Highlights

Cyclical Task Changes in Occupational Transitions: Evidence for the UK

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- We study the change in task content and complexity of job transitions using multidimensional measures.
- A Double-Hurdle model captures both the intensive and extensive margins of task content and complexity changes.
- We control for selection effects in the types of individuals that move employers in adverse labour market conditions.
- Those who are able to transition when the unemployment rate is high are more likely to make task moves and to make larger such moves.

Cyclical Task Changes in Occupational Transitions: Evidence for the UK

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Abstract

Using quarterly data for the UK period over the period 2001q1-2020q3, we measure the task content and task complexity changes during employment transitions. We examine both the extensive margins (the likelihood of moving) and intensive margins (the amount), and control for selection effects in the types of individuals that transition in adverse labour market conditions. We find that, as the unemployment rate rises, the aggregate effect is a reduction in average task content and task complexity moves. However, our evidence suggests the importance of selection effects: we find that as the unemployment rate rises, individuals are more likely to make task moves and to make larger such moves.

Keywords: occupational mobility, tasks, business cycles, selection
JEL Codes: J62, E32

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1. Introduction

Employment transitions are a key driver of macroeconomic outcomes. While a well-functioning labour market efficiently allocates workers to jobs that are a good match, periods of increased aggregate unemployment entail changes to these reallocation processes by introducing frictions. It is well-documented that the volume of job-to-job transitions exhibit a pro-cyclical relationship in both the UK and US Carrillo-Tudela et al. (2016), Murphy and Topel (1987), Moscarini and Thomsson (2007) and Kambourov and Manovskii (2008), and many labour market models explicitly account for such cyclical changes. Employment transitions also matter for career trajectories for the individual. Yet, comparatively little is known about what happens to the content of those transitions in terms of the task content and task complexity undertaken as part of occupational change.

Characterising an occupation as a group of separate tasks is a well-established practice in the literature. Among applied papers, Poletaev and Robinson (2008) are one of the first to map occupational titles to tasks from the US Dictionary for Occupational Titles. Gathmann and Schönberg (2010) and Yamaguchi (2010) detail how heterogenous occupational transitions can be in terms of differences in tasks. Gathmann and Schönberg (2010) construct a measure of occupational distance based on tasks, subsequently used by Robinson (2018), and which we modify to use in this paper. Using German administrative data, they find that individuals tend to switch to occupations with similar task requirements, and the change in task composition of occupational moves tends to decrease over time. Pioneered by Autor et al. (2003) and furthered by Acemoglu and Autor (2011), Autor and Dorn (2013) and Goos et al. (2014), a large body of literature studies changes in the returns to skills and the evolution of earnings inequality. In particular, this literature categorises tasks as manual or cognitive and finds that labour demand is changing as a result of automation, leading to wage and employment gains for cognitive tasks relative to manual tasks and leading to job polarization.

A much smaller literature focuses on cyclical changes in reallocation of workers across tasks for individual workers. Cortes and Gallipoli (2017) focus on task-specific transition costs differences for the US; Summerfield (2016) also focus on intensive and extensive margins of task change for Canada, finding that the cycle affects the task mobility of transitions differently depending on whether an individual experiences a spell of unemployment. Carrillo-Tudela et al. (2016) focuses on cyclical changes in the reallocation of workers across occupations for the UK and find occupational transitions to also be strongly pro-cyclical. However, to our knowledge there has so far been no measurement of the multidimensional task content and complexity of labour market transitions in the UK. This is for two reasons. Firstly, the UK does not compile a standardised measure of task content and complexity that form the content of occupations. Secondly, the UK Labour Force Survey only publishes full standardised occupational codes for current, not previous occupations held by individuals.

The current paper seeks to provide evidence on the task content and task complexity content of occupational transitions in the UK, and how this content changes with cyclical labour market conditions. To this end, this paper recovers full labour market histories from the UK Labour Force Survey for transitions that result in employment and that may experience up to 12 months of inactivity and/or unemployment. This means that we are able to match detailed task data for most labour market transitions that result in employment, with the exception of the long-term (>12 months) unemployed or inactive. In doing so, we add evidence for the UK to the existing literature which provides evidence on US and European labour markets. Using the recovered occupational codes for previous employment spells, we match to US O*NET data and measure the task content and task complexity distances for each transition. Something that, to our knowledge, the literature has not yet directly accounted for is that the types of people that change task content and task complexity during adverse labour market conditions may differ from those that do not, i.e. selection effects in the types of people who move. A contribution of this paper is that we explicitly account for these demand-side determinations of labour market reallocations. Our results are in accordance with previous studies which find pro-cyclical aggregate effects: in periods of high unemployment, average task content and task complexity moves are smaller. However, at the individual level, a higher aggregate unemployment rate is associated with an increase in both extensive and intensive task content and task complexity changes. Our results suggest that the aggregate effect is driven by differences in the types of people who move jobs in adverse labour markets.

The rest of this paper is as follows: in section 2 the algorithm which creates our synthetic two-quarter longitudinal sample for the UK Labour Force Survey (LFS), and how we match this labour market data to task data from the US O*NET. Section 3 presents the measures of task content and task complexity differences between occupations. Section 4 describes the econometric specification, and section 5 reports the results. Finally, section 6 concludes, and further details on the data and empirical analysis are outlined in the Appendices.

2. Data

2.1. UK Labour Force Survey (LFS)

We use the UK Quarterly Labour Force Survey (LFS) published by the Office for National Statistics (ONS) for the years 2001q1 - 2020q3. For this time period we are able to construct consistent classification of occupations, Standard Occupational Classification (SOC) codes throughout the sample. We do this by using an ONS-provided cross-walk between the two occupational codes used over the period, SOC2000 for the years 2001-2010 and SOC2010 codes for the years 2011-2020.[3] In the LFS survey, respondents are followed over a maximum of five quarters, and in each quarter a fifth of the sample is replaced by an incoming group. In our analysis, we are interested in job transitions and so we focus on individuals over a period of two quarters who have a spell of employment in the second quarter. We are interested in observing three types of quarterly employment transitions: employment-to-employment (EE), inactivity to employment (IE) and unemployment-to-employment (UE). The ONS releases a two-quarter (2Q) dataset ([dataset] (Office for National Statistics (2020b)), which subsamples and stacks each two-quarter transition. However, it is not suitable for our purposes as it does not include information on previous employment spells for IE and UE transitions. In particular, we require the 4-digit occupational codes which allow us to match task data to the LFS, a process which we explain in greater detail in section 2.2, below. Instead, we develop an algorithm which recovers employment information from the previous employment spell in the five-quarter (5Q) longitudinal survey ([dataset] Office for National Statistics (2020a)), and stacks these transitions into a 2Q dataset, which we call the synthetic 2Q.[4] As such, we are able to create multidimensional task content and task complexity measures of transitions that involve up to 12 months of inactivity or unemploymen, something that has not previously been possible in UK data.

Figure 1 shows a visual explanation of the algorithm which recovers employment information from the previous employment spell from the 5Q survey. In this example, we focus on a particular employment history in the 5Q in which individuals have a first quarter of employment, second quarter of unemployment, third and fourth quarter employment and fifth is a spell of inactivity, i.e. 'EUEEI'. In total there are

[3]While occupational classifications are available for the 1990s, they are classified according to a very different set of criteria and, when compared over time it is unclear what is genuine variation in occupations and what is simply reclassification.

[4]The code to create this synthetic 2Q dataset is available at https://github.com/racheljoyforshaw/taskSkillsCycle_publish/releases/tag/v1.0

4^5 possible employment histories, given that ‘out of the labour force’ is the fourth possible status in any quarter. For this set of transitions, there are two relevant two-quarter transitions, the UE transition in resulting in employment in Q3 and the EE transition which results in employment in Q4. In the original ONS 2Q dataset the EE transition has all of the data for each employment spell, but the UE transition does not. So that we can study the latter transition, our algorithm takes the full occupational data from the first quarter employment spell which includes the full occupational SOC code, but individual-specific data from the second quarter to create a synthetic 2Q UE transition. In order to avoid over-selection of EE transitions, we exclude those EE transitions which occur in the first and second quarters for each rolling wave, since necessarily we exclude all IE and UE first and second quarter transitions owing to lack of data for the previous employment spell. Table **??** shows the number of observations by transition type for all transitions which end in employment (column 1) and for those who also move jobs (column 2). The distribution of transition types is very similar to the ONS 2Q distribution, but has a slightly greater mass of EE transitions, since we are excluding the long-term unemployed or inactive. As such, we report our results separately: for all transitions; and EE and IE/UE transitions, respectively.

