Does good work have a positive effect on productivity? Building the evidence base

Empirical findings on the effect of good work on productivity at the sector level in the UK

By

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Table of Contents

Note: This research was commissioned by the Carnegie UK Trust and undertaken by the Warwick Institute for Employment Research in 2019. The first summary of the research findings was published in the Carnegie UK Trust's essay collection *Can Good Work Solve the Productivity Puzzle* in January 2020. Publication of this data analysis was delayed by the onset of the coronavirus pandemic. We publish now believing that the findings are highly pertinent as the phased lifting of many coronavirus restrictions allows businesses to turn their focus to their business models and approaches for the reopening and recovery of their operations. If businesses are to build back better from the pandemic and contribute to improved wellbeing, a focus on good work should be at the heart of plans for the economic recovery.

- *Gail Irvine, Senior Policy and Development Officer, Carnegie UK Trust*
  June 2021

1. Introduction

This report presents findings of the empirical work that explores the association between good work and productivity performance. The supposition is that good work can be a key factor in improving productivity. Exploring their relationship is a complex task, both conceptually and empirically. However, the positive findings of our study provide a sound basis for further future research into this association.

This report uses the Skills and Employment Survey (SES) matched with a variety of other data sources to examine this association. In the first dataset, we have integrated sectoral productivity data into the individual data in SES, so every worker in a given sector has the same level of productivity (following the ONS, defined as output per person or output per person hour) but retains their individual good work responses. In this way the sector output (gross value added) or labour productivity (output per person or per person hour) are the dependent variables; sector labour and capital (e.g. machinery and equipment) are the controls; and the individual responses to the good work variables are able to influence the sector outcome for individuals reported to work in that sector.

In the second dataset, the data are integrated at the sector level, so each good work variable is aggregated across individuals at the sector level. The sector output (GVA) or labour productivity are then determined by the control variables (employment and capital or employment, hours and capital) and the sector level good work variables. Data have been compiled for 60 Office for National Statistics (ONS) sectors.[1]

This Report presents descriptive statistics from the analysis. The next section presents findings on linking cross-sector labour productivity performance to the seven dimensions of good work recommended by the Measuring Job Quality Working Group (Irvine et al. 2018): terms of employment; pay and benefits; job design and the nature of work; social support and cohesion; health, safety and psychosocial wellbeing; work-life balance; voice and representation. The following section drills into the effects of good work on productivity cross sector, using examples from the sub-dimensional indictors of the different patterning of effect. The subsequent section presents the effect of the seven dimensions of good work on productivity performance for nine broad sectors. The final section offers some initial conclusions, as well as some suggestions for further development of the research that might usefully underpin policy thinking.

[1] This is mainly 2-digit level in the ONS classification hierarchy of sectors. However, occasionally (because of ONS worries about confidentiality) data are only published at the 1-digit level (e.g. Mining and quarrying) which reduces the number of sectors that can be matched to the productivity data and control variables.

2. Findings

The rationale for considering good work as a route to improving the UK's poor productivity performance is confirmed in our new dataset. Eighteen of our 60 sectors experienced declines in output (gross value added) per person hour over the period of 2007 to 2017, while 23 of them experienced declines over the period 2012 to 2018. However, what our data also show are the marked differences in performance across sectors. By contrast, 18 sectors had average annual rates of growth of over two per cent 2007 to 2017, with 20 sectors experiencing average annual rates of growth over two per cent from 2012 to 2017. The issue is whether the addition of good work variables adds to the understanding of the determinates of labour productivity. This section presents findings from both cross-sectoral and sectoral analyses.

2.1 Good work and productivity across sectors

The findings presented in this section are cross sectoral. Using the new database, we sought to explain productivity using the two control variables – employment and capital stock[2] – and the seven dimensions of good work (aggregated from 20 sub-dimensional indicators outlined in Table A1 in the Appendix). The 2012 and 2017 good work datasets have been merged and a separate variable is included to account for shifts in their effect over time (it is not significantly different from zero and can be ignored). The nature of the good work variables has implications for the specification of the model used to estimate their effects on labour productivity.

The focus here is on the role of the good work variables. Only the effects of the good work variables are shown in Table 1 below. Five of the seven dimensions have a positive relationship with productivity. Work-life balance is positive but not statistically significant. However, two of the dimensions are negative (we return to this finding below). The value associated with each good work variable in Table 1 represents the difference in productivity between the poorest and the best work categories (e.g. very satisfied and very dissatisfied).

Table 1: Individual regression with good work dimensions cross-sector (change in productivity, %)

Variables	Change in productivity (%)
Terms of employment	-7
Pay and benefits	8
Health, safety and psychosocial wellbeing	-9
Job design and nature of work	8
Social support and cohesion	8
Voice and representation	14
Work-life balance	2

Note: all coefficients apart from that of work-life-balance are significant at 5% level or higher (most at the 1% level)

The results suggest that there is 8% higher productivity in those workers most satisfied with pay vis-a-vis those least satisfied. The same outcomes are found for job design and social support, and there

[2] These are the control variables in our study, as increases in capital per person increase labour productivity. Note however that the coefficients on labour and capital take the same signs as suggested from a conceptual perspective, the coefficients are similar in magnitude to that found in the empirical literature and both coefficients are significantly different from zero.

is 14% higher productivity for the best voice and representation than in the poorest. Of the sub-indicators, we highlight just a few examples. The opportunity to use knowledge (part of Job design and nature of work) and teamwork (part of Social support and cohesion) are both strongly positively related to labour productivity. In addition, both voice and representation are separately positively related to productivity.

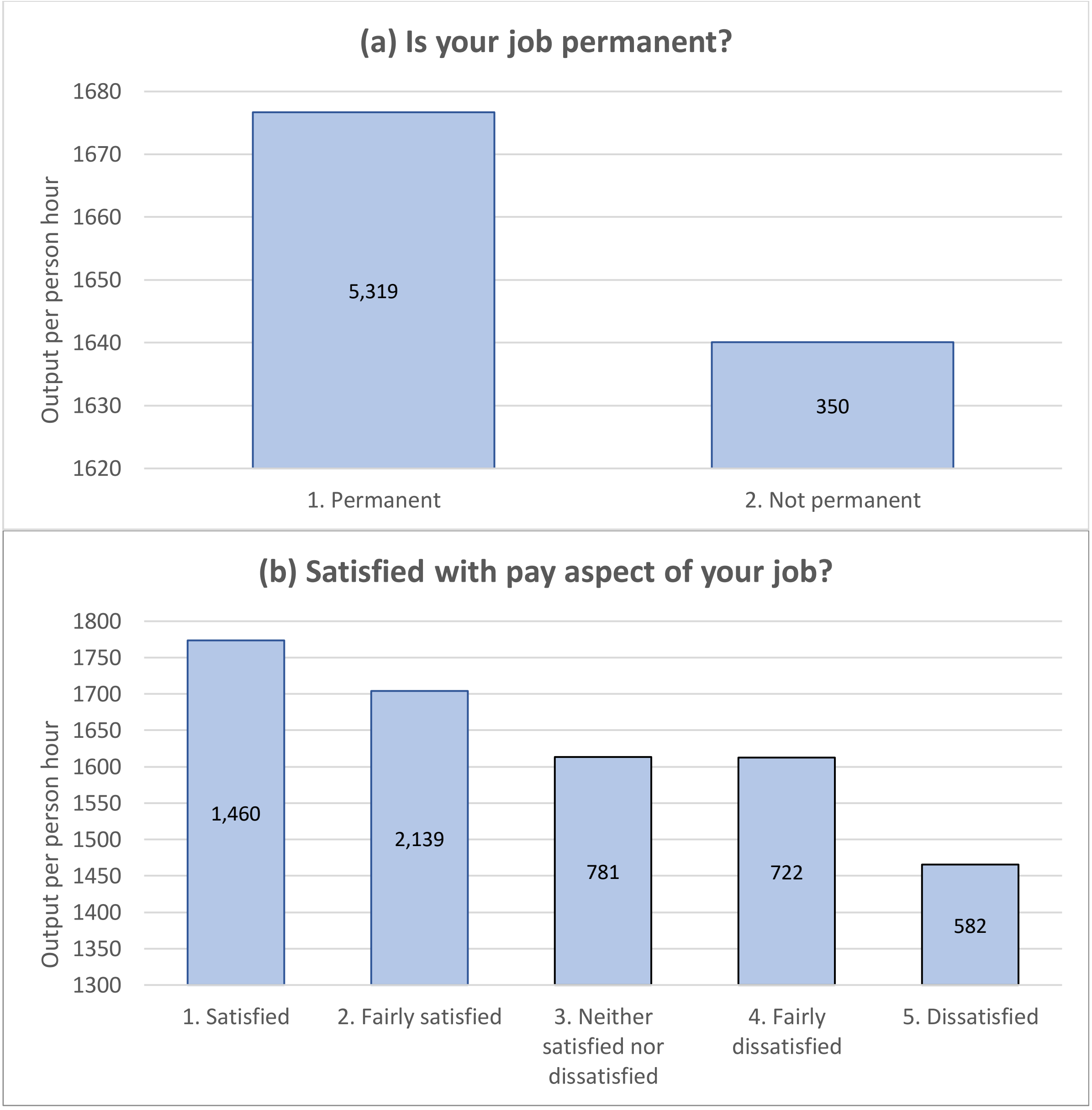
The negative value for terms of employment is caused by the considerably greater productivity performance amongst those who think they might lose their job in the next twelve months compared with those workers who do not think so. This finding is interesting and needs to be explored further, as it is also the case that job insecurity is considered to be detrimental for wellbeing. While the short-run effect of job insecurity might be to produce higher work effort and, thereby, higher productivity, the long-term effects may be negative.

