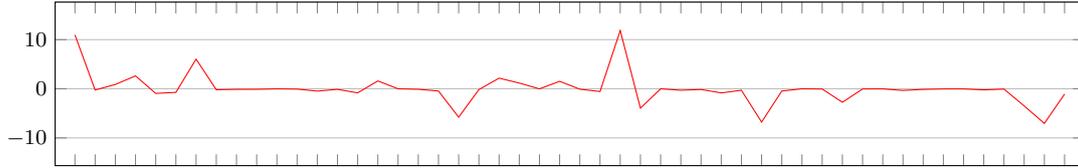
	2. MIN	3. EXT	4. OMI	5. MSS	12. MOT	13. ELE	14. GAS	16. CON	23. FIN	26. RND
1. AGR	- 0.07	- 0.92	- 0.29	- 0.14	- 2.19	- 1.89	- 0.76	- 11.40	- 8.65	- 1.00
2. MIN	- 100	- 1.68	- 0.86	- 0.28	- 4.26	- 84.71	- 6.67	- 19.89	- 13.68	- 1.50
3. EXT	- 0.09	- 100	- 0.28	- 0.16	- 1.61	- 29.25	- 16.38	- 6.66	- 5.10	- 0.58
4. OMI	- 0.02	- 0.37	- 100	- 0.07	- 0.75	- 1.03	- 0.41	- 12.30	- 2.78	- 0.29
5. MSS	- 0.08	- 77.61	- 0.25	- 100	- 1.50	- 23.65	- 13.22	- 6.33	- 5.02	- 0.56
6. FAD	- 0.06	- 0.96	- 0.29	- 0.15	- 2.23	- 1.98	- 0.80	- 10.56	- 8.84	- 0.98
7. TEX	- 0.08	- 0.79	- 0.22	- 0.13	- 2.70	- 1.93	- 0.69	- 16.02	- 7.72	- 0.74
8. COK	- 0.38	- 0.82	- 0.28	- 0.14	- 1.62	- 3.57	- 1.05	- 7.88	- 6.06	- 1.07
9. CHE	- 0.05	- 0.35	- 0.13	- 0.06	- 2.96	- 1.02	- 0.31	- 6.23	- 2.41	- 0.30
10. RUB	- 0.05	- 0.55	- 0.38	- 0.12	- 4.88	- 1.65	- 0.40	- 18.68	- 2.89	- 0.31
11. MEL	- 0.10	- 1.28	- 0.15	- 0.29	- 3.72	- 2.89	- 0.73	- 10.11	- 3.33	- 0.33
12. MOT	- 0.06	- 0.32	- 0.09	- 0.06	- 100	- 1.43	- 0.32	- 3.76	- 2.86	- 0.29
13. ELE	- 0.18	- 1.37	- 0.60	- 0.23	- 3.44	- 100	- 6.32	- 13.92	- 10.73	- 1.16
14. GAS	- 0.16	- 2.33	- 0.64	- 0.62	- 3.62	- 25.30	- 100	- 14.46	- 10.13	- 1.18
15. WTR	- 0.06	- 0.82	- 0.26	- 0.13	- 1.85	- 2.08	- 0.85	- 9.09	- 6.77	- 0.83
16. CON	- 0.03	- 0.89	- 0.12	- 0.15	- 0.96	- 1.27	- 0.60	- 100	- 4.05	- 0.36
17. WHO	- 0.08	- 1.02	- 0.32	- 0.17	- 3.77	- 2.20	- 0.84	- 12.55	- 8.97	- 0.99
18. TRW	- 0.04	- 1.58	- 0.20	- 0.20	- 1.51	- 1.50	- 0.67	- 6.65	- 5.71	- 0.62
19. TRA	- 0.07	- 0.94	- 0.30	- 0.14	- 2.23	- 1.82	- 0.76	- 10.60	- 9.10	- 1.03
20. TRL	- 0.08	- 1.18	- 0.63	- 0.18	- 2.64	- 2.37	- 0.93	- 12.28	- 13.57	- 1.03
21. ACC	- 0.08	- 1.09	- 0.34	- 0.17	- 2.56	- 2.18	- 0.90	- 12.80	- 10.35	- 1.13
22. ICT	- 0.06	- 0.99	- 0.26	- 0.16	- 2.05	- 2.23	- 0.87	- 10.17	- 11.18	- 0.91
23. FIN	- 0.08	- 1.57	- 0.43	- 0.27	- 2.94	- 2.87	- 1.08	- 12.21	- 100	- 1.09
24. INS	- 0.07	- 1.04	- 0.33	- 0.16	- 2.61	- 2.07	- 0.87	- 12.13	- 11.08	- 1.14
25. PRO	- 0.06	- 1.82	- 0.23	- 0.32	- 2.36	- 2.78	- 1.04	- 13.29	- 16.14	- 0.94
26. RND	- 0.04	- 0.86	- 0.12	- 0.18	- 1.01	- 1.47	- 0.65	- 4.96	- 3.93	- 100
27. ADM	- 0.07	- 1.16	- 0.26	- 0.20	- 2.12	- 2.28	- 0.94	- 12.53	- 10.96	- 1.40
28. PUB	- 0.01	- 0.16	- 0.05	- 0.03	- 0.35	- 0.33	- 0.12	- 2.25	- 1.42	- 0.16
29. EDU	- 0.02	- 0.37	- 0.11	- 0.06	- 0.82	- 0.73	- 0.30	- 4.10	- 3.68	- 0.49
30. OTR	- 0.07	- 1.08	- 0.30	- 0.18	- 2.30	- 2.35	- 0.94	- 11.68	- 10.58	- 1.04