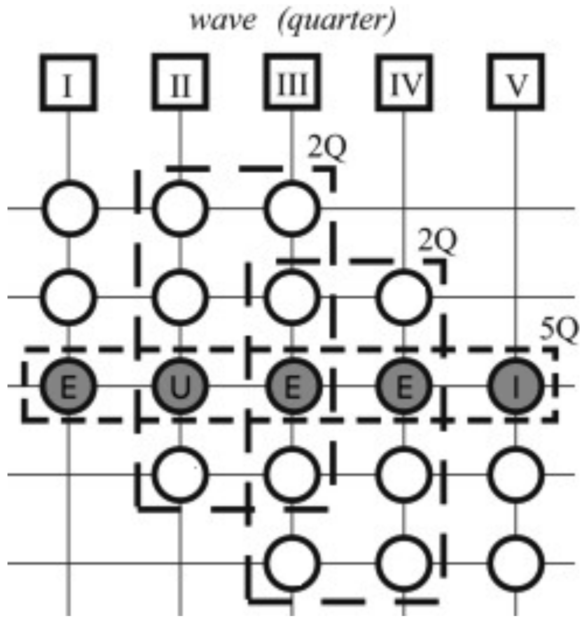

Figure 1: Synthetic 2Q LFS Sample Example

Notes: The LFS is surveyed in five quarter rolling panels. The example transition takes values 'EUEEI' or employment, unemployment, employment, employment, inactive. To create the synthetic 2Q panel we take all transitions that end in employment (here, the UE ending in Q3 and the EE ending in Q4) and recover previous occupational data for all IE and UE transitions from the previous employment spell - in this case, data from the first quarter is used for the UE transition.

Table 1: Observations by Transition Type

	All transitions pct	Job Movers pct	All transitions pct	Job Movers pct
EE	96.67	49.30	98.68	64.79
IE	1.89	28.81	0.62	16.44
UE	1.44	21.89	0.70	18.77
N	2317075	152055	418600	15672

*2.2. US O*NET*

The US Department for Labor's O*NET ([dataset] O*NET 25.1 Database (2020)) is a highly detailed survey which provides us with a picture of the tasks that are used in occupations. We use Standard Occupational Classification (SOC) codes available in the LFS to match occupations to the US O*NET. We choose to map the O*NET to UK occupational codes as, while some data about the task content of UK jobs exists in the UK Skills Survey, the O*NET is much more suitable for our purposes.[5] Hillage and Cross (2015) use the method employed in this paper to map the O*NET to UK SOC codes. They find the method to be robust, to create useful and reasonable data for occupations, and to accord with Skills Survey data in the variables that feature in both.

Alongside task data, the O*NET allows us to recover information on the required level at which each task is used in each occupation. We refer to this as 'task complexity level', since the O*NET gives us information about both the type of task in the occupation and the level at which it is performed. To illustrate, figure 2 shows the question asked for the job task 'mathematical reasoning'. The task complexity score ranges from 1 to 7. In this particular example, a task complexity level of 1 corresponds to "Determine how much 10 oranges will cost when they are priced at 2 for 20 cents", and a score of 6 corresponds to "Determine the mathematics required to simulate a spacecraft landing on the moon", the latter being clearly more complex. In the following section, we show the measures used to ascertain the difference between two occupations and to separate out task content and task complexity information.

[5] While The UK Skills Survey contains both labour market variables found in the LFS and task data found in the O*NET, however its sample size is too small for focusing only on job-to-job transitions to run our estimations. Furthermore, the questions are much more qualitative than the O*NET - variables include 'Importance of looking the part' and 'how often come home from work exhausted'; which, although interesting in their own right, do not readily map to tasks. It also doesn't cover all occupations because they are not sampled.

SOC 2010	Description
2425	Actuary
	Adviser, Economic
	Adviser, Statistical
	Analyst, Campaign
	Analyst, Economic
	Analyst, Political
	Analyst, Quantitative
	Analyst, Statistical
	Analyst, Web
	Assistant, Actuarial
	Assistant, Economic
	Assistant, Statistical
	Bioinformatician
	Consultant, Actuarial
	Consultant, Economic
	Consultant, Statistical
	Controller, Economics
	Controller, Statistical
	Demographer
	Economist

O*NET code	Description	Oral Comprehension
15-2014.00	Statisticians	0.58
19-3011.00	Economists	0.72
15-2011.00	Actuaries	0.61
15-2041.00	Biostatisticians	0.66
15-2021.00	Mathematicians	0.61
43-9111.00	Statistical Assistants	0.64
	Average	0.64

Figure 3: Example of mapping the SOC2010 to the O*NET

Notes: The SOC2010 code that covers occupation 'Economist' is 2425 and also covers a number of other occupations, including Actuary and Bioinformatician. Code 2425 maps to multiple O*NET occupations. Taking an average over all of the Oral Comprehension scores for the different O*NET occupations gives a score for the SOC2010 code.

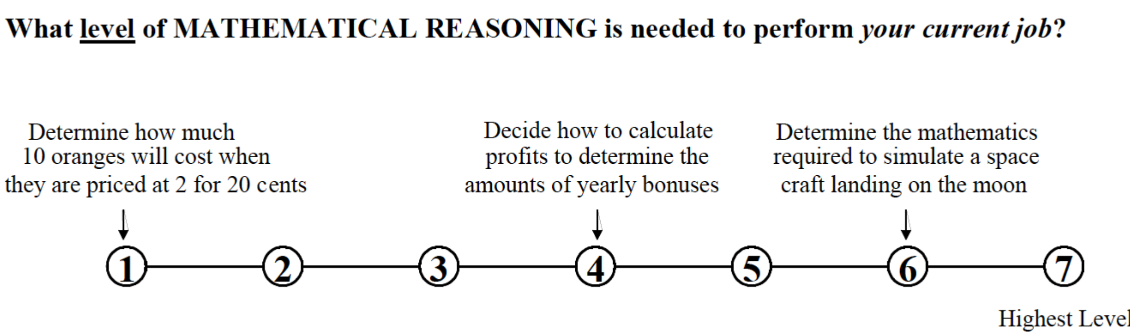

Figure 2: O*NET Example Question

Notes: Example question concerning mathematical reasoning from the O*NET, source: US O*NET Abilities Questionnaire

*2.3. Matching the US O*NET task data to the UK LFS*

A crucial element in this study is the ability to match UK SOC codes from the LFS with task information from the O*NET. To do this we utilise CASCOT (Computer-Assisted Structured Coding Tool), a software tool developed by the Warwick Institute For Employment Research.[6] CASCOT is a computer program designed to make a semantic match between occupational titles and standard occupational codes. This mapping is created by comparing text descriptions of UK SOC2010 occupations to text descriptions of O*NET occupations, which takes into account the differences in vocabulary between the two countries (e.g. 'Company President' in the US would be 'CEO' in the UK; 'Janitor' in the US would be 'Caretaker' in the UK.)

The O*NET contains task profiles for 974 occupations, which we map onto the 374 SOC2010 occupations of the UK LFS using the CASCOT software. Since the number of separate occupation categories in the US are almost 3 times as many as the number of occupational categories in the UK Standard Occupational Classification that is used in the LFS, the mapping is not one-to-one, but one-to-many, with an average of 3 matches per SOC code. Summary statistics for the distribution of SOC-O*NET matches are provided in Appendix B. In order to get a single task vector for each UK SOC code, we follow two steps: first we use a confidence-weighted average over all matching O*NET occupations, where the confidence weights for the mapping of O*NET codes to UK SOC codes are provided by the CASCOT software.[7] We obtain a mapping similar to the one shown in Figure 3, where SOC code 2425 (left panel) is mapped with 6 different O*NET codes (right panel). Each O*NET occupation has scores for each of the 147 tasks in terms of the level of task complexity. In this example, we look at the task 'oral comprehension'. In figure 3 SOC code 2425 that covers occupation 'Economist' is mapped with several possible occupations from the O*NET, including 'Actuary' and 'Statistician'. Taking an average over all of the oral comprehension scores for the different O*NET matches gives a single score for this task in the SOC2010 code, which we then repeat for all possible tasks in all possible matches. Figure 4 provides an illustration of the average score for every task that is part of an Economist's portfolio, as calculated in Figure 3.