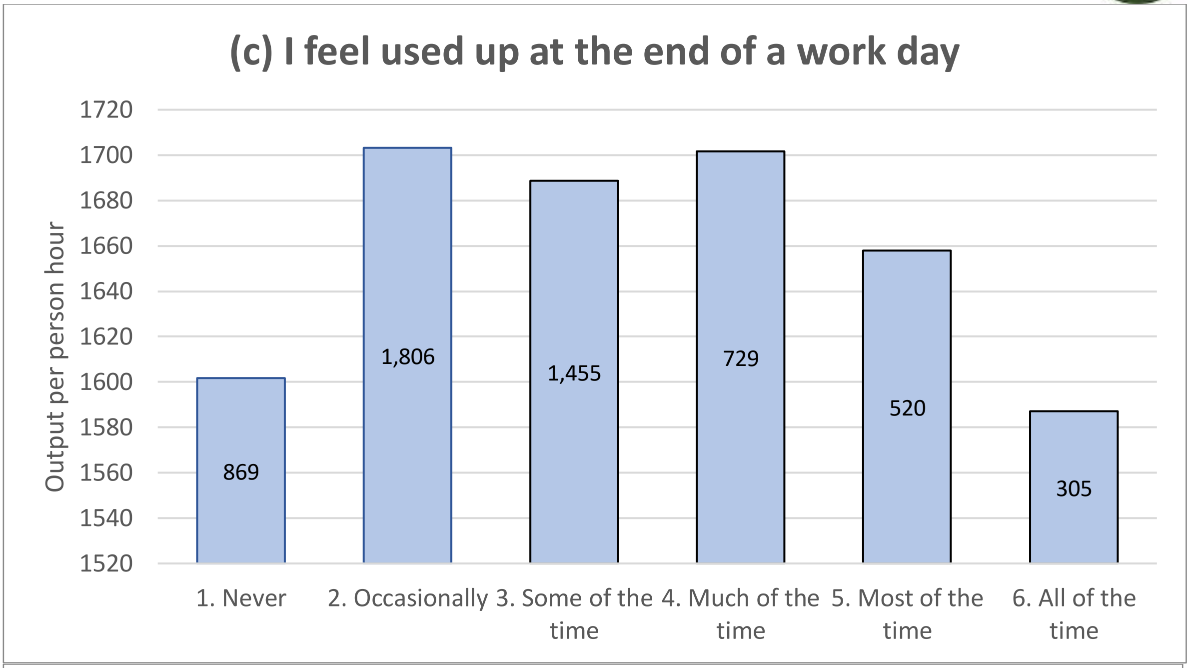
In the case of the health, safety and psychosocial wellbeing, its three sub-dimensional indicators are all negatively related to productivity, though inclusion of more indicators for this dimension will be explored in future analysis. However, one of the indicators further illustrates the need to be careful in the interpretation of the finding, as the response of “never” to the statement “After I leave work I keep worrying about job problems” is significantly negatively related to productivity, while the response of occasionally, which seems an acceptable job characteristic, is associated with the highest productivity outcome and significantly higher than the never outcome.

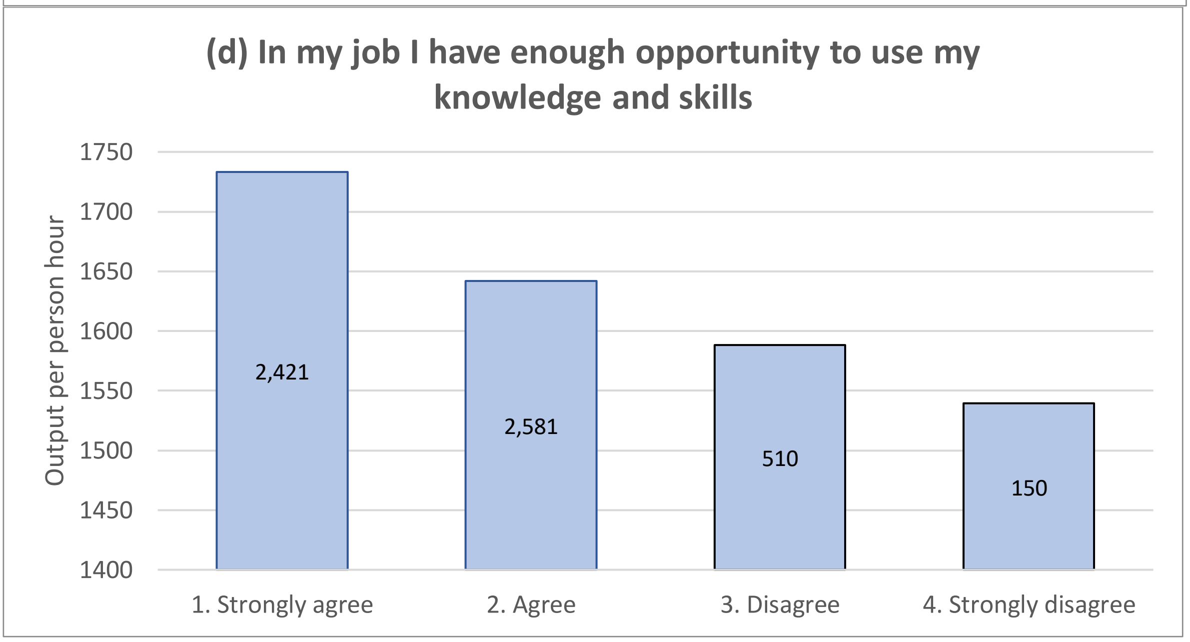
2.2 Patterns within the good work and productivity cross sectoral analysis