Appendix C: Direct employment by educational attainment. % point difference to the UK

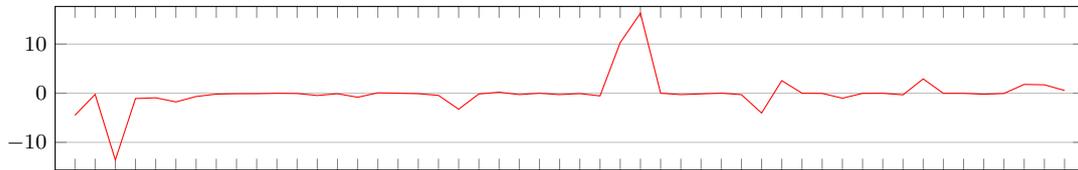
a) S2. MIN



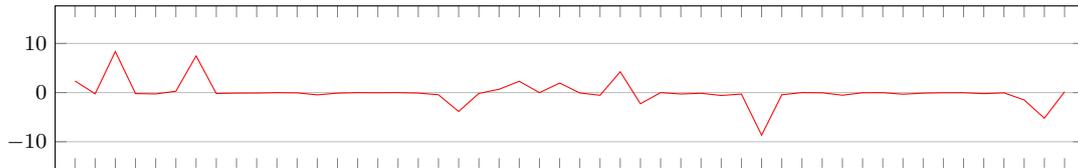
b) S3. EXT



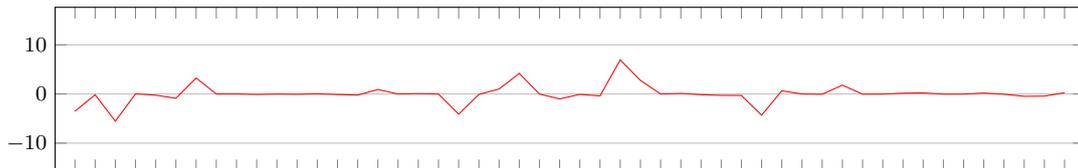
c) S4. OMI



d) S5. MSS



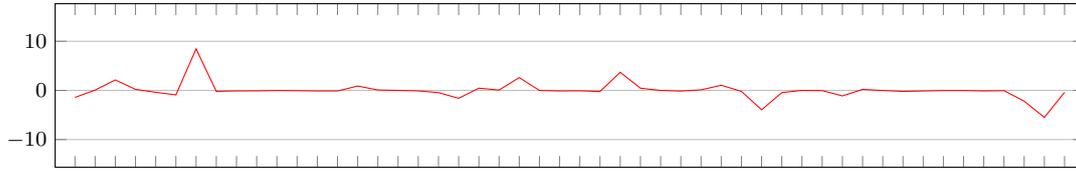
e) 12. MOT



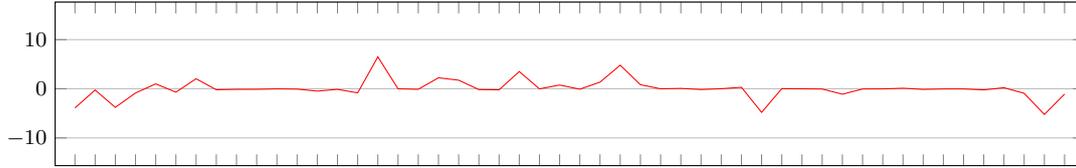
1. Higher degree
2. NVQ level 5
3. First & Foundation degree
4. Other degree
5. NVQ level 4
6. Diploma in higher educ
7. HNC,HND,BTEC etc higher
8. Teaching, further educ
9. Teaching, secondary educ
10. Teaching, primary educ
11. Teaching foundation stage
12. Teaching, level not stated
13. Nursing etc
14. RSA higher diploma
15. Other higher educ below degree
16. NVQ level 3
17. Advanced Welsh Bac'te
18. International Bac'te
19. GNVQ & GSVQ advanced
20. A level or equivalent
21. RSA advanced diploma
22. OND,ONC,BTEC etc, national
23. City & Guilds advanced craft & pl
24. Scottish CSYS
25. SCE higher or equivalent
26. Access qualifications
27. A,S level or equivalent
28. Trade apprenticeship
29. NVQ level 2 or equivalent
30. Intermediate Welsh Bac'te
31. GNVQ & GSVQ intermediate
32. RSA diploma
33. City & Guilds craft & p2
34. BTEC,SCOTVEC first & general diploma etc
35. O level, GCSE, grade A-C or equivalent
36. NVQ level 1 or equivalent
37. Foundation Welsh Bac'te
38. GNVQ,GSVQ foundation level
39. CSE below grade I,GCSE below grade c
40. BTEC,SCOTVEC first & general certificate
41. SCOTVEC modules
42. RSA other
43. City & Guilds Foundation & pl
44. Y,T,YTP certificate
45. Key Skills Qualif
46. Basic Skills Qualif
47. Entry Level qualif
48. Other qualif
49. No qualif
50. Do not know

Appendix C continued: Direct employment by educational attainment. % point difference to the UK