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[6] More information available at https://warwick.ac.uk/fac/soc/ier/software/cascot/

[7] We use a confidence threshold of 70%, dropping any matches that fall below this confidence level. A visual inspection of the mapping confirms that the matches are sensible.

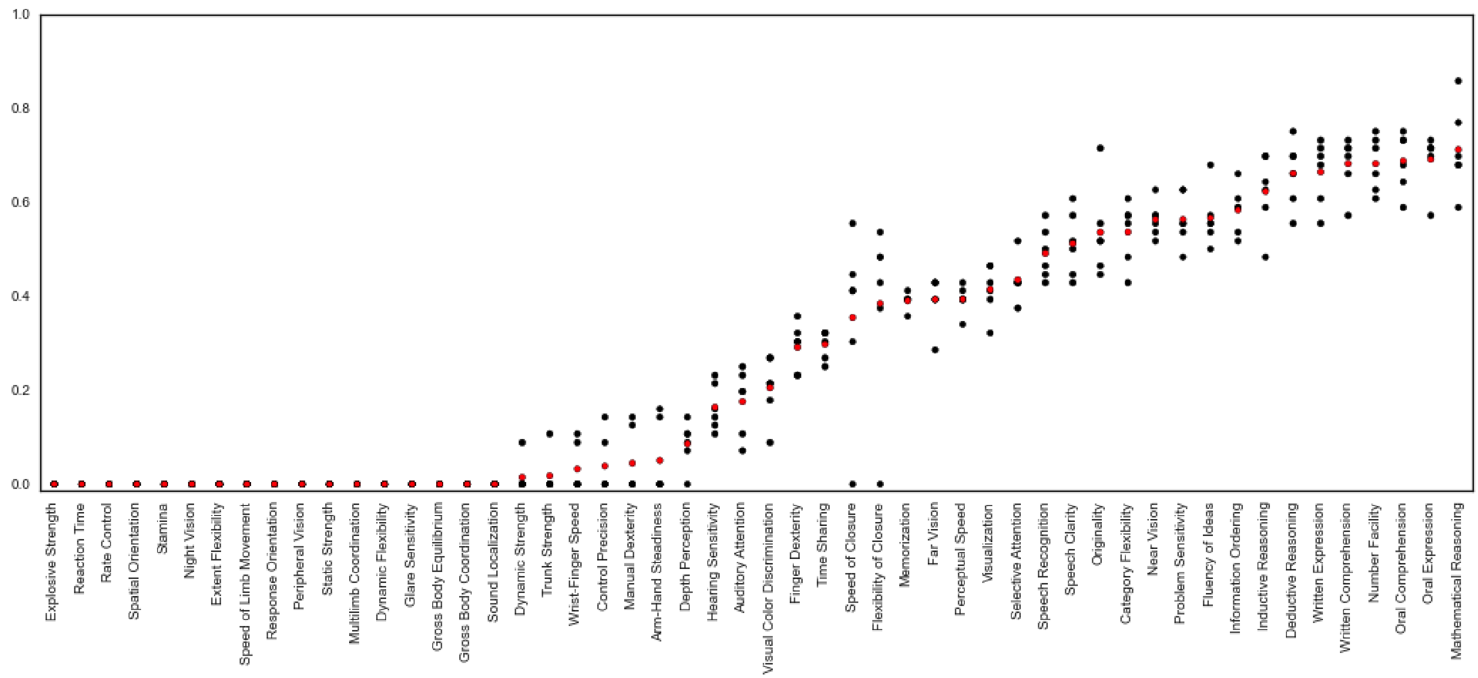


Figure 4: O*NET Task Vector Example - Economist

Notes: Example task vector. The y axis lists all the tasks in occupation 2425 (Economist), the x axis is a normalised score of the complexity level required for each task. Black dots are the O*NET exact matches for occupation 2425, red dots are the average values across the different possible matches and constitute the final scores that we use in our analysis for this occupation. Source: author's calculations using US O*NET and CASCOT.

3. Capturing task content and complexity changes across occupations

Measuring the Change in Task Content: To measure the change in task composition between two occupations we use the measure of angular separation from Gathmann and Schönberg (2010), which has also been used in the innovation literature (Jaffe (1986)). The measure of the change in task composition between two occupations is as follows:

$$\Delta \text{Tasks}_{o,o'} = \left(1 - \frac{\sum_{t=1}^{T} (q_{t,o} \times q_{t,o'})}{\left[(\sum_{t=1}^{T} q_{t,o}^2) \times (\sum_{t=1}^{T} q_{t,o'}^2) \right]^{\frac{1}{2}}} \right) \in [0,1] \tag{1}$$

where o, o' is a pair of different occupations, t is tasks, $q_{t,o}$ represents the complexity level of a task t within occupation o. The change in task composition between a set of occupations o and o' are compared by measuring the cosine angle between their respective vectors. The scores in the vectors range between 0 (this task is not used in an occupation) and 7 (this task is used at the highest level), which we normalise within $[0, 1]$, so that the entire measure is within $[0, 1]$. Each occupation is represented by a vector of equal length dimension and each element of the vector gives a task score, i.e. the intensity with which the task is used in the given occupation. Some of the elements of the vector are zeros, since occupations do not use all available tasks. The way we apply equation 1 is different to the usage by Gathmann and Schönberg (2010), in which they use data on the fraction of employees using task t in occupation o to comprise $q_{t,o}$. Their data carries information about the composition of tasks but not the task complexity, whereas our task vectors include both. Therefore we develop another measure, detailed below, which captures the difference in complexity between task vectors.

Measuring the Change in Task Complexity: In our dataset, since the length of the task vector for each occupation is determined by the difficulty - or complexity level - at which the tasks is required, by measuring its length we can capture the differences between occupations. We propose the following measure, which takes into account the differences in magnitude between two vectors, to capture the change in task complexity:

$$\Delta \text{Task Complexity}_{o,o'} = \left[\left[\sum_{t=1}^{T} (q_{t,o'}^2) \right]^{\frac{1}{2}} - \left[\sum_{t=1}^{T} (q_{t,o}^2) \right]^{\frac{1}{2}} \right] / \sqrt{T} \in [-1,1] \tag{2}$$

Equation 2 calculates the difference in length of two occupation task vectors and has range $[-1, 1]$; -1 means that moving occupations results in lowered complexity in every task, 0 means two occupations are equally complex in every task, 1 an increase in complexity in every task.[8] The measure is therefore symmetric, i.e. $\Delta\text{Task Complexity}_{AB} = -1 * \Delta\text{Task Complexity}_{BA}$.

Appendix C.1 outlines a simple two-task example of both the task content and task complexity measures. In using the ΔTask Complexity measure, equation 2, we are implicitly assuming that vector length of occupations is a good proxy for complexity or skill requirement of the tasks completed in an occupation. If the measure is capturing this we should expect it to be positively correlated with wages. To test this assumption, Appendix C.2 details the results of a Mincerian wage regression which confirms this positive association.

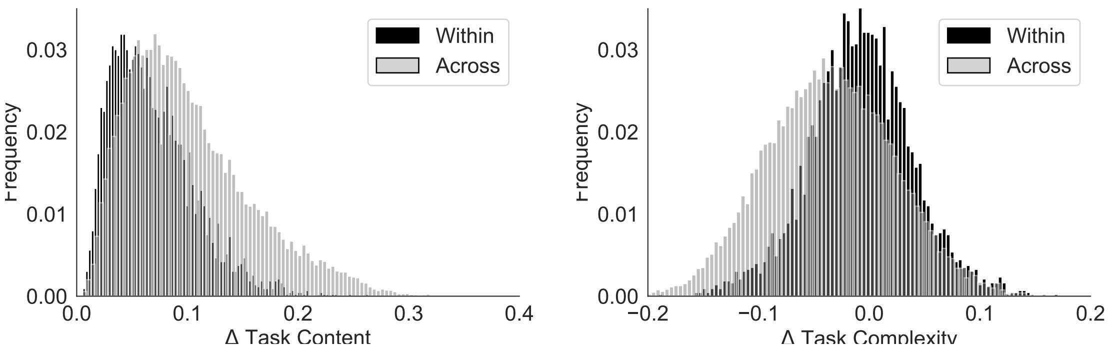
3.1. The Advantage of Using Disaggregated Task Data

Before proceeding to apply the above measure in our analysis, we take a moment to highlight the way in which we use task data to characterise how the content of two occupations might be different. We differ from the mobility literature, which usually use highly aggregated occupational codes, as in Carrillo-Tudela et al. (2016) who use 1-digit SOC codes, Kambourov and Manovskii (2009) who use 1- and 2- digit occupational codes in the PSID. We argue that such aggregated measures, while useful for capturing occupational change, may be only a rough proxy for capturing task content difference between two occupations. This can be seen anecdotally by looking at the occupation titles across different 1-digit occupations which can be more similar than transitions within the same 1-digit occupation. For example, moving from being a 'Manager, food and beverage' employee (5436) to working in 'Textiles, garments and related trades' (5419) would not be recorded as a change according to the 1-digit SOC definition of content change whereas the move to 'Manager, public house' (1224) would.