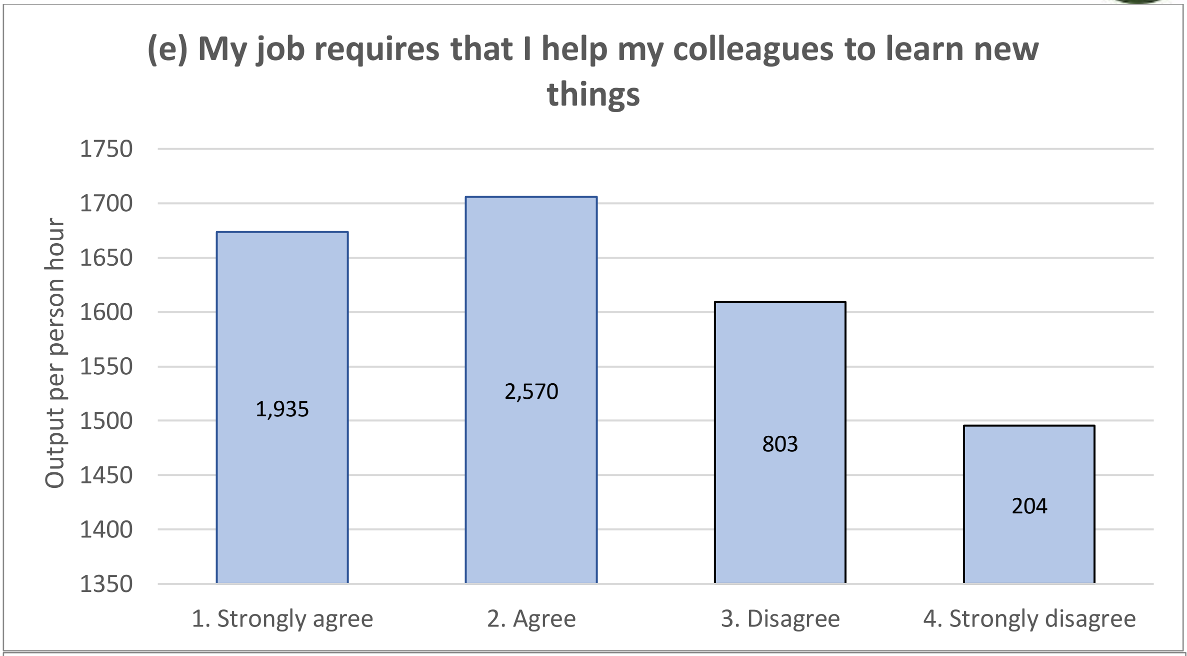
Looking at the patterns from the indicator examples within the dimensions is useful. The six charts below in Figure 1 show the (bivariate) relationship between labour productivity (GVA per employee hour) and six examples of good work. The examples have been chosen to display the range of patterns in the data, rather than for their support (or contradiction) of the good work hypothesis. The number of respondents for each category of response is shown within each column of the bar chart. Note that the number of respondents can be relatively small (e.g. there are two columns in Importance of cooperating with colleagues with less than 100 – not shown here) and this tends to be most frequent amongst the poorest good work category.

Figure 1: Example relationships between productivity and good work




(c) I feel used up at the end of a work day
Output per person hour
1720
1700
1680
1660
1640
1620
1600
1580
1560
1540
1520
869
1,806
1,455
729
520
305
1. Never
2. Occasionally
3. Some of the time
4. Much of the time
5. Most of the time
6. All of the time


(d) In my job I have enough opportunity to use my knowledge and skills
Output per person hour
1750
1700
1650
1600
1550
1500
1450
1400
2,421
2,581
510
150
1. Strongly agree
2. Agree
3. Disagree
4. Strongly disagree


(e) My job requires that I help my colleagues to learn new things
Output per person hour
1750
1700
1650
1600
1550
1500
1450
1400
1350
1,935
2,570
803
204
1. Strongly agree
2. Agree
3. Disagree
4. Strongly disagree

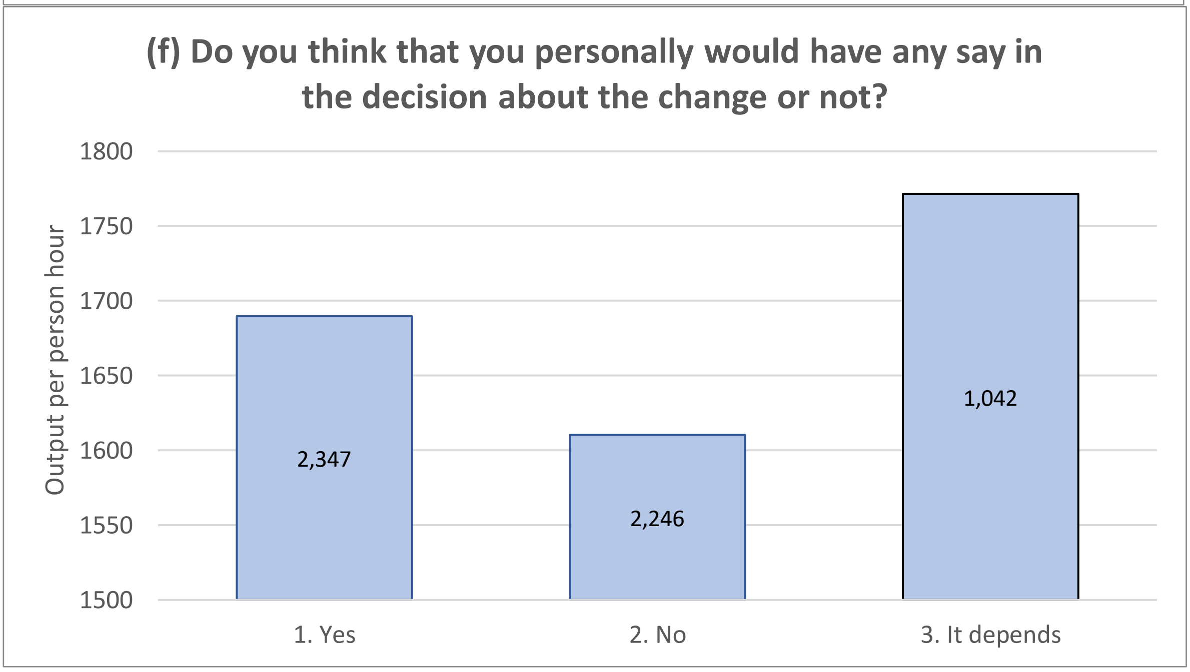

(f) Do you think that you personally would have any say in the decision about the change or not?
Output per person hour
1800
1750
1700
1650
1600
1550
1500
2,347
2,246
1,042
1. Yes
2. No
3. It depends

Figure 1(a) shows a binary choice example in which the better good work outcome has a higher productivity than the poorer. Figures 1(b) and 1(d) show monotonic declines in productivity with poorer good work outcomes. Figures 1(c) and 1(e) are examples of inverse U-shaped relationships, while Figure 1(f) is a lone example of where the respondents were given the chance to say that the outcome probably depends on the nature of the decision being made. Overall, the relationships are generally either positive (good work is associated with higher productivity, approximately seven of the sub-dimensional indicators) or inverse-U shaped (productivity is lower for the two extreme ends of good work and higher in the middle, for approximately eight indicators). The poorest good work category had the lowest productivity in 12 of the indictors and in the 14 cases where it was possible to move from the poorest good work category up to the second poorest, in 13 the move is associated with an increase in productivity.