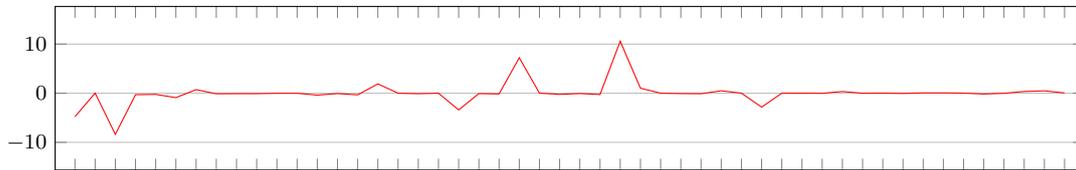
f) S13. ELE



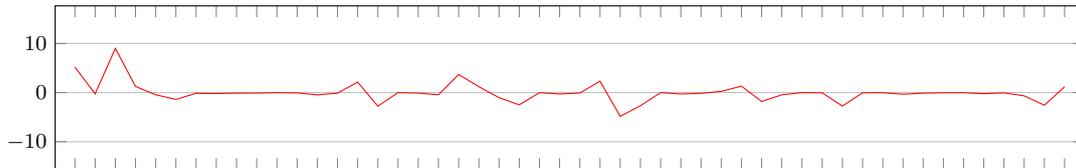
g) S14. GAS



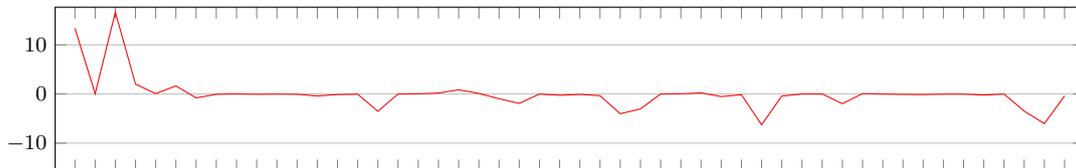
h) S16. CON



i) S23. FIN

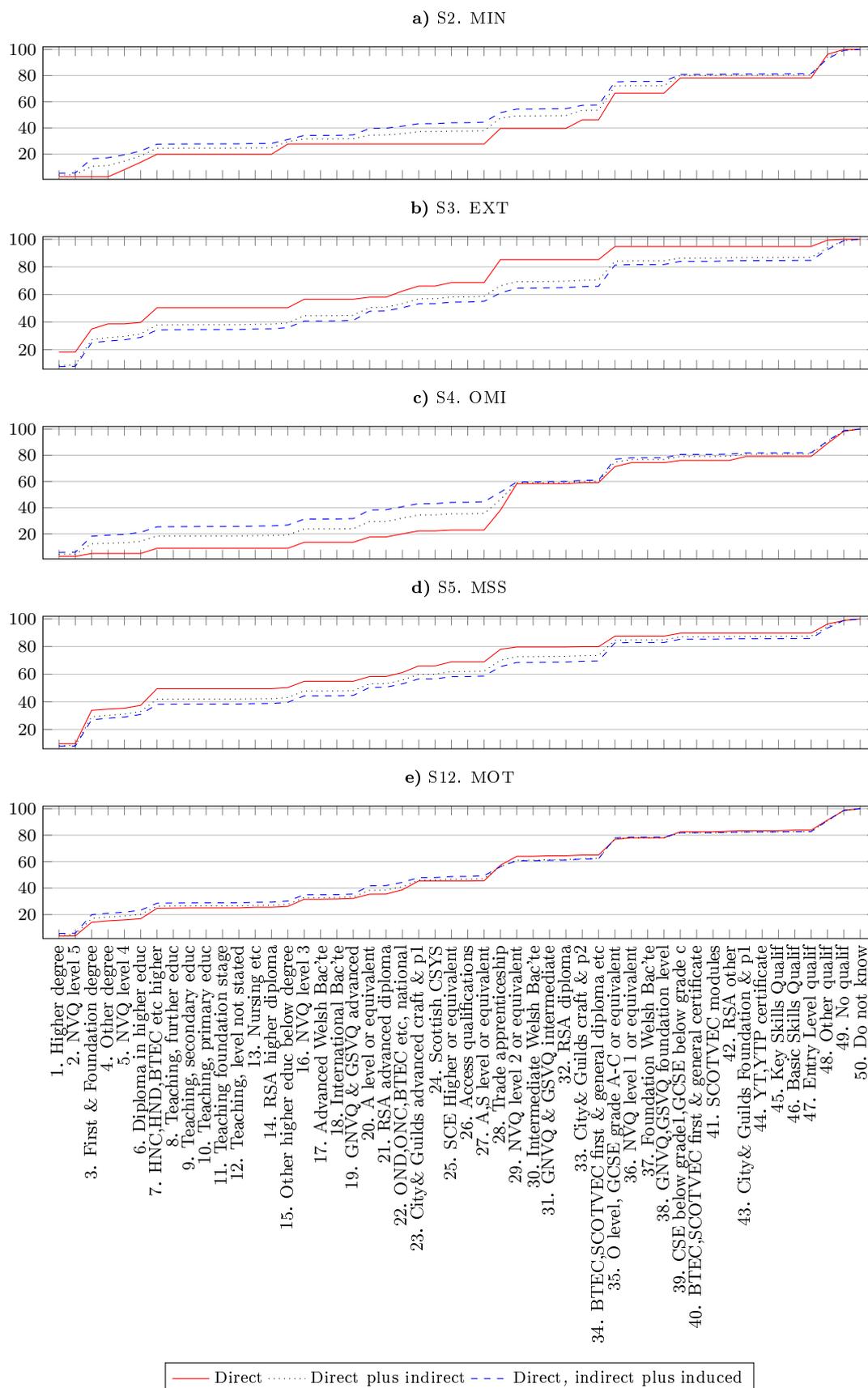


j) S26. RND

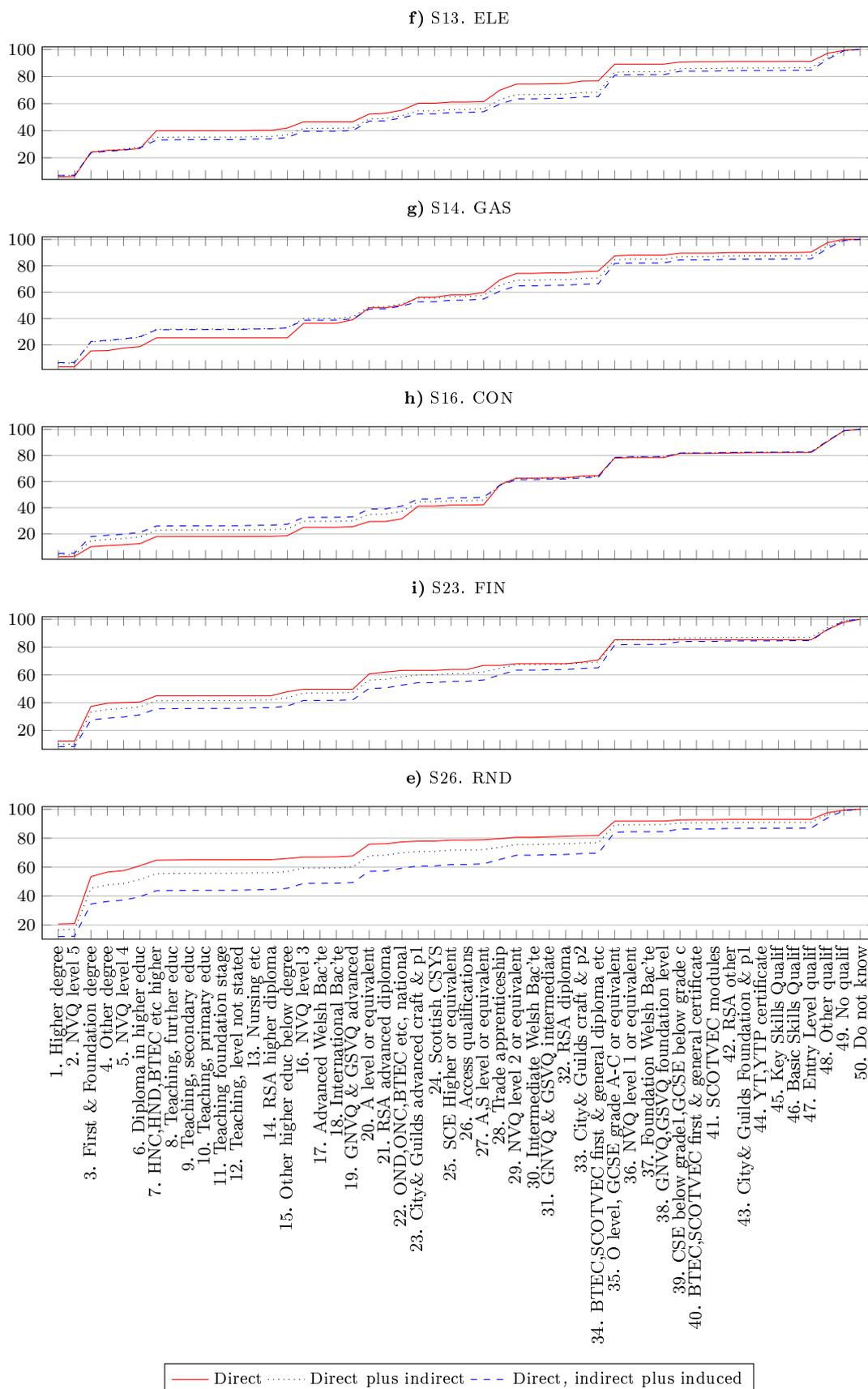


1. Higher degree
2. NVQ level 5
3. First & Foundation degree
4. Other degree
5. NVQ level 4
6. Diploma in higher educ
7. HNC,HND,BTEC etc higher
8. Teaching, further educ
9. Teaching, secondary educ
10. Teaching, primary educ
11. Teaching foundation stage
12. Teaching, level not stated
13. Nursing etc
14. RSA higher diploma
15. Other higher educ below degree