To formalise this anecdotal evidence, we calculate Δ Task Content (equation 1) and Δ Task Complexity (equation 2) for all possible occupational transitions within- and across-1 digit SOC codes. An 'across' 1-digit change is the type of occupational move usually recorded as a large difference between occupations or 'career change' in the literature, while a 'within' 1-digit change is recorded as no difference. Figure 5

[8] Theoretically, a value of 0 could mean that the two vectors do not have the exact same scores for each task but the differences happen to offset each other perfectly. However, we do not observe this in the data - i.e., no two pairs of different SOC codes return a value of exactly 0.

shows the resulting theoretical distributions.[9] In both figures, we see that this 1-digit



	ΔTask Content$_{o,o'}$		ΔTask Complexity$_{o,o'}$	
	Within	Across	Within	Across
Mean	0.07	0.1	-0.01	-0.04
Std Dev	0.04	0.06	0.05	0.06
Intersection	0.53		0.37	

Figure 5: Example of Task Content and Task Complexity Measures

Notes: Figures ΔTask Content (left) and Δ Task Complexity (right) show potential occupational moves across and within 1-digit SOC codes (excluding zeros). Table reports mean, standard deviation and histogram intersection for each measure.

SOC code proxy does capture some of the differences between occupations. In the left-hand of figure 5, the 'across' distribution mean is to the right of the 'within' distribution, and the standard deviation is greater. Similarly, the right-hand figure shows for changes in task complexity, 'across' moves mean is greater in magnitude and negative than 'within' moves, showing that it it more likely to capture occupational moves which entail a reduction in task complexity. On average, it is capturing larger magnitudes of task content and task complexity changes in occupational moves. However the differences between the distributions are strikingly modest. This is best demonstrated by the calculated histogram intersections, which show that the Δ

[9]Note that these plotted distributions exclude zeros (i.e., no change in task content or complexity) which would represent 51.42 % and 50.22 % of the within and across potential moves, respectively, for both measures.We exclude these because in practice, if the content of tasks are the same between two jobs, then all complexity levels are also the same since both measures are only zero when comparing two identical SOC codes.

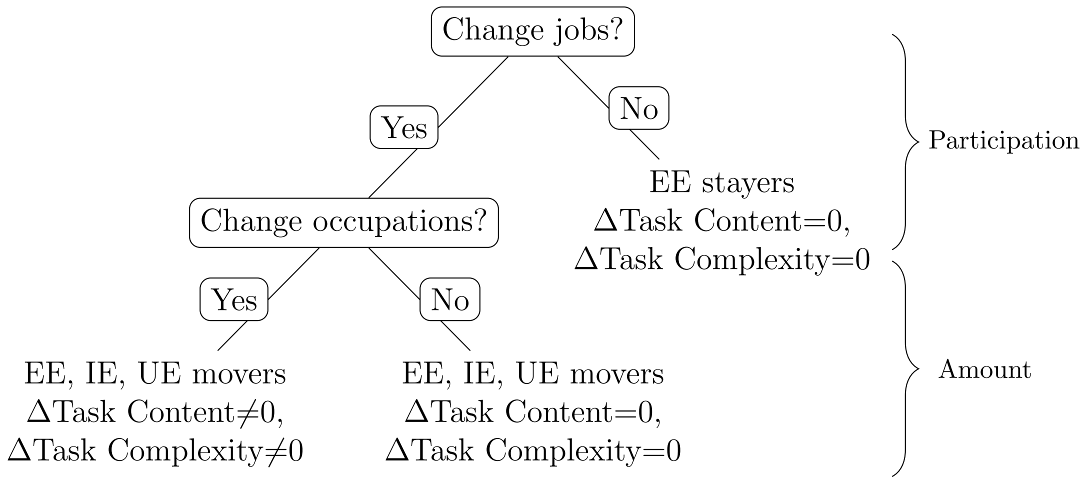


Figure 6: Illustration of Double Hurdle model

Notes: In labour market transitions, either an an individual changes jobs or stays in their current position. If an individual changes jobs they may also change occupations and therefore have a task content or task complexity change

Task Content distributions overlap by 53%, and the Δ Task Complexity distributions overlap by 37%. This motivates our use of disaggregated task data to understand how the content and complexity of occupations changes over the business cycle.

4. Methodology

Our empirical specification must capture the two-step nature of the decision to change tasks, as illustrated in figure 6. The first step participation decision is whether or not to change jobs between the first and second quarters of an individual transition. Importantly, this step typically incurs fixed costs. Therefore a Tobit specification - which would assume a single mechanism to drive both the participation and amount decision - is inappropriate. A familiar modelling approach in such two-step problems is the Heckit model advanced by Heckman (1979). However, this model assumes first hurdle dominance - ie. that in the second stage there will be no zero observations. This is not appropriate in the current setting as a zero task content/complexity move is a valid choice, shown by those who change jobs but do not move occupations in figure 6, and represents approximately 40% of all job changers. This motivates our choice of a Double Hurdle specification, proposed by Cragg (1971), and applied in a labour market setting by Blundell and Meghir (1987) and Blundell et al. (1989). This model captures both the extensive (participation decision) and intensive (amount decision) of task content and task complexity change during employment transitions and allows them to be governed by distinct stochastic processes. It also allows the outcome variable to take the value of zero in the second stage. Concretely, the equations of the Double Hurdle model are:

$$d^{*}_{it,2} = \tilde{\alpha}_0 + \tilde{\alpha}_1 u_{t,2} + \sum_j \tilde{\beta}_j \hat{X}_{j,it,1} + \sum_k \tilde{\gamma}_k \mathrm{Q}_{k,2} + \sum_l \tilde{\delta}_l \mathrm{R}_{l,1} + \sum_m \tilde{\zeta}_m \mathrm{I}_{m,1} + \tilde{\epsilon}_{it} \tag{3a}$$

$$y^{**}_{it,2} = \check{\alpha}_0 + \check{\alpha}_1 u_{t,2} + \sum_j \check{\beta}_j X_{j,it,12} + \sum_k \check{\gamma}_k \mathrm{Q}_{k,2} + \sum_l \check{\delta}_l \mathrm{R}_{l,1} + \sum_m \check{\zeta}_m \mathrm{I}_{m,1} + \hat{\lambda}_{it} + \check{\epsilon}_{it} \tag{3b}$$

$$d_{it,2} = \begin{cases} 1, & \text{if } d^{*}_{it,2} > 0 \\ 0, & \text{if } d^{*}_{it,2} \leq 0 \end{cases} \tag{3c}$$

$$y^{*}_{it,2} = \max(0, y^{**}_{it,2}) \tag{3d}$$

$$y_{it,2} = d_{it,2}\; y^{*}_{it,2} \tag{3e}$$

Where subscripts refer to individual i, subscripts $_1$, $_2$ and $_{12}$ refer to data in the first quarter, second quarter, and both quarters of a transition at time t, respectively. Q are quarter, R region and I industry fixed effects; $\tilde{\epsilon}_{it}$ and $\check{\epsilon}_{it}$ are error terms. Equations 3a and 3b represent the participation and amount hurdles, respectively. $\hat{X}$ and X are a set of controls which include demographic characteristics, namely age and age squared, marital status, sex, level of education,[10] number of children. We also add a set of variables related to the individual's current and previous job: the duration of the previous employment and whether the separation was voluntary/involuntary or related to retirement, as well as controls for whether either job is temporary, part- or full-time, self-employed, and in the public or private sector. Finally, we have a set of controls for the method by which the individual searches for new jobs: through a job centre, ads, direct applications, family/friends, or some other method. Note that control variables in the participation equation, $\hat{X}$, differ from those in the amount equation, X, in 3b. This is because this hurdle uses the full estimation sample, which includes those who do not change jobs. As such, we only include controls for the first-period job (or, as we will use interchangeably, 'previous' job.) For the same

[10] We split education into low, medium and high. In the low category we only include individuals with no qualifications; in the middle we include those with at least an Entry Level Qualification and at most A levels (a UK pre-requisite for university entry); and in the high we include all those with any qualification above A levels.

reason we also omit search method and separation type. Finally, $\hat{X}$ also includes an exclusion restriction, which we discuss below. The independent variable of interest is the aggregate unemployment rate, $u_{t,2}$. $\hat{\lambda}$ is the estimated inverse Mills ratio obtained from estimating equation 3a.