2.3 Good work and productivity by sector

There is a large range of sectors in any economy. For ease of presentation in the sectoral analysis, the detailed sectors have been aggregated into nine broad groups, see Table 2 below. Details of this grouping can be found in Table A2 in Appendix A. Here it suffices to indicate that the Primary sector includes agriculture, mining and forestry; Low-Tech Manufacturing covers food, paper and water treatment and supply; Knowledge Intensive covers film & television, telecommunications and computer programming; Less Knowledge Intensive covers accommodation, food & beverage and travel. The analysis is the same as before, with the exception of the addition of variables that attempt to identify within-sector effects on productivity over and above the all sector effects shown in the final row of Table 2. As the within-sector effects of good work account for some of the explanation of productivity, it produces a difference in the all sector results between Tables 1 and 2.

Table 2: Individual level regression with good work dimensions for nine broad sectors (change in productivity, %)

Variables	Primary	Construction	Low-Tech Manufacturing	High-Tech Manufacturing	Less Knowledge	Knowledge Intensive	Public Administration	Education	Health	Overall
Terms of employment	-33	+	-	-	-7	-	-	+	7	-7
Pay and benefits	-	+	-	-	+	23	+	+	+	8
Health, safety and psychosocial wellbeing	-	+	+	-	-	-11	+	+	+	-8
Job design and nature of work	-	+	-	-	13	14		+	-42	10
Social support and cohesion	+	+	-15	+	-	22	+	14		+
Voice and representation	60	+	-13	+	-	17	+	+	-	14
Work-life-balance	55	-	3	13	-	10	+	+	30	+

Note: only statistically significant coefficients are shown. Where values are insignificant, only the possible direction of the impact on productivity is shown.

The results suggest that there are some important differences between sectors in the effects of good work on productivity. The overall results (final column), when the sector effects are included, are almost the same as those reported in Table 1, although one or two percentage effects are marginally smaller. Even bearing in mind the earlier discussion that the estimates reflect the difference between the poorest quality work and the best (e.g. very dissatisfied and very satisfied), some of the sector estimates seem large. The primary sector and the health sector stand out in this regard, though we have already noted the problem defining productivity in the public sector. On the other hand, the knowledge intensive sector suggests considerable support for the link between good work and productivity, with the exception of health, safety and psychosocial wellbeing.

3. Conclusions

Through this research, we have established both a conceptual and empirical framework for the analysis of the effects of good work on labour productivity. Important parts of this framework have been tested on data drawing on the results of the 2012 and 2017 SES. The dataset is micro, individual level with merged sector level data. The data have been used to produce descriptive statistics about the links between labour productivity and good work, and have been explored using multivariate techniques that also control for the inputs of capital and labour.

The datasets have been tested for validity, showing that they produce similar results to the literature on log-linear production functions. The results are consistent with output being positively and significantly related to capital and labour inputs (although hours of work did not appear to play a significant role). They are also consistent with labour productivity being negatively related to employment level, other things being equal. These results continued to hold even when the good work variables were added to the framework.

The bivariate descriptive analysis linking each good work sub-dimensional indicator to productivity showed two main patterns emerging: one where productivity was positively linked across sectors to the degree to which good work was reported; the second was an inverse U-shape between productivity and the degree to which good work was reported. The relationship is positive (good work is associated with higher productivity) in seven sub-dimensions out of 17) and inverse-U shaped (productivity is lower for the two extreme ends of good work and higher in the middle) in eight sub-dimensions. The poorest good work category had the lowest productivity in 12 of the sub-dimensional indicators and in 13 of the 14 cases where it is possible to move from the poorest good work category up to the second poorest, the move is associated with an increase in productivity.

Initial tests suggest that there may be important differences between sectors with regard to the effects of good work. The positive effect of good work on productivity is, however, particularly marked in the knowledge intensive sector – a sector that attracts much policy attention in the UK, most obviously in industrial strategies (See for example, HM Government 2017).

The relative importance of the inverse-U shape suggests that this non-linearity needs testing in the multivariate analysis, something that has not yet been undertaken but needs to be a next step. If it was confirmed by the multivariate analysis it would suggest that increases in productivity might be best stimulated by concentrating on improvements to the poorest good work situations, rather that spreading efforts across the spectrum of good work. Relatedly, the highest performance category may not always be the ‘best’, for example in the cases of After I leave my work I keep worrying about job problems and I feel used up at the end of a workday, it might be natural to *occasionally* worry in this way or feel used up. It also suggests that more needs to be known about whether different dimensions and indicators tend to go together (e.g. and work together or off-set one another – work as a system or not).

The results obtained so far from the micro-individual data, suggest that Pay, Job design, Social support, Voice and Representation all play their part in raising labour productivity, while more needs doing to investigate the role of Terms of employment and Health consequences of work.

Another obvious next step is to examine the effect of productivity on good work. In other words, whether there is a feedback mechanism by which good work impacts on productivity but higher productivity also encourages the quality of work. Some simple results are available from our new dataset. Relating the earnings data for 2017 to the productivity data for 2015 suggests causality may also run from productivity to earnings. While there may be a number of reasons why this relationship is not causal, the results do suggest that higher labour productivity is associated with higher earnings, with a one percent increase in productivity per person hour in 2015 associated with 0.22 percent higher average earnings in 2017.

A more rigorous test of the potential feedback from productivity to earnings is to estimate the relationship between the change in earnings and the change in productivity. Estimating the partial relationship between the change in earnings on the change in productivity over the period 2007 to 2017 suggests no relationship exists. However, when productivity change is lagged (e.g. 2007 to 2012) vis-a-vis earnings (2012-2017) a correlation coefficient of 0.22 is found (where 0 is no correlation and 1 is a perfect correlation). Running a regression of the change in earnings on productivity change, shows a low explanatory power (e.g. many other factors affect the change in earnings) but the coefficient on the change in productivity is both positive and significantly different from zero.[3] A one per cent increase in prior labour productivity is associated with approximately a 0.1 per cent increase in subsequent earnings.[4]

Thus, there is some initial evidence to support a feedback mechanism, such that an increase in satisfaction with pay leads to higher labour productivity and higher labour productivity results in a subsequent increase in earnings. If this finding is sustained in analysis across the other dimensions of good work, it would suggest that a virtuous circle might exist – and be promoted in UK policy – by which good work improves productivity and productivity delivers good work.

[3] At the 10 per cent level.

[4] The results also suggest that the residual from the production function (e.g. the element of output that cannot be explained by labour and capital, which includes good work) is also significantly positively related to earnings (with a coefficient significant at the 10 per cent level in the log-linear function and at the 1 per cent level in the linear relationship). A one per cent per cent higher residual (e.g. one per cent higher role for factors other than capital and labour) is associated with 0.1 per cent higher average annual earnings.

Acknowledgements

We would like to thank Professor Alan Felstead of Cardiff University and Professor Duncan Gallie, of Nuffield College, Oxford University, for providing advance access to data from the 2017 Skills and Employment Survey at the time when we were compiling this research.

Appendix A

Table A1: List of indicators used in the final indices

Number of indicators	Variable name	Questions
1. Terms of employment		
1	Bperm	Whether job is permanent or not?
2	BLoseJob	Do you think there is any chance at all of you losing your job and becoming unemployed in the next twelve months?
2. Pay and benefits		
3	Ksat2	Satisfaction with this aspect of your job – your pay
3. Health, safety and psychosocial wellbeing		
4	IWorry	After I leave my work I keep worrying about job problems
5	IUnWind	I find it difficult to unwind at the end of a workday
6	IUsedUp	I feel used up at the end of a workday
4. Job design and nature of work		
7	BUseSkil	How much do you agree or disagree with the following statement: "In my current job I have enough opportunity to use the knowledge and skills that I have"
8	Bchoice	How much choice do you have over the way in which you do your job
9	Btimeoff	How difficult is it arranging to take an hour or two off during working hours to care of personal things
10	BMe2	And how much influence do you personally have on … 'deciding what tasks you are to do?'
11	Einspire	And to what extent do you agree that 'this organisation really inspires the very best in me in the way of job performance'?
5. Social support and cohesion		
12	BHelpOth	'My job requires that I help my colleagues to learn new things'
13	Cteamwk	(And how important is …) 'working with a team of people?'
14	Ccoop	(And how important is …) 'cooperating with colleagues?'
6. Voice and representation		
15	Eviews,	At your workplace, does management hold meetings in which you can express your views about what is happening in the organisation?

