Highlights

The Task & Skill Content of Occupational Transitions over the Business Cycle: Evidence for the UK

Aspasia Bizopoulou, Rachel Forshaw

- We study the change in tasks and skill content of job transitions using multi-dimensional task and skill measures.
- We create a synthetic two-quarter labour force sample to analyse job-to-job transitions and those with a spell of inactivity or unemployment.
- A Double-Hurdle model captures both the intensive and extensive margins of task and skill 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.

The Task & Skill Content of Occupational Transitions over the Business Cycle: Evidence for the UK

Aspasia Bizopoulou[1]

VATT Institute for Economic Research
Economicum
Arkadiankatu 7
PL 1279, 00101 Helsinki, Finland

Rachel Forshaw[2,*]

Heriot-Watt University,
Campus The Avenue,
Edinburgh, EH14 4AS UK

Abstract

We create a synthetic UK Labour Force Survey sample for the period 2001q3-2020q4 which recovers the job histories of labour market transitions resulting in employment. This enables us to match measures of multidimensional tasks and skills from the O*NET. With a Double-Hurdle model, we capture both the intensive and extensive margins of task and skill changes, and control for selection effects in the types of individuals that transition in adverse labour market conditions. The aggregate effect - driven by fewer transitions - is a reduction in average task and skill moves as the unemployment rate rises. However, 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.

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

[*]Corresponding author
Email addresses: aspasia.bizopoulou@vatt.fi (Aspasia Bizopoulou), r.forshaw@hw.ac.uk (Rachel Forshaw)
URL: https://sites.google.com/site/aspasiabizopoulou (Aspasia Bizopoulou), https://sites.google.com/site/racheljoyforshaw (Rachel Forshaw)
[1]Senior Researcher, VATT Institute for Economic Research
[2]Assistant Professor, Heriot-Watt University

1. Introduction

Periods of increased unemployment entail changes to the reallocation processes of the labour market. It is well-documented that 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). Comparatively little is known about what happens to the content of those transitions in terms of the tasks and skills undertaken as part of occupations. Poletaev and Robinson (2008), Gathmann and Schönberg (2010) and Yamaguchi (2010) detail how heterogenous occupational transitions can be in terms of differences in tasks. Previous literature, including Murphy and Topel (1987), Moscarini and Thomsson (2007), Kambourov and Manovskii (2008), Carrillo-Tudela et al. (2014), Carrillo-Tudela et al. (2016), have used occupational titles as a proxy for the content of occupations, finding occupational transitions to be strongly pro-cyclical. A much smaller literature, including Cortes and Gallipoli (2017), Carrillo-Tudela et al. (2014), Summerfield (2016), focuses on cyclical changes in reallocation of workers across tasks for individual workers. Until now, measurement of the multidimensional task and skill content of labour market transitions in the UK has not been possible. This is for two reasons. Firstly, the UK does not compile a standardised measure of tasks and skills 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 and skill content of occupational transitions in the UK, and how this content changes with labour market conditions. To this end, this paper's first contribution is to develop an algorithm which recovers labour market histories from the UK Labour Force Survey for transitions that result in employment and that may experience up to 3 consecutive quarters of inactivity and/or unemployment. This means that we are able to capture all labour market transitions that result in employment, with the exception of the long-term unemployed or inactive. Secondly, we contribute to the existing evidence on US and European Labour Markets by creating multidimensional task and skill distance measures for the UK. Using the recovered occupational codes for previous employment spells, we match to US O*NET data and measure the task and skill 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 tasks and skills during adverse labour market conditions may differ from those that do not, i.e. selection effects in the types of people who move. This may occur on the worker or firm side:

for example, workers that decide to move during uncertain times may have different risk profiles; the larger available pool of candidates may induce firms be pickier in their hiring decisions than during normal economic times. As such, our third and final contribution is to directly account for these selection effects. Our results are in accordance with previous studies which find procyclical aggregate effects: in periods of high unemployment, average task and skill moves are smaller. However, we find that selection effects - the types of people that move - drive these aggregate results.