Equation 3a is the participation hurdle which captures desired task content or complexity move d^*, which is latent. Equation 3b and 3d are the amount hurdle, which is a Tobit model. In equation 3e, $y_{it,2}$ describes the data actually observed, which captures the combined effect of the participation decision (equations 3a, 3c) and the amount decision (equation 3b and 3d). $y_{it,2}$ is either $\Delta \textit{Task Content}_{it,2}$ or $|\Delta \textit{Task Complexity}_{it,2}|$. For the latter we take the absolute value of the change in task complexity since we cannot have an upper and lower truncation limit for the Tobit equal to zero as this would imply no truncated values.

We allow for correlation in the error terms of the first and second hurdles, since table 2 suggests there are significant differences in observable characteristics between the recession and and non-recession samples. Those that transition in a recession are older, more likely to be married, and have longer tenure. Fewer are in temporary roles for their previous job, and a larger fraction are self employed or work for the public sector in either their previous or current job. Fewer are medium-educated and a higher fraction are low- educated. More have quit (made a voluntary separation) from their previous employer, and a smaller fraction have been fired (made an involuntary separation). It is likely, therefore, that there are unobserved factors that affect the participation decision and also affect the amount decision.

To identify the effect of the first hurdle we include the exclusion restriction *Wait*, whether the individual is waiting to start a job that they have already obtained. The exclusion restriction for the selection equation is a dummy which captures whether an individual is waiting to start working in a job that they have already obtained. This applies to all flow types: EE, IE and UE. It captures those still employed but that have obtained a new job (EE). It also covers those who are inactive as they are not currently employed and not seeking work but are waiting to take up a position (IE). Finally, those unemployed and waiting to take up a position (UE) are distinguished from those who are inactive as they have been actively seeking employment in the last 4 weeks. It is also highly but not perfectly predictive of the dependent variable in the selection equation - whether the individual changed jobs between the first and second quarter of their survey - since many people that are waiting to take up a job will change jobs within the survey window, as table **??** in the appendix demonstrates. However, it is not related to the size of the task content or complexity change that an individual makes upon changing jobs conditional on transition type, as a difference in mean task move between those who waited to take up a position and those that didn't (**??** - **??**, appendix) confirms.

Table 2: Difference in Means Of Observable Characteristics

Variable	0	1	Diff
Female	0·48	0·50	0·019**
	(0·00)	(0·01)	(0·009)
Age	37·34	39·07	1·729***
	(0·13)	(0·21)	(0·242)
Married	0·47	0·47	0·000
	(0·00)	(0·01)	(0·009)
Number of Children	0·79	0·81	0·020
	(0·01)	(0·02)	(0·018)
High Education	0·16	0·16	−0·002
	(0·00)	(0·01)	(0·007)
Medium Education	0·56	0·40	−0·158***
	(0·00)	(0·01)	(0·009)
Low Education	0·28	0·44	0·160***
	(0·00)	(0·01)	(0·008)
Previous Employment Duration	3·98	4·20	0·221***
	(0·03)	(0·04)	(0·048)
Full Time, Previous Job	0·66	0·61	−0·047***
	(0·00)	(0·01)	(0·008)
Full Time, Current Job	0·66	0·61	−0·055***
	(0·00)	(0·01)	(0·008)
Temporary, Previous Job	0·20	0·23	0·023***
	(0·00)	(0·01)	(0·007)
Temporary, Current Job	0·22	0·26	0·033***
	(0·00)	(0·01)	(0·008)
Public Sector, Previous Job	0·18	0·19	0·013*
	(0·00)	(0·01)	(0·007)
Public Sector, Current Job	0·19	0·20	0·004
	(0·00)	(0·01)	(0·007)
Self Employed, Previous Job	0·11	0·14	0·029***
	(0·00)	(0·01)	(0·006)
Self Employed, Current Job	0·12	0·16	0·034***
	(0·00)	(0·01)	(0·006)
Looking for Job	0·33	0·37	0·043***
	(0·00)	(0·01)	(0·008)
Involuntary Separation	0·72	0·79	0·067***
	(0·00)	(0·01)	(0·008)
Voluntary Separation	0·10	0·09	−0·006
	(0·00)	(0·00)	(0·005)
Other Separation	0·14	0·08	−0·061***
	(0·00)	(0·00)	(0·006)
Method of Seeking: Not Looking	0·91	0·87	−0·032***
	(0·00)	(0·01)	(0·005)
Method of Seeking: Job Centre	0·01	0·01	0·000
	(0·00)	(0·00)	(0·002)
Method of Seeking: Ads	0·06	0·09	0·026***
	(0·00)	(0·00)	(0·004)
Method of Seeking: Direct Application	0·01	0·01	0·002
	(0·00)	(0·00)	(0·002)
Method of Seeking: Family/Friend	0·01	0·01	0·001
	(0·00)	(0·00)	(0·002)
Method of Seeking: Other	0·01	0·01	0·003**
	(0·00)	(0·00)	(0·002)
N	11263	4409	15672

Notes: Difference in longitudinal-weighted means when the aggregate unemployment rate is above=1 and below=0 the unemployment rate average for all transitions resulting in a job move in the synthetic 2Q sample. Significance levels: $^{*} < 10\%$ $^{**} < 5\%$ $^{***} < 1\%$. Standard errors in parentheses. Source: author's calculations.

5. Results

Table 3 details the estimation results of equations 3. Columns 2 - 7 show the results with with dependent variable Δ Task Content. ‘ALL’, ‘EE’ and ‘IE & UE’ headings refer to the sample used in the estimation which depends on labour market transition type. ’Above’ and ’Hurdle’ refer to the participation and amounts equations, respectively.

For all transition types (EE and IE/UE) , we see an increase in the aggregate unemployment rate is associated with an increase in the likelihood of changing tasks content by 0.23 standard deviations.

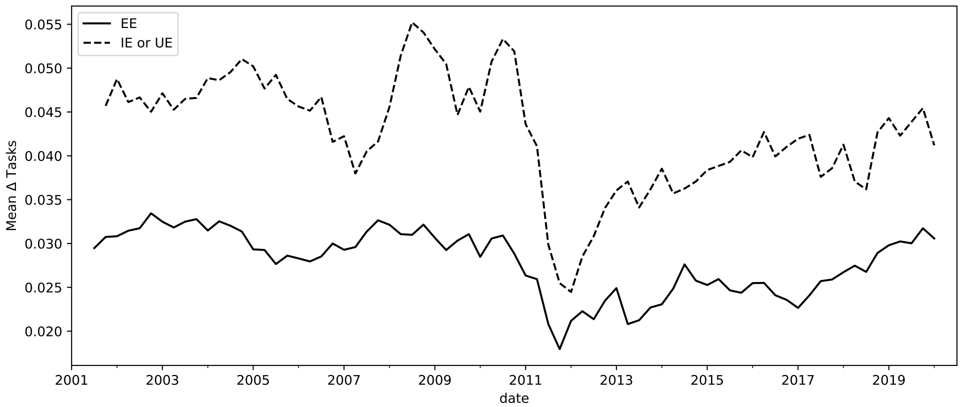
Table 3: Double-Hurdle Regression Output