16	Emesay,	Suppose there was going to be some decision made at your place of work that changed the way you do your job. Do you think that you personally would have any say in the decision about the change or not?
17	Eunions,	At your place of work, are there unions or staff associations?
18	Emember	Are you a member of a trade union or staff association?
7. Work life balance		
19	BOTime,	'I often have to work extra time, over and above the formal hours of my job, to get through the work or to help out':
20	Bexhaust	How often do you come home from work exhausted …

Table A2: Grouping SIC 2007 2-digit classification into 9 broad sectors

Sector	**2-digit SIC2007**
Primary	
	01 Crop, animal production, hunting
	02 Forestry and logging
	05 Mining of coal and lignite
	06 Extraction crude petroleum and gas
	08 Other mining and quarrying
	09 Mining support service activities
Construction	
	41 Construction of buildings
	42 Civil engineering
	43 Specialised construction activities
Low-Tech Manufacturing	
	10 Manufacture of food products
	11 Manufacture of beverages
	13 Manufacture of textiles
	14 Manufacture of wearing apparel
	15 Manufacture of leather and related
	16 Manufacture wood and wood products
	17 Manufacture paper & paper products
	18 Printing and recorded media
	19 Manufacture of coke & refined petro
	22 Manufacture rubber plastic products
	23 Manuf non-metallic mineral products
	24 Manufacture of basic metals
	25 Manuf fab metal prods, ex machinery
	31 Manufacture of furniture
	32 Other manufacturing
	33 Repair and installation of machinery
	35 Electricity, gas and air cond supply
	36 Water collection, treatment & supply

High-Tech Manufacturing	
	20 Manufacture of chemicals
	21 Manufacture of pharmaceuticals
	26 Manuf computer, electronic & optical
	27 Manufacture of electrical equipment
	28 Manuf of machinery n.e.c.
	29 Manuf vehicles and trailers
	30 Manufacture of other transport
Less Knowledge Intensive Private Businesses	
	37 Sewerage
	38 Waste collectn, treatment, disposal
	45 Wholesale retail trade repair vehcl
	46 Wholesale trade, except vehicles
	47 Retail trade, except vehicles
	49 Land transport inc via pipelines
	52 Warehousing & support for transport
	53 Postal and courier activities
	55 Accommodation
	56 Food and beverage service activities
	77 Rental and leasing activities
	79 Travel, tour operator, reservation
	81 Services to buildings and landscape
	82 Office admin, support and other
	94 Activities membership organisations
	95 Repair of computers and other goods
	96 Other personal service activities
Knowledge Intensive Private Businesses	
	50 Water transport
	51 Air transport
	58 Publishing activities
	59 Film, video, television sound record
	60 Programming and broadcasting
	61 Telecommunications
	62 Computer programming and consultancy
	63 Information service activities
	64 Financial ex insurance and pension
	65 Insurance, reinsurance and pension
	66 Auxiliary to financial and insurance
	68 Real estate activities
	69 Legal and accounting activities
	70 Head offices; management consultant
	71 Architectural and engineering
	72 Scientific research and development
	73 Advertising and market research
	74 Other prof, scientific and technical
	75 Veterinary activities
	78 Employment activities

	80 Security & investigation activities
	90 Creative, arts and entertainment
	91 Libraries, archives, museums
	92 Gambling and betting activities
	93 Sports, amusement, recreation
Public Administration	
	84 Public admin, defence, social sec
Education	
	85 Education
Health	
	86 Human health activities
	87 Residential care activities
	88 Social work without accommodation

Note: This grouping follows Eurofound (2015) and incorporates the 60 sectors included in the productivity analysis

Appendix B

Options assessed for carrying out good work and productivity sectoral analysis

Critical to our research was identifying the most lucrative datasets available to empirically investigate the effect of good work on productivity at the sector level. We have included this appendix, which recounts our analyses of the strengths and limitations of available datasets for this task, to highlight the data gaps which exist, and with the aim of supporting further research in this area.

1| Modelling productivity

Productivity measures the efficiency with which inputs into production are converted into the outputs of goods and services. The ONS generally uses labour productivity – the level of gross domestic product (GDP) per person or per person hour of labour input – as its standard measure of productivity for reasons set out below. GDP is a measure of the value added at each stage of production (e.g. a sector may buy in goods and services, which are modified and sold on, the difference in the cost of buying in and the revenue from selling on is the value added). The value added can be distributed, directly (e.g. through wages and dividends) or indirectly (e.g. through taxes and government spending) to workers and other individuals in society.

The productivity literature generally adopts an underlying production function to represent the relationship between inputs and outputs, from which a measure of productivity can be derived (Bosworth, 2005, pp. 47-58). In a value added (VA) function, intermediate inputs (the products produced by other firms, including energy and materials) do not appear, but appear in the value added of suppliers of those products, but each sector's capital (K, e.g. equipment), labour (e.g. individuals, E and hours, H) and the level of technology (T) are present. The literature also suggests that value added can be increased through people by improvements in working conditions (e.g. good work, G) – by enhancing employee capabilities, as well as their motivation and willingness to give 'discretionary effort' (Appelbaum et al. 2000).

The Warwick Institute for Employment Research (IER) has data on value added, employment and hours at the two-digit SIC (75 sectors) annually over a long period of time, constructed by Cambridge Econometrics from ONS data and used in modelling Working Futures 7. This will form the basis for the dependent variable (VA) labour productivity.

Capital inputs: concepts and data sources

Inputs of physical capital (like machinery, equipment or buildings) is one driver of productivity. ONS publish data on gross and net capital stock, by type of capital. Gross stock is the current day replacement cost associated of buying the equivalent items today, irrespective of how old the existing items are (Harris, 2014 p. 4). The net stock reflects the market value of the capital (e.g. what it can be sold for), which will be lower than the gross value of capital stocks and will reflect the market's view of the depreciation of the assets with age (op cit. p. 4). Both gross and net stock are available for about 75 sectors by type of capital.[5]

[5] Buildings and structures (other than dwellings, which not largely not relevant), Transport equipment, Cultivated biological resources, Machinery, equipment and weapons systems, Other machinery, equipment and weapons systems and various assets related to computers and other technologies (see Appendix A.4).

ONS uses what is called a perpetual inventory method (PIM) for the calculation of the stock (Harris, 2014, p. 6). This cumulates the investment in capital assets (gross domestic fixed capital formation) over time within a sector and assumes that the assets depreciate with age, so assets at the end of their tenth year will have undergone ten years of depreciation. The depreciation rate is constant over the life of each asset, based upon an estimated average life of each asset (e.g. it is not influenced by differences in the utilization of capital across sectors), but differs between types of capital (e.g. transport equipment versus buildings). The PIM assumes a symmetric retirement distribution around the estimated mean of the asset's length of life.

Technology inputs: understanding the relationship with good work

The distinction between capital (K) and technology (T) is made because of the need to explore the way in which the technologies linked to automation have a different impact on labour productivity than traditional capital stock.

To give an example, suppose a firm's office space is too small and employees are not able to operate efficiently, if the firm extends the office (increases K) without changing employee hours, then labour productivity rises.