In this paper, we break down occupational titles to actual job tasks and specific skill levels, and show that this strong pro-cyclical relationship is no longer evident: recessions negatively impact the number of job transitions but have very little impact on individuals' propensity to change their occupational content.

Characterising an occupation as a group of separate tasks is a relatively recent but already well-established practice in the literature studying job transitions. 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. They study content difference in occupational switchers, defined as the situation when the new occupation employs the previous occupation's main skill with much lower or much higher intensity. They find that wage losses are closely associated with switching skill portfolio, in particular a decrease in skills. The key difference to our study is that their sample is of displaced workers, whereas we focus on all job-to-job transitions. In a similar vein, Gathmann and Schönberg (2010) and subsequently Robinson (2018) construct a measure of occupational distance based on tasks, 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. Our work differs from this literature in that it looks at the long-term trends of task change whereas our concern is the variation over the business cycle.

A separate literature studies job transitions over the business cycle. Carrillo-Tudela et al. (2016) look at the propensity for individuals to change careers over the cycle and find that the probability of a career change co-moves positively with the cycle. In addition, they find that career movers receive higher wages than those who do not change occupations. Devereux (2000) offers an early study of the cyclicality of task assignment, focusing within the firm. He finds that firms tend to re-assign individuals to tasks of lower quality during recessions. Summerfield (2016) shows that recessions lead to an increase in the share of tasks in the economy that are classified as manual. The contribution of the current paper to this literature is to address whether individuals overall tend to move to more or less similar jobs in terms of tasks during recessions, and whether the direction of these moves in terms of the required skill level is affected by economic conditions.

The intuition for why our paper finds results that are contradictory to the literature is twofold. Firstly, we are able to calculate the combined impact of recessions on both i) the probability of changing tasks at all as measured by an occupational transition (which we will call the *extensive* margin) and ii) the extent of the task change for those undertaking an occupational change (which we will call the *intensive* margin). Using the McDonald and Moffitt (1980) decomposition we estimate that 43% of the overall relationship that we estimate is the result of the latter intensive margin, i.e. the part attributable to a change in task or skill content. Previous studies captured only the extensive margin and as such tended to over-estimate the relationship between business cycles and occupational transitions. The second reason for why we find contradictory results is that there is selection in the types of individuals that change occupations in recessions. We use a Double Hurdle model to explicitly capture both the intensive and extensive margins, and allow for correlation in the errors of the two processes. When we control for selection this further reduces the magnitude of the total relationship between business cycles and occupational change.

In our analysis we focus on the part of the working population that makes employment-to-employment (henceforth E2E) moves, which represents just over 50% of new hires in the UK. This population of new hires is an important barometer of the labour market's relationship with business cycles since, adjusting for productivity, the rate of job-to-job transitions is a sufficient statistic for the average real wage in the economy (Moscarini and Postel-Vinay (2016)). Our analysis requires a way to quantify task and skill changes, leading us to focus the first part of the paper on presenting a suitable measure of change in task composition from the literature which we modify to fit our specific purposes. We also propose a second measure to extract skill level information from the task data. We then detail the Double Hurdle model used to understand the relationship between tasks and skill content of occupational changes and the business cycle. Since the decision to change tasks consists of two parts, namely i) the decision to change tasks at all and ii) how big a task move to make, we decompose the estimates to obtain separate figures for each element. We find that the cyclical nature of task and skill changes is quantitatively small, and when we control for the composition effects of the types of people who get hired in a recession, it is statistically insignificant.

In section 2 we describe the data that we use. Section 3 presents the measures of task and skill difference between occupations. Section 4 describes the econometric models used, and section 5 reports the results. Finally, section 6 concludes.

2. Data

We first describe the data on job transitions in section 2.1, then the data on task and skill content of occupations in section 2.2. Section 2.3 describes how we match the two datasets.