	Δ Task Content						ΔTask Complexity					
	ALL		EE		IE & UE		ALL		EE		IE & UE	
	Above	Hurdle	Above	Hurdle	Above	Hurdle	Above	Hurdle	Above	Hurdle	Above	Hurdle
Aggregate Unemployment Rate	0.43***	0.23***	0.42***	0.093***	0.041	-0.061***	0.36***	0.063**	0.52***	-0.27***	-0.0060	-0.081*
	(0.021)	(0.018)	(0.019)	(0.019)	(0.027)	(0.023)	(0.021)	(0.026)	(0.024)	(0.020)	(0.025)	(0.046)
Regional-Aggregate Unemployment Rate	-0.013	0.0066	-0.019	-0.0015	-0.023	0.021	-0.016	0.00053	-0.037*	0.025	-0.0043	0.023
	(0.019)	(0.015)	(0.018)	(0.022)	(0.026)	(0.024)	(0.021)	(0.027)	(0.021)	(0.018)	(0.024)	(0.044)
Female	-0.44***	0.14***	-0.61***	0.18***	-0.18***	0.11*	0.20***	-0.82***	-0.20***	-0.040	0.092	-0.41**
	(0.054)	(0.035)	(0.050)	(0.069)	(0.066)	(0.063)	(0.070)	(0.15)	(0.056)	(0.048)	(0.069)	(0.18)
Age	-0.0034	-0.034***	0.020	0.0072	-0.016	-0.028*	0.013	0.0082	0.044***	-0.0082	-0.011	-0.069*
	(0.014)	(0.010)	(0.013)	(0.018)	(0.016)	(0.015)	(0.014)	(0.017)	(0.015)	(0.013)	(0.015)	(0.037)
Age^2	-0.000050	0.00035***	-0.00034**	0.000039	0.00016	0.00029	-0.00011	-0.00031	-0.00050***	0.000035	0.000081	0.00073*
	(0.00017)	(0.00012)	(0.00015)	(0.00021)	(0.00020)	(0.00018)	(0.00017)	(0.00021)	(0.00018)	(0.00015)	(0.00019)	(0.00044)
Married/Cohabitating	0.033	-0.080**	0.086*	-0.020	-0.083	-0.034	0.040	-0.014	0.11*	-0.068	-0.035	-0.12
	(0.055)	(0.038)	(0.051)	(0.061)	(0.080)	(0.074)	(0.057)	(0.072)	(0.058)	(0.052)	(0.074)	(0.15)
Number of Children	-0.088***	-0.0037	-0.11***	0.011	0.061*	-0.066**	-0.088***	-0.034	-0.13***	0.013	-0.049	-0.024
	(0.027)	(0.017)	(0.024)	(0.028)	(0.035)	(0.030)	(0.026)	(0.034)	(0.028)	(0.024)	(0.032)	(0.065)
High Education	0.93***	-5.64	1.51***	0.29***	0.29***	-0.095	0.64***	0.27*	1.74***	-1.39***	0.27***	-0.49**
	(0.12)	(94.4)	(0.13)	(0.11)	(0.10)	(0.094)	(0.093)	(0.14)	(0.11)	(0.16)	(0.099)	(0.19)
Medium Education	0.56***	-5.50	0.96***	0.21***	0.42***	-0.20***	0.91***	0.057	1.88***	-1.42***	0.34***	-0.57***
	(0.099)	(94.4)	(0.096)	(0.071)	(0.081)	(0.073)	(0.087)	(0.078)	(0.10)	(0.16)	(0.070)	(0.16)
Previous Employment Duration	-0.049***	0.0059	-0.024**	-0.084***	-0.012	-0.046***	-0.093***	0.069***	-0.059***	0.0054	-0.028**	-0.080***
	(0.012)	(0.0075)	(0.011)	(0.015)	(0.015)	(0.013)	(0.016)	(0.018)	(0.013)	(0.011)	(0.013)	(0.025)
Full time, Previous Job	-0.058	-0.14***	0.014	-0.49***	-0.058	0.13*	-0.30***	0.49***	-0.14	0.0052	0.015	0.27**
	(0.097)	(0.045)	(0.12)	(0.093)	(0.076)	(0.066)	(0.11)	(0.096)	(0.12)	(0.055)	(0.075)	(0.13)
Full time, Current Job	0.41***		0.66***		-0.10		0.29***		0.58***		-0.026	
	(0.092)		(0.11)		(0.064)		(0.094)		(0.11)		(0.066)	
Temporary, Previous Job	0.069	0.38***	-0.050	4.24	0.054	-0.30***	-0.24**	0.45***	-0.23*	0.27***	-0.032	-0.59***
	(0.11)	(0.077)	(0.13)	(242.2)	(0.093)	(0.079)	(0.12)	(0.13)	(0.14)	(0.097)	(0.084)	(0.16)
Temporary, Current Job	0.48***		0.87***		-0.14**		0.52***		0.84***		-0.13**	
	(0.10)		(0.13)		(0.061)		(0.10)		(0.13)		(0.063)	
Public Sector, Previous Job	-0.57***	-0.23***	-0.15	-4.49	-0.048	-0.33***	-0.37***	-0.098	-0.27*	-0.036	0.069	-0.90***
	(0.12)	(0.042)	(0.17)	(107.3)	(0.12)	(0.082)	(0.13)	(0.097)	(0.15)	(0.055)	(0.15)	(0.17)
Public Sector, Current Job	0.20*		0.081		0.13*		0.19		0.063		0.39***	
	(0.12)		(0.15)		(0.076)		(0.12)		(0.15)		(0.085)	
Self-employed, Previous Job	-0.66***	-0.37***	1.43***	-6.16	0.24	-0.61***	-0.79***	1.43***	-0.28*	-0.036	-0.49***	-0.065
	(0.14)	(0.049)	(0.24)	(107.3)	(0.18)	(0.085)	(0.13)	(0.48)	(0.16)	(0.075)	(0.097)	(0.27)
Self-employed, Current Job	-0.21		0.081		0.11		-0.44***		-0.47***		-0.22***	
	(0.13)		(0.18)		(0.085)		(0.13)		(0.16)		(0.081)	
Looking for Job	0.66***	6.11	0.22**	0.88***	-0.25**	0.51***	0.0045	5.35	-0.035	0.72***	0.13*	0.77***
	(0.12)	(2409.6)	(0.11)	(0.19)	(0.11)	(0.067)	(0.10)	(166.4)	(0.11)	(0.13)	(0.077)	(0.15)
Job Mover	7.23***		7.63***				7.02***		7.40***			
	(0.077)		(0.097)				(0.077)		(0.096)			
Involuntary Separation	1.03***		1.53***		0.058		1.17***		1.42***		0.12	
	(0.15)		(0.19)		(0.087)		(0.16)		(0.19)		(0.090)	
Voluntary Separation	1.36***		1.73***		-0.015		1.13***		1.32***		-0.043	
	(0.15)		(0.17)		(0.12)		(0.14)		(0.17)		(0.12)	
Other	0.94***		1.48***		-0.046		1.06***		1.30***		0.060	
	(0.20)		(0.25)		(0.12)		(0.21)		(0.25)		(0.12)	
Method of seeking: Job Centre	0.023		0.061		-0.021		0.10		0.075		0.13	
	(0.23)		(0.27)		(0.16)		(0.23)		(0.27)		(0.17)	
Method of seeking: Ads	-0.068		-0.12		0.22**		-0.10		-0.14		0.20**	
	(0.093)		(0.11)		(0.088)		(0.093)		(0.11)		(0.090)	
Method of seeking: Direct application	0.53*		0.62*		0.098		0.37		0.45		0.031	
	(0.28)		(0.33)		(0.27)		(0.29)		(0.33)		(0.25)	
Method of seeking: Family/Friend	0.17		0.26		-0.13		0.17		0.26		-0.085	
	(0.25)		(0.29)		(0.25)		(0.25)		(0.29)		(0.24)	
Method of seeking: Other	0.24		0.24		0.10		0.24		0.29		0.13	
	(0.23)		(0.27)		(0.26)		(0.23)		(0.26)		(0.25)	
Wait		2.33		-6.02		0.27***		5.19		-6.55		0.27*
		(1.94)		(107.3)		(0.096)		(260.2)		(108.2)		(0.16)
λ	1.70***		-3.56***		-0.50		-2.86***		-4.39***		0.86**	
	(0.34)		(0.22)		(0.59)		(0.18)		(0.22)		(0.41)	
Quarters	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	418600		413082		5518		418600		413082		5518	
R^2												
pseudo R^2												
Log llik.	-160161.7		-151728.7		-6991.4		-159526.6		-150794.3		-6993.9	

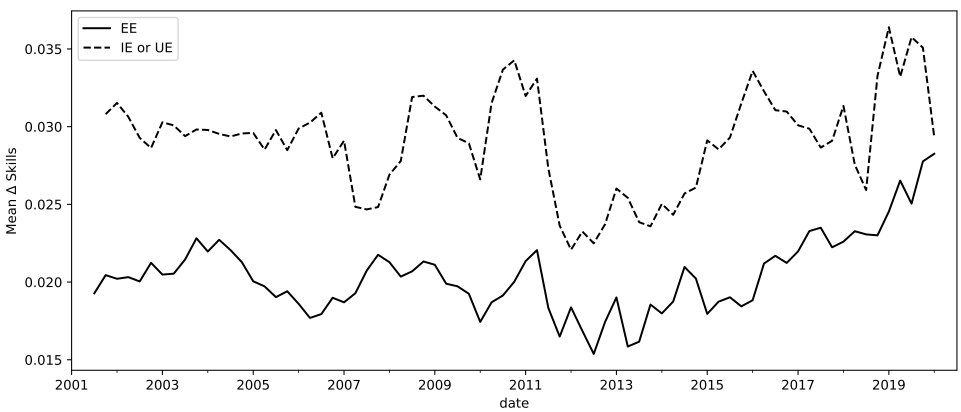
Marginal effects; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