On the other hand, if a firm automates a set of tasks by means of new computers and software (an increase in T), this increases labour productivity as long as the technology does the task more efficiently (and cost effectively) than humans.

Box 1: Deriving Output per Person Hour from a Production Function

Equation (1) shows the key determinates of value added, VA,

$$VA = f(E, H, K, G, T) \tag{1}$$

employment (E), hours per person (H), the capital input (K) and the level of technology (T). Our hypothesis that good work affects the output, other inputs constant. The link with productivity can be shown using a log-linear production function, one of the simplest forms,

$$VA = AE^{\alpha}H^{\beta}K^{\gamma}G^{\delta}T^{\varepsilon}GT^{\theta} \tag{2}$$

where α, β, γ, δ, ε and θ are parameters (constants) to be estimated empirically. Dividing both sides by person hours yields,

$$\frac{VA}{EH} = AE^{\alpha-1}H^{\beta-1}K^{\gamma}G^{\delta}T^{\varepsilon}GT^{\theta} \tag{3}$$

Equation (2) is normally estimated, as the presence of E and H on both sides of the equation can lead to a spurious correlation, but then the influences on productivity can be estimated using equation (3).

The measurement problems associated with each of the variables in the production function model are discussed in Appendix A.

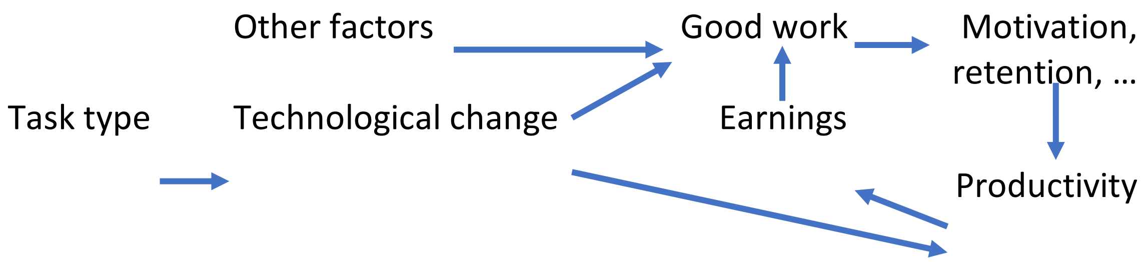
Changing the tasks carried out by humans may also change the quality of work. Technological change literature focuses on the likelihood that certain tasks are more susceptible to automation than others, for example, routine tasks (Autor et al. 2003). By implication, occupations that are routine-task rich are most likely to be susceptible to having their human element to be at least partly replaced by non-human technologies (e.g. artificial intelligence, machine learning, robotics, etc.). This would change the nature of the work tasks carried out by a worker with implications for both job quality and productivity. However, the impact of these changes on quality of work and productivity may vary.

The replacement by automation of workers in routine tasks, for example, may raise the quality of work for the individuals remaining in employment. The complementarity of the automation of abstract tasks may free individuals from, for example, high-level mathematical calculations, but allow them to explore new applications for high-level mathematics. The use of drones may reduce the risks of high-altitude surveillance work or the danger of injury or death in military operations (Frey, 2015, p. 41). However, the impact of task displacement on job quality depends on the extent to which displacement takes place (e.g. the extent to which tasks within the occupation are susceptible) and the extent to which the workers remaining to fulfil non-affected tasks can capture the returns to technology in higher wages and the product price elasticity of demand (Bessen, 2016, p. 22).

This all suggests that the effect of the key potential driver we are investigating**, the effects of good work on enterprise** performance, are unlikely to be identified without explicitly controlling for technological change, which is complex to do given the potential interactions between technology, work tasks and occupations, and wider good work considerations.

Box 1 (p.2) suggested a simple specification based upon a log linear production function. However, it should be noted that the empirical specification of production functions has become increasingly complex over time, mainly introducing more and more flexible forms, including the complexity we are illustrating with regards to technology, that do not constrain the relationships between inputs and outputs so greatly.

To illustrate the potential linkages, the flow diagram on p.4 sets out a simplified causal system. It assumes that the type of task (e.g. routine, abstract, etc.) determines the opportunity for technological change (e.g. automation). As automation only occurs when the automated outcome is an improvement on human input, then labour productivity rises (the direct link between technological change and productivity in the illustration). Assuming, for example, that routine tasks are repetitive and a source of poor work, then the removal of such tasks raises the quality of work which, in turn, can be a source of increased productivity (the indirect link between technological change and productivity). Of course, a variety of other factors will impact on the quality of work.



Given that the gains from higher productivity are generally at least partly shared with the workforce in the form of higher pay, and earnings are a component of good work, there is a further feedback into motivation, retention, etc., which causes a virtuous circle for performance and good work.

Data on technological change

Traditional treatment of technological change

In the early work on production functions, and thereby productivity, technological change was often measured as a residual (e.g. the improvements in output not accounted for by changes in the labour and capital inputs) (e.g. Solow, 1957). A subsequent raft of work then took place using proxy measures such as patent counts and quality adjusted patent counts (using the number of citations as a measure of quality) (e.g. Jaffe and Trajtenberg, 2002). However, patents are not relevant to the present study as they are highly restricted in terms of the number of sectors where they are relevant.

- ***Technology-related capital stock***

Computer use has been used as a proxy for automation (e.g. see Bessen, 2016). ONS publish data on gross and net computer hardware (CH) and computer software and databases (CS&D), but also on telecommunications equipment (telecom), information communications equipment (ICT), R&D equipment (R$DS) and intellectual property stocks (IPS). As with the traditional capital stock data, the technology-related data are available from 1995 onwards for 75 sectors, but some kinds of capital stock are not relevant for some sectors. The methodology used in constructing the capital stock is set out in Harris (2014) and in brief in Section 3.4 above.

- ***Tools and technology***

O*net contains a "Tools and Technology" (T2) module[6], which is a massive dataset mainly collected through internet searches (Handel, p.162) that identifies the tools and technology used by each occupation. According to the O*NET web site, over 32,000 tools and technologies are represented in the database, coded into over 18,000 non-duplicative UN Standard Products and Services Codes. Nevertheless, it would be possible to include tools/technology like robotics as a dummy (1,0 e.g. do use, do not use) variable.

- ***Likelihood of automation***

There are a number of studies that produce statistics on the likelihood of automation. Autor, *et al*. (2003), for example, explore the effects of the degree of susceptibility for each occupation to be automated on subsequent employment growth (which is negative for routine cognitive- and routine manual-rich groups), which can be replicated by the model developed here. ONS have produced two cross sections (2011 and 2017) of the susceptibility of occupations and sectors to automation (369 occupations and 75+ sectors).[7] The 2011 data, in particular, can be used to look at subsequent output, employment and productivity growth.

- ***Technology surveys***

The main "technology" survey in the UK is the UKIS (the UK Innovation Survey, which is part of the European Community Innovations Survey, CIS)[8]. It is carried out every two years and covers innovation and related activities over the previous two years. Sample sizes are large, for example, 13,194 businesses in 2017 and slightly larger numbers of respondents in 2015 and 2013. The sectoral coverage is at the 2-digit SIC level, but some sectors are not sampled and some are amalgamated, yielding 25 sectors (compared with the 75+ relevant 2-digit ONS Divisions). So, although the potential questions are highly relevant to modelling the effects of technological change (e.g. product and process innovation, with some information on organisational change), using the UKIS would constrain the number of sectors available.

While the above present some potential data sources, as yet it is not clear whether the data will enable one or more of these more complex functions to be estimated.