2.1. UK Labour Force Survey (LFS)

We use the UK Quarterly Labour Force Survey (LFS) for the years 2001q3 - 2020q4. We focus on this time period as our data allows us to create a consistent classification of occupations, Standard Occupational Classification (SOC2010) codes throughout the sample.[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 (see figure 1). For our analysis, we focus on individuals over two quarters who have spell of employment in the second quarter. To do this, we combine two datasets, the two-quarter (2Q) longitudinal survey [DATASET] (Office for National Statistics (2020b)) and the five-quarter (5Q) longitudinal survey [DATASET] (Office for National Statistics (2020a)). Using the 2Q dataset we are able to study job-to-job transitions that do not involve a quarter or more of unemployment or inactivity between employment spells. Henceforth, we call these 'EE' transitions. We are also interested in transitions that involve spells of inactivity or unemployment, something that is not possible in the 2Q dataset. This is because, for 'IE' and 'UE' transitions, occupational SOC2010 codes and other employment-related data are not available for the previous spell of employment. To study this, we create a new dataset that utilises both 2Q and 5Q data. This involves creating an algorithm which, for each transition that results in employment, recovers data from the previous spell of employment. The standard 2Q LFS sample, plus the recovered job history for IE and UE we term

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

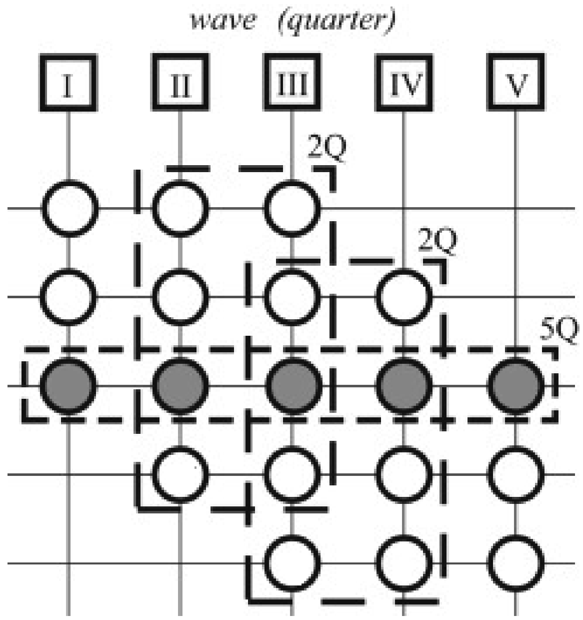


Figure 1: LFS Structure

Panel Structure of the UK Quarterly LFS Survey

the 'synthetic' 2Q sample.[4] Figure 2 shows a visual explanation of the algorithm. In red is the transition for which we need data. This is a transition which results in employment in the fifth quarter of this individual's survey with an intervening quarter of unemployment in the fourth quarter. In the original 2Q data, this would appear as UE transition, but there would be very limited job history about the employment spell in the third quarter.[5] We use the full occupational data from the third quarter that this individual is seen in, which includes the full occupational SOC code and tenure, but individual-specific data from the fourth quarter to create a synthetic 2Q UE transition. As such, we are able to include in our data transitions that involve up to three quarters of inactivity or unemployment, and allows us to match a multidimensional task and skill measure of these transitions, something that has not previously been possible in UK data. Table **??** shows the number of observations by transition type for all transitions which end in employment (column 1) and for

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

[5] Specifically, there would only be the first digit of the occupational SOC code, hence why many studies use the a change in the first-digit of the SOC code as a proxy for occupational change.