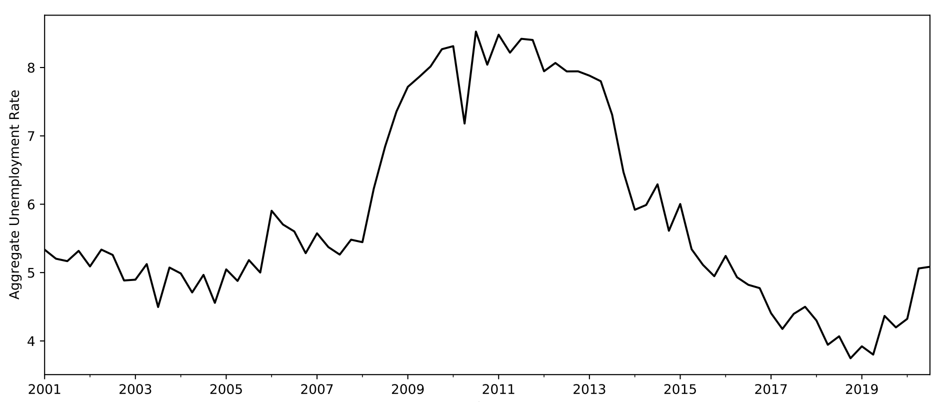
Double Hurdle at the 4-digit occupation category level. ALL refers to all labour market transitions, EE refers to direct job-to-job transitions, IE & UE refers to employment transitions with between 1 and 3 quarters of unemployment and/or inactivity in between. The coefficient on age squared is multiplied by 1000. The reference category for education is Low Education; for Job Separation it is 'No Separation'; for Job seeking method it is 'Not Looking'. The regression includes quarter and regional fixed effects. Standard errors in parentheses.



(a)



(b)



(c)

Figure 7: Five quarter moving average of the (a) Δ Task Content and (b) Δ Task Complexity within-quarter for EE, IE transitions.(c) Aggregate Unemployment Rate.

6. Concluding Remarks

7. Acknowledgements

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Appendix A. Description of Regression Variables

Name	Description
Aggregate Unemployment Rate	Aggregate unemployment rate, calculated using 2Q Quarterly LFS and ONS definitions
Regional-Aggregate Unemployment Rate	Regional minus aggregate unemployment rate
Female	Sex dummy, 1 = female 0 = male
Age	Age in years in first quarter of transition
Age^2	Age squared
Married/Cohabitating	Dummy, 1=Married/Cohabitating
Number of Children	Number of children in household
High Education	Education above university entry-level (above A-level, Highers or IB)
Medium Education	Education up to university entry-level
Low Education	No Qualifications
Previous Employment Duration	Time spent at previous job according to LFS definition:
	1 = less than 3 months, 2 = 3-6 months, 3 = 6-12 months, 4 = 1-2 years,
	5 = 2-3 years, 6 = 3-4 years, 7 =4-5 years, 8 = 5+ years
Full time, previous job	Dummy, 1 = full time in previous job
Full time, current job	Dummy, 1 = full time in current job
Public sector, previous job	Dummy, 1 = public sector in previous job
Public sector, current job	Dummy, 1 = public sector in current job
Self-employed, previous job	Dummy, 1 = self-employed in previous job
Self-employed, current job	Dummy, 1 = self-employed in current job
Looking for job	Dummy, 1 = was looking for job in first quarter
Job Mover	Dummy, 1 = moved jobs
Separation: Involuntary	Dummy, 1 = fired or made redundant
Separation: Voluntary	Dummy, 1 = quit
Separation: Other	Dummy, 1 = retired, health issues, other
Method of seeking: Agency	Dummy, 1 = got job through employment agency (reference category)
Method of seeking: Job Centre	Dummy, 1 = got work through job centre
Method of seeking: Ad	Dummy, 1 = got work through applying to advertisement
Method of seeking: Direct Application	Dummy, 1 = direct application to employer
Method of seeking: Family/Friend	Dummy, 1 = through family/friends
Method of seeking: Other	Dummy, 1 = other method
Wait	Dummy, 1 = waiting to take up job already obtained
Quarters	Quarters, 1-4
Regions	Regions of the UK according to LFS definitions, 1-20

Appendix B. Summary Statistics

Table B.1: Summary Statistics for SOC 2010 - O*NET matches

	Mean	Median	StDev	Max	Min
SOC-O*NET matches	3.327338129	2	3.675075691	38	1

Summary statistics for the number of O*NET occupation matches for each 4-digit SOC code.

Table B.2: Number of job movers by transition type, 0 = did not move jobs, 1= moved jobs

	Job Mover=0	Job Mover=1
EE	402928	10154
IE		2576
UE		2942
N	402928	15672

Table B.3: Mean and sd of Δ task content and Δ task complexity by job move, 0 = did not move jobs, 1= moved jobs

	Job Mover=0		Job Mover=1	
	mean	sd	mean	sd
Δ Task Content	.0030222	.0150903	.030682	.0446252
Δ Task Complexity	.0025333	.0134382	.0237359	.0373353
Observations	402928		15672	

Table B.4: Number of task movers by transition type, 0 = did not move jobs, 1= moved jobs

	Task Mover=0	Task Mover=1
EE	385559	27523
IE	1519	1057
UE	1281	1661
N	388359	30241

Table B.5: Mean and sd of Δ task content and Δ task complexity by task move

	Task mover=0		Task mover=1	
	mean	sd	mean	sd
Δ Task Content	0	0	.056168	.0389971
Δ Task Complexity	0	0	.0460537	.0372157
Observations	388359		30241	

Table B.6: Mean and sd of job mover by task move, 0 = did not move tasks, 1= moved tasks

	Task mover=0		Task mover=1	
	mean	sd	mean	sd
Job Mover	.0217325	.1458089	.2391455	.4265688
Observations	388359		30241	

Table B.7: Mean and sd of dependent variables by job move, 0 = did not move jobs, 1= moved jobs

	Job Mover=0		Job Mover=1	
	mean	sd	mean	sd
Female	.4875486	.4998456	.4887698	.4998898
Age	43.63524	11.72275	37.82644	13.63442
Married	.6270078	.4836007	.4714778	.4992017
Tenure	6.546641	2.05135	4.042879	2.695525
Full time	.7316468	.443103	.6465033	.4780705
Temporary	.039208	.1940897	.2103114	.4075428
Public	.2905159	.454001	.181853	.3857356
Self-employed	.143857	.3509451	.1164497	.3207737
Education	2.201202	.6897428	2.161626	.6775242
Region	10.84361	4.940485	10.56023	4.627446
Reason left last job	.0176558	.2037333	.4583971	.8548127
Industry	2.732399	.4822588	2.736345	.472225
Number of Children	.7713984	1.022428	.7927514	1.034189
Time between jobs	0	0	.4627999	.7149512
Whether looking	.0421192	.2008613	.3409265	.4740358
N	402928		15672	

Table B.8: Mean and sd of independent variables by transition type; all job movers

	EE		IE	
	mean	sd	mean	sd
Aggre_Ur_pct	5.574814	1.148565	5.729024	1.269878
Sex, 1=female 0=male	.4846366	.4997885	.6090839	.4880504
Age of respondent	36.88862	12.86671	41.158	15.67419
Maried/cohabitating, 1=yes, 0=no	.4680914	.4990054	.5399845	.4984954
Employment duration with current employer, 1-8 steps	3.677369	2.644971	5.111025	2.62403
Full-time, 1=yes, 0=no	.692338	.4615486	.4029503	.4905862
Temporary job, 1=yes 0=no	.1920425	.3939257	.242236	.4285196
Public job, 1=Yes, 0=No	.1868229	.3897885	.2193323	.4138745
Self-employed, 1=Yes, 0=No	.0893244	.2852255	.2185559	.4133468
Why left last job, 1=involuntary, 2=voluntary, 3=other	2.143392	.6780036	2.173137	.6879775
Region of usual residence	10.52994	4.623705	10.57997	4.542594
f_v_retire2	.5358479	.8885192	.300854	.8033517
Industry category, 1=primary 2=secondary 3=tertiary	2.732125	.4683818	2.788432	.4711874
Observations	10154		2576	

Appendix C. Robustness Checks

Appendix C.1. Two-Task Example of the Task Content and Complexity Change Measures

Figure C.8 provides an illustration of how the ΔTask Content and ΔTask Complexity measures can provide us with information about the content of occupational moves. We construct a basic example in which there are a total of four different occupations (A, B, C, D) which comprise two tasks: task 1 and task 2. Moving from occupation A, which has a high level of complexity in task 1 and task 2, to B, which has a low level of complexity in both tasks gives a change in task content of 0, since the tasks are still used in the same proportion. The ΔTask Complexity$_{o,o'}$ of -0.86 reflects the fact that occupation B is much lower skilled than A. Moving from occupation C to A represents both a change in task content and increased complexity, whereas the change in tasks from A to D constitutes reduced complexity. Finally, moving from and to the same occupation A results in zeros for both measures.