Management

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[6] https://www.onetcenter.org/reports/T2Development.html

[7] The probability of automation in England: 2011 and 2017. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/theprobabilityofautomationinengland/2011and2017

[8] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/750539/UKIS_2017_stats_annex_fin.ods

It is hard to integrate the role of management within such a formulation as we set out above, seeking to clarify the inputs of capital, and technology, and (explored below) good work on productivity. From a conceptual point of view management is pervasive; from an empirical point of view management and leadership are difficult to measure.

It is possible, however, to identify some key decisions that management have to take: (i) the nature of working practices (good work) prior to (further) automation, of which the nature of management, leadership and supervision are a part; (ii) the decision to automate (e.g. based on whether machines carry out one or more tasks more efficiently or more cost effectively than humans); (iii) whether to share part of the efficiency gains in the form of higher earnings for workers (also an element of good work).

2 | Assembling the sector level dataset

Why undertaken sector level analysis?

The competitive dynamics and characteristics of different sectors exert an influence on constraints on and enablers of quality of work in the sector, which means developing our sector-level understanding is useful in shaping policy solutions. From a data perspective there are other more practical reasons for doing so: i) there is little or no usable productivity data by occupation; ii) while productivity data are available at the enterprise level (e.g. via BRES and ABS, which are confidential but can be accessed), there are no good work data or occupational data at this level. Therefore, empirical work is largely restricted to sectors, where occupational data are available and good work by occupation can be matched on (with occupational weights for the sector). Other control variables (e.g. capital stock and technology) and potentially endogenous variables (e.g. which have feedback mechanisms within a system of variables, such as good work) are available by sector.

Given that productivity data are not available by occupation, only by enterprise, sector or economy-wide and “good work” data are not available by enterprise, this effectively determines that the dataset will be organized by sector. As the occupational mix of each sector is also known, then an occupational breakdown of good work can also be calculated by sector, weighting the measures of “good work” for each occupation by the relative importance of each occupation within the sector. However, it is also possible to examine the distribution of individuals by measures of job quality within each sector.

Working at the sector level has the advantage that data from different sources can be merged together. So surveys such as the LFS, which have a small number of very useful good work variables, can be added to other datasets such as SES or O*net (IER). In addition, if a good work dataset spanning a number of years can be constructed, then a panel of sectors can yield a more rigorous way of testing the causal link between good work and productivity.

Datasets on job quality – what are the options?

Six datasets have been identified with questions relating to good work. While some of these datasets have, at best, partial coverage of the dimensions of good work, a sectoral approach means that these questions can be amalgamated with questions from surveys with coverage of other dimensions and productivity data by sector.

The data challenge is that many surveys have sample sizes that do not allow very disaggregated analysis. For example, while there are 615 4-digit occupations and 369 4-digit sectors[9] classified in UK national statistics, no surveys relating to good work have this level of detail. In practice the level of sector disaggregation for the present study is largely fixed by the availability of the productivity variable, which is available at the two-digit (Division) level.[10] The ONS 2-digit sectors of which there are about 85, contain a number of sectors that are normally not used in statistical work[11], resulting in 75 usable sectors, where we intend to focus our analysis.

While data on occupations is often more disaggregated (e.g. UK version of O*net is available at the 4-digit level, which yields about 390 occupations) it is the sector that drives the level of detail in the statistical work as the occupational detail has to be aggregated to the sector level. However, the occupational detail will enable something to be said, for example, about the distribution of the measure of good work within each sector.

Conclusions

Taking these restrictions into consider, we assessed the most optimal analytical options to be:

1. Using **SES**, years 2012 and 2017 (if available) mean cell sample 43 per year
2. Using **EWCS**, years 2010 and 2015, mean cell sample 23 per year
3. Using **O*net**, 2013-2018, mean cell sample unknown, but probably much larger than available from SES.

To clarify, the higher the cell sample, the more reliable the use of the data for statistical analysis we wish to undertake examining the relationship between good work and productivity. While it may be possible to undertake some combination of the options for analysis given above, given the timeframe of this project, we would recommend proceeding with one of these options. This is a discussion for the Expert Group.

Below, we highlight the strengths and limitations of these three most optimal data modelling options. Following this, we highlight some other potential sources of data, which are less optimal for these purposes, but the group may nevertheless like to consider. Finally, table 1 (p. 12) summaries the characteristics of all the datasets.

Options

- **UK Skills and Employment Survey (SES)**

The UK Skills and employment Survey is a nationally representative survey that follows a random sampling design. The first SES was funded by ESRC and was carried out in 1986 and then subsequently in 1992, 1997, 2001, 2006, 2012, and 2017. Its primary objective was to provide information on skills and measure ten generic skills including computing skills of employed individuals aged between 20

[9] https://www.ons.gov.uk/file?uri=/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/adhocs/008439employmntbydetailedoccupationandindustrybysexandageforgreatbritainukandconstituentcountries/4digitoccupationand4digitindustrybyagebandsfinal.xls

[10] It is possible to use the Business Register and Employment Survey with the Annual Business Survey to construct labour productivity and total factor productivity at the enterprise level, but this has to be done within the ONS Virtual Laboratory.

[11] E.g. Activities of households as employers of domestic personnel, Undifferentiated goods- and services-producing activities of private households for own use and Activities of extraterritorial organisations and bodies. https://www.ons.gov.uk/file?uri=/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities/uksic2007/uksic2007web.pdf

and 60 (extended to 65 in 2006 and 2012). In addition, 2006 and 2012 skills surveys have also added the extra dimensions of skills in the workplace and collected the information on those dimensions. The extra dimensions are, in your job, how important is: a) looking the part; b) sounding the part; c) handling the feelings of other people? The surveys consider aesthetic and handling emotion as some important skills which may affect the labour market outcomes. A total of 4800 workers have been surveyed in 2006 and 3,200 workers are surveyed in 2012.

In addition to the individual details, the survey covers –

1. Broad Questions about the Job
2. Detailed Job Analysis Questions
3. Computing Skills and Qualifications Questions
4. Work Attitudes
5. The Organisation
6. Pay Questions
7. Recent Skill Changes and Future Perspectives
8. Well-being at Work

The individual questions for each of the seven dimensions of 'good work' are presented in Appendix B.2. It looks like SES covers all the dimensions of 'good work'. However, it does not have any indicator which could be used as a measure of productivity at any level.

The dimensions of "good work" are measured at occupational and industry level using the Standard Occupational Classification (SOC) and Standard Industrial Classification (SIC). The surveys used SOC 2010 and SIC 2007, both at 4-digit level in 2012. As the 2012 survey only interviewed around 3,200 workers in the UK,[12] this will lead to small cell sizes for many of the four-digit occupations and industries. There are 335 occupations following SOC 2008 4-digit classification and 369 industries following SIC 2007 4 digit classification in the 2012 SES data, hence, many of the cells will be empty.

- **European Working Conditions Survey**

The last EWCS was carried out in 2015. Fieldwork for the new wave of the survey was terminated in 2020 due to the coronavirus pandemic, but has resumed in 2021, with findings expected to be published in 2022. The sixth survey interviewed around 44,000 workers in 35 countries, providing detailed information on a range of issues linked to the quality of working life, including exposure to physical and psychosocial risks, work organisation, work–life balance, and health and well-being.[13] It also contains a number of variables that help to put this information into context, for example, sector, occupation, enterprise size, etc. Note that there is a sister survey, the European Company Survey that contains a considerable number of questions on the management of the companies. The main problem with both surveys is the sample size. In most countries, the target sample size was 1,000, in

[12] https://www.cardiff.ac.uk/research/explore/find-a-project/view/117804-skills-and-employment-survey-2012
[13] https://www.eurofound.europa.eu/surveys/european-working-conditions-surveys/sixth-european-working-conditions-survey-2015

the UK it was raised to 1600 and 2000 in Germany.[14] Although occupations are coded at the 4-digit level and sectors at the 3-digit level, the sample sizes are not sufficiently large to provide comprehensive coverage at these levels.