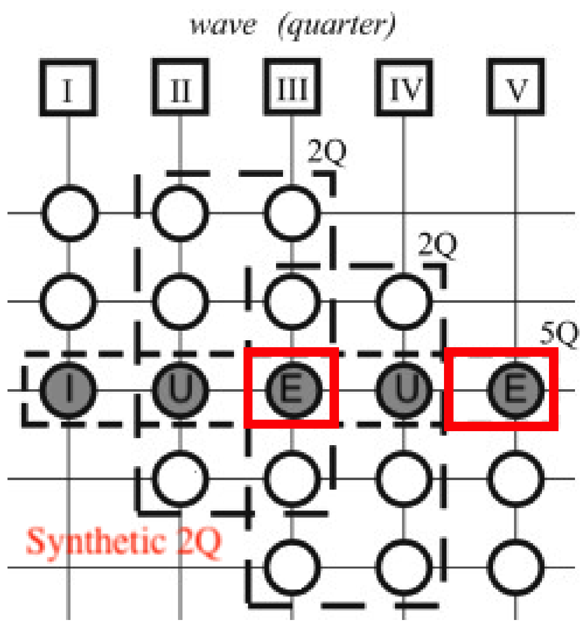


Figure 2: Synthetic 2Q Sample

Example of the Synthetic 2Q UK LFS Sample

those who also move jobs (column 2). Necessarily this synthetic 2Q dataset excludes those who are longer-term unemployed or inactive, and so our sample has a large proportion of EE transitions. As such, we report our results for the whole synthetic 2Q as well as separately for EE, and IE & UE transitions, respectively.

*2.2. US O*NET*

We combine the labour market data with the US Department for Labor's O*NET [DATASET] O*NET 25.1 Database (2020), a highly detailed survey which provides us with a picture of the tasks that are used in occupations. We standardise occupational classifications available in the LFS to match occupations to the US O*NET. Our aim is to obtain a detailed task content and difficulty profile for each occupation and to subsequently measure the distance between different occupations based on similarity of task content and level of skill. 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.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. For the task data, it would

Table 1: Observations by Transition Type

	All transitions	Job Movers
EE	1518538	46783
IE	3096	3096
UE	3676	3676
N	1525310	53555

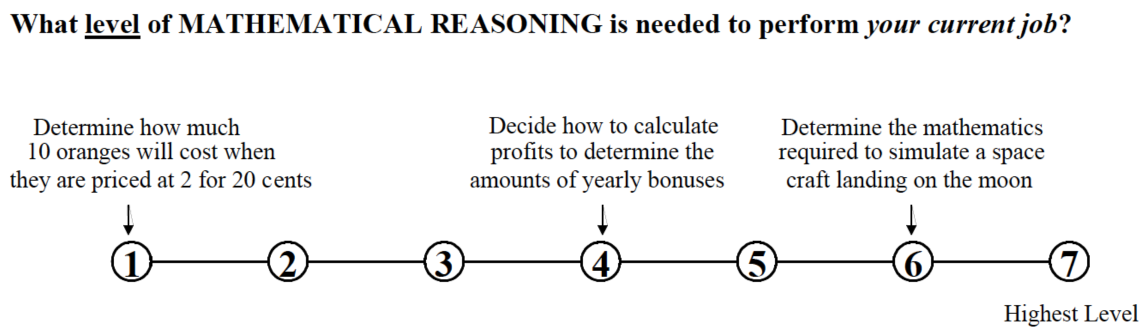


Figure 3: O*NET Example Question

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

be theoretically possible to average over the observations to get job content for occupations. However, 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. 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 skill level at which each task is used in each occupation. We refer to this as 'skill 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 3 shows the

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 4: Example of mapping the SOC2010 to the O*NET

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.

question asked for the job task 'mathematical reasoning'. The skill level score ranges from 1 to 7. In this particular example, a skill 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 higher-skilled. In section 3.1, below, we show the measures used to ascertain the difference between two occupations and to separate out task and skill information.

*2.3. Matching the 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

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

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. 'President' in the US would be 'CEO' 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 A. 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 4, 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 skill needed to perform a job. In this example, we look at the task 'oral comprehension'. In figure 4 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 5 provides an illustration of the average score for every task that is part of an Economist's portfolio, as calculated in Figure 4.

[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.