Table B.9: Mean values of Δ task content and Δ task complexity by transition type and whether waited to start new job, 1= yes , 0=no

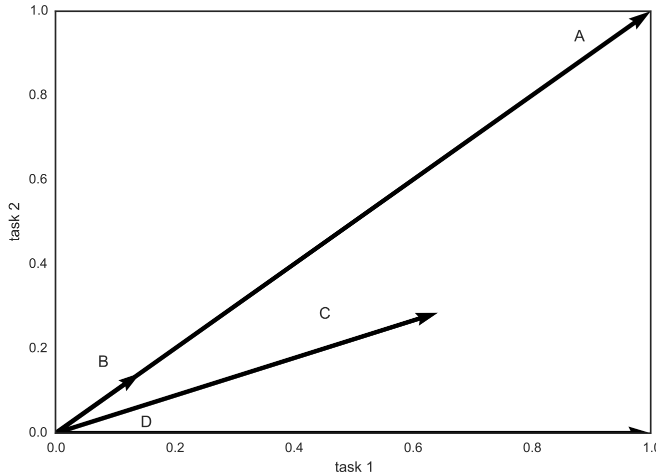
Variable	0	1	Diff
Δ Task Content, EE job movers	0·03	0·02	−0·010
	(0·00)	(0·02)	(0·022)
Δ Task Complexity, EE job movers	0·02	0·01	−0·010
	(0·00)	(0·01)	(0·019)
N	10150	4	10154
Δ Task Content, UE job movers	0·04	0·04	0·000
	(0·00)	(0·00)	(0·003)
Δ Task Complexity, UE job movers	0·03	0·03	−0·002
	(0·00)	(0·00)	(0·003)
N	2698	244	2942
Δ Task Content, IE job movers	0·03	0·03	0·005
	(0·00)	(0·00)	(0·004)
Δ Task Complexity, UE job movers	0·02	0·02	0·002
	(0·00)	(0·00)	(0·003)
N	2398	178	2576

[1] Significance levels: * < 10% ** < 5% *** < 1%
[2] Standard errors in parentheses

Table B.10: Likelihood of job move for all transitions by whether waiting to start job, 1= yes , 0=no

Variable	0	1	Diff
JobMover	0·04	0·97	0·938***
	(0·00)	(0·01)	(0·009)
N	418163	437	418600

[1] Significance levels: * < 10% ** < 5% *** < 1%
[2] Standard errors in parentheses



	ΔTask Content$_{o,o'}$	ΔTask Complexity$_{o,o'}$
A $\rightarrow$ B	0	-0.86
C $\rightarrow$ A	0.07	0.5
A $\rightarrow$ D	0.29	-0.29
A $\rightarrow$ A	0	0

Figure C.8: An example of ΔTask Content and ΔTask Complexity with 2 tasks and 4 occupations

Notes: In this example, there are two tasks, task 1 and 2 and 4 occupations, A, B, C and D with differing task content (the angle of the vector) and task complexity intensities (the magnitude of the vector). The tables report calculated Δ Task Content and Δ Task Complexity for reported occupation pairs.

Appendix C.2. The Relationship between Task Complexity and Wages

In using the ΔTask Complexity measure, equation 2, we are assuming that vector length of occupations is a good proxy for complexity or skill requirement of the tasks completed in an occupation. If the measure is capturing this we should expect it to be positively correlated with wages. To test this assumption we calculate the task complexity level for each occupation in the LFS:

$$\text{Task Complexity Level}_o = \left[\sum_{t=1}^{T}(q_{t,o}^2)\right]^{\frac{1}{2}}$$

i.e. it is a measure of the vector length of an occupation in the task space, or the left hand side of the term in brackets of equation 2. We use this measure in a standard

Mincerian wage estimation:

$$\ln w_{it} = \alpha + \beta_1 \text{Task Complexity Level}_o + \sum_k \beta_k X_{k,it} + e_{it}, \tag{C.1}$$

where $\ln w_{it}$ are log real gross weekly wages for individual i at time t. The vector X_{it} includes controls for age, age squared, a dummy equal to 1 for female, years of tenure in the current job and dummies for high, medium and low eduction. Task Complexity Level is standardised by subtracting its mean and dividing by its standard deviation to facilitate interpretation. We use the five quarter LFS which records wage in the first and fifth quarter of interview, we take the wage to be the one seen in the last quarter of interview. The sample includes all types of job histories ending with employment in the fifth quarter of interview.

The estimation of Equation C.1 can been seen in table C.11. A one standard deviation increase in task complexity level is associated with an increase of 11 % in weekly gross real wages. This result suggests that our measure of the length of the vector as a task complexity proxy is reasonable since it is strongly positively correlated with wages.

	$\ln w_{it}$
Task Complexity Level	0.11***
	(0.00)
Age	0.07***
	(0.00)
Age^2	-0.83***
	(0.01)
Female	-0.22***
	(0.00)
High Education	0.69***
	(0.01)
Medium Education	0.27***
	(0.01)
Years Tenure	0.01***
	(0.00)
N	85119
R^2	0.371

Table C.11: Estimated Returns to Task Complexity

Notes: Dependent variable is log real gross weekly wages. Estimated on the LFS 5Q sample of full time workers using wages observed in the first interview quarter for years 2000-2010. Task Complexity Level is proxied by linked O*NET data and standardised. The coefficient on Age^2 is multiplied by 1000. The reference category for education is Low Education (no qualifications). Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.12: Changes in Task Content and Task Complexity over the Cycle

	angSep_p_CASCOT_ALL careerChange_angSep
Aggregate Unemployment Rate	-0.050***
	(0.0048)
Regional-Aggregate Unemployment Rate	-0.0052
	(0.0065)
Female	0.045***
	(0.013)
Age	-0.025***
	(0.0030)
Age^2	0.00025***
	(0.000039)
Married/Cohabitating	-0.021
	(0.014)
Number of Children	-0.013**
	(0.0060)
High Education	0.034*
	(0.018)
Medium Education	0.14***
	(0.013)
Previous Employment Duration	0.079***
	(0.0023)
Full time, Previous Job	-0.15***
	(0.016)
Full time, Current Job	0.037**
	(0.016)
Temporary, Previous Job	-0.0033
	(0.016)
Temporary, Current Job	0.15***
	(0.016)
public1	-0.21***
	(0.020)
public2	0.080***
	(0.019)
Self-employed, Previous Job	0.020
	(0.022)
Self-employed, Current Job	0.018
	(0.021)
Looking for Job	0.49***
	(0.013)
Job Mover	
Involuntary Separation	0.37***
	(0.019)
_If_v_retir_2	0.41***
	(0.015)
Other	0.31***
	(0.023)
Method of seeking: Job Centre	0.11**
	(0.049)
Method of seeking: Ads	0.056**
	(0.025)
Method of seeking:Direct application	-0.12*
	(0.063)
Method of seeking: Family/Friend	-0.0048
	(0.067)
Method of seeking: Other	0.090
	(0.067)
wait	
Quarters	Yes
Regions	Yes
N	53555
R^2	
pseudo R^2	0.077
Log llik.	-34225.8

Marginal effects; Standard errors in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(1) Tobit at the 4-digit occupation category level. (2) Tobit at the aggregated 1-digit occupation category level (3) Double Hurdle at the 4-digit occupation category level. The sample in the selection equation of specification (3) is all individuals aged 16-64 years old over the period 2001q1-2020q3 and employed

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