16. NVQ level 3
17. Advanced Welsh Bac'te
18. International Bac'te
19. GNVQ & GSVQ advanced
20. A level or equivalent
21. RSA advanced diploma
22. OND,ONC,BTEC etc, national
23. City & Guilds advanced craft & pl
24. Scottish CSYS
25. SCE higher or equivalent
26. Access qualifications
27. A,S level or equivalent
28. Trade apprenticeship
29. NVQ level 2 or equivalent
30. Intermediate Welsh Bac'te
31. GNVQ & GSVQ intermediate
32. RSA diploma
33. City & Guilds craft & p2
34. BTEC,SCOTVEC first & general diploma etc
35. O level, GCSE, grade A-C or equivalent
36. NVQ level 1 or equivalent
37. Foundation Welsh Bac'te
38. GNVQ,GSVQ foundation level
39. CSE below grade I,GCSE below grade c
40. BTEC,SCOTVEC first & general certificate
41. SCOTVEC modules
42. RSA other
43. City & Guilds Foundation & pl
44. Y,T,YTP certificate
45. Key Skills Qualif
46. Basic Skills Qualif
47. Entry Level qualif
48. Other qualif
49. No qualif
50. Do not know

Appendix D: Direct, indirect, and induced employment by educational attainment: running total. % of total FTE employment



Appendix D continued: Direct, indirect, and induced employment by educational attainment: running total. % of total FTE employment



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