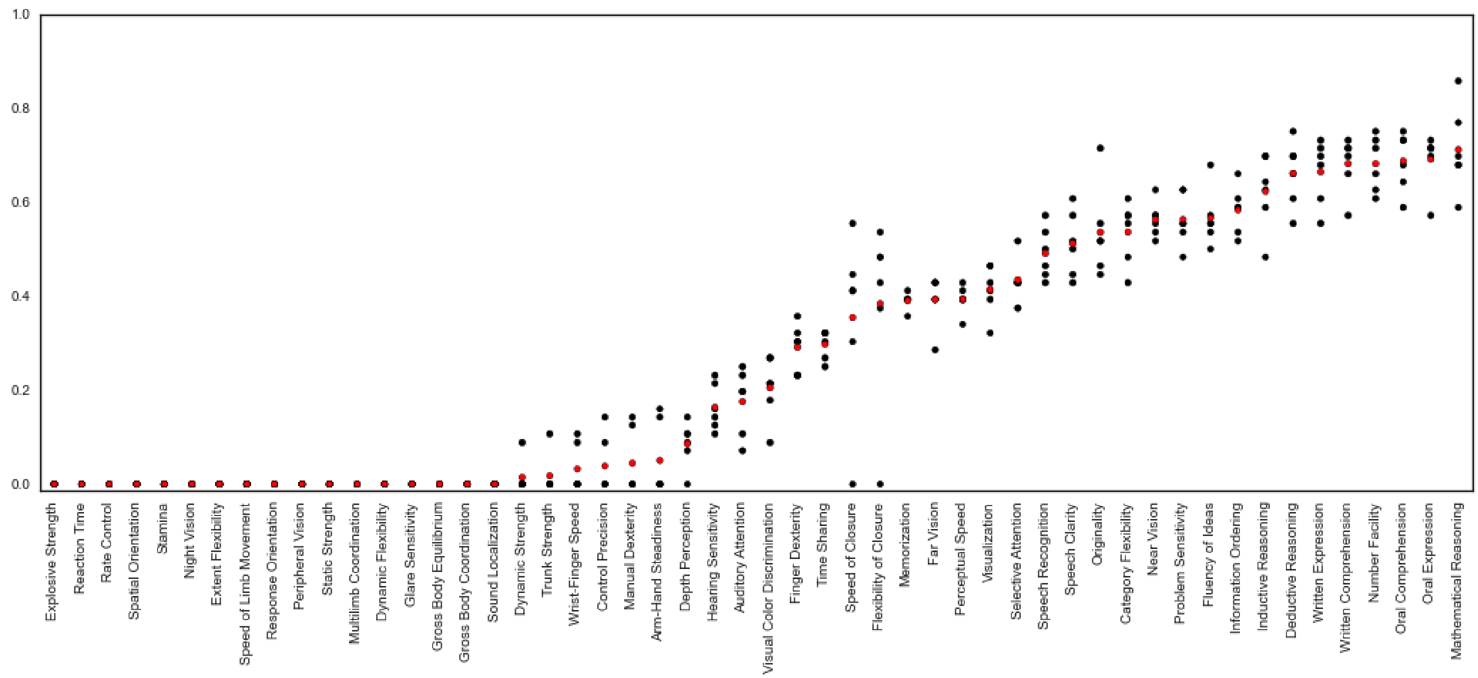


Figure 5: O*NET Task Vector Example - Economist

Example task vector. The y axis lists all the tasks in occupation 2425 (Economist), the x axis is a normalised score of the skill 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 content changes across occupations

We first detail our measure of tasks in section 3.1, then our measure of skills in section 3.2. Section 3.3 shows a simplified example of the two measures and section 3.4 establishes that higher skill level is associated with higher wages in the data. Finally, section 3.5 discusses why it is important to incorporate these measures of tasks and skills when considering occupational changes.

3.1. Measuring the Change in Tasks

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:

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

where o, o' is a pair of different occupations, t is tasks, $q_{t,o}$ represents the skill level of a task t within occupation o. Intuitively, the change in task composition between a set of occupations o and o' are compared by measuring the 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 only carries information about the composition of tasks, rather than the skill level, whereas our task vectors include both. Therefore we develop another measure, detailed below in section 3.2 which captures the difference in skill level between task vectors.

3.2. Measuring the Change in Skills

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

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

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

3.3. Two-Task Example of the Task and Skill Change Measures