- **O*net**

The O*net and its predecessor (DOT) have been widely used in the investigation of the effects of skill-biased technological change. O*net is a US database; however, it has been used in UK studies to model these same effects, with the presumption being that the nature of the working environment has significant read across to workers in the UK context. This contention is nevertheless subject to debate. Warwick Institute for Employment Research have produced a concordance between the US occupational classification and that of the UK, at the four-digit level, which allows UK individuals to exploit the extremely detailed occupation information of O*net. The *European Skills, Competences, Qualifications and Occupations* (ESCO)[15] appears to offer a similar, though less comprehensive, bridge between occupations and tasks for European Member States and a small number of other countries.

The "Working Context" section of the US O*net, at the time of writing, has 57 different dimensions of the working environment for every occupation. These fall into three main categories:

- interpersonal relationships comprises 14 elements, which describe human interaction processes that occur as part of that occupation;
- physical work conditions comprises 30 elements, which describe the work content in terms of the interactions between the worker and the physical environment within which their work takes place;
- structural characteristics of the job comprises 13 elements, that describe relationships or interactions between the individual and other actors and processes related to their job.[16]

The full listing can be found in Appendix B.5. The listing includes many of the variables found in the Eurofound's European Working Conditions Survey (EWCS)[17], although not all the O*net elements necessarily imply something about poor or good conditions of work.

O*net draws its information from a variety of sources, but relies heavily on standardized surveys of a representative sample of those employed in each occupation (Handel, 2016, p. 159), as well as inputs by job analysts (e.g. where the questions were more abstract). Eight different areas are surveyed, of which the "work context" is the most relevant to the present study. Note, however, that a number of elements, may have a similar focus but may be found in different surveys, so it is important to check in the other six areas (researchers are not given access to the seventh other area on respondents' personal characteristics and other background information).[18] Generic versions of the questionnaires are made available for other potential users.[19]

The first completed version of O*net was finalized in 2008 and occupations are resurveyed on a continuous basis in 5-year cycles, so a completely new set of ratings was completed in 2013 (*op cit*. p.

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14 See the Technical Report, p. 65. https://www.eurofound.europa.eu/sites/default/files/ef_survey/field_ef_documents/6th_ewcs_-_technical_report.pdf
15 https://ec.europa.eu/esco/portal/howtouse/21da6a9a-02d1-4533-8057-dea0a824a17a
16 https://www.onetonline.org/find/descriptor/browse/Work_Context/
17 https://www.eurofound.europa.eu/surveys/european-working-conditions-surveys/sixth-european-working-conditions-survey-2015/ewcs-2015-questionnaire
18 https://www.onetonline.org/find/descriptor/browse/Work_Activities/
19 https://www.onetcenter.org/questionnaires.html

159). Responses are averaged across respondents within each occupation and the individual response data are not made available for research purposes, so the published data may conceal significant variation within occupations (*op cit*. p. 160). Response rates are relatively high for this type of survey and, it appears that all the measures are based on at least 15 respondents, often more (*op cit*. p. 160). When aggregated to two-digit level sample sizes will be much higher. Sample weights are not applied and, therefore, there are issues about the representativeness of the sample (op cit. p. 161). The O*net data have been reclassified to UK SOC at the 4-digit level (615 occupations).

Other potential data sources

- **CIPD: UK Employee Outlook (EO) Survey and UK Working Lives (UKWL) Survey**

Employee outlook. The EO surveys are conducted by CIPD and commissioned by YouGov. The first survey was carried out in Spring 2009 and the last one in Spring 2017. CIPD commissioned YouGov to conduct regular surveys of a sample of 2,000 to 3,000 UK employees and sole traders, to identify their opinions of and attitudes towards working life. The surveys cover job satisfaction, employee engagement, well-being and work-life balance, perceptions of line managers and senior leaders, pressure at work, voice, and job-seeking.

YouGov conducted the latest survey for CIPD in February and March 2017. A sample of 2,224 UK employees was drawn from a panel of more than 350,000 individuals who had agreed to take part in surveys. The sample is weighted to be representative of the UK workforce in relation to sector (private, public, voluntary) and size, industry type and full-time/part-time working by gender. The size of organisation was classified in the following way: sole trader (one-person business), micro business (2–9 employees), small business (10–49), medium (50–249) and large (more than 250).

The survey covers all of the good work dimensions (presented in Appendix B.3). However, it does not cover anything on productivity. There are about 50 occupational groups and 35 sectors, neither of which appear wholly consistent with the official SOC and SIC.

UK Working Lives. UK Working Lives (UKWL) is the successor of EO. In 2017, CIPD worked with the Institute for Employment Research (IER) at Warwick University and the Manchester Alliance Business School, to develop the EO into UKWL a survey focused on job quality. The main aim was to measure the key dimensions of job quality and assess this at national level annually. UK Working Lives is a survey of around 6,000 UK employees launched in 2018 and commissioned by YouGov; the latest round being surveyed in 2021.

Similar to the EO, UK Working Lives covers all of the good work dimensions (presented in Appendix B.4). However, it does not cover anything on productivity. In addition, both the surveys use occupation and industry classifications which do not appear to be consistent with the ONS SOC and SIC. The occupation list has around 50 occupations, while the industry list has around 35 industries.

Some of the CIPD reports have focused on productivity. One such is the *Labour Market Outlook* report. However, the report mostly uses productivity data from ONS. The Labour Market Outlook survey, a survey of 1,254 senior HR professionals and decision makers in the UK, uses some questions on productivity. However, the questions are not directly related to measuring productivity at employee or organisation level. They are rather related to how important it is to measure productivity or improve productivity in an organisation (CIPD Labour Market Outlook, winter 2018-19).

- **Annual Survey of Hours and Earnings (ASHE)**

Earnings are an important dimension of measures of good work. While other forms of pecuniary and non-pecuniary reward should be included, they are much more difficult to measure and are omitted (e.g. Wright, 2018). While a number of other surveys collect information on earnings (e.g. the Labour Force Survey), ASHE is the largest and the most rigorous. It also provides statistics on hours of work. According to the government website, the sample size is 300 thousand[20], although other sources put it somewhat lower than this. ASHE is based on a 1% sample of employee jobs drawn from HM Revenue and Customs' Pay As You Earn records.

The following variables are available: a) gross weekly pay; b) weekly pay excluding overtime; c) basic pay including other pay; d) overtime pay; e) gross hourly pay; f) hourly pay excluding overtime; g) gross annual pay; h) annual incentive pay; i) total paid hours; j) basic paid hours; k) paid overtime hours. The data are available by 4-digit SOC and SIC, as well as other dimensions such as age group and region. At these very disaggregate levels, however, confidentiality becomes an issue and some data are not reported.

- **Labour Force Survey**

The LFS is not primarily designed to examine good work, nevertheless it contains a number of questions that provide valuable data on some of the dimensions of interest. The questions include: a) hours of work; b) shiftwork pattern; c) type of agreed work arrangement; d) voice and representation; e) accidents at work and work-related health problems. Further information can be found in Appendix B.6.

The LFS is a quarterly survey with five-quarter rolling cohorts of respondents. The quarters are: a) January to March (Q1/Winter); b) April to June (Q2/Spring); c) July to September (Q3/Summer); d) October to December (Q4/Autumn). So a household that first appears in Q1 2017, for example, will last appear in Q1 2018. While it is a household survey, it contains data on 89 thousand individuals in 2017. It classifies individual occupation and sector information at the 4-digit level.

[20] https://www.ons.gov.uk/surveys/informationforbusinesses/businesssurveys/annualsurveyofhoursandearningsashe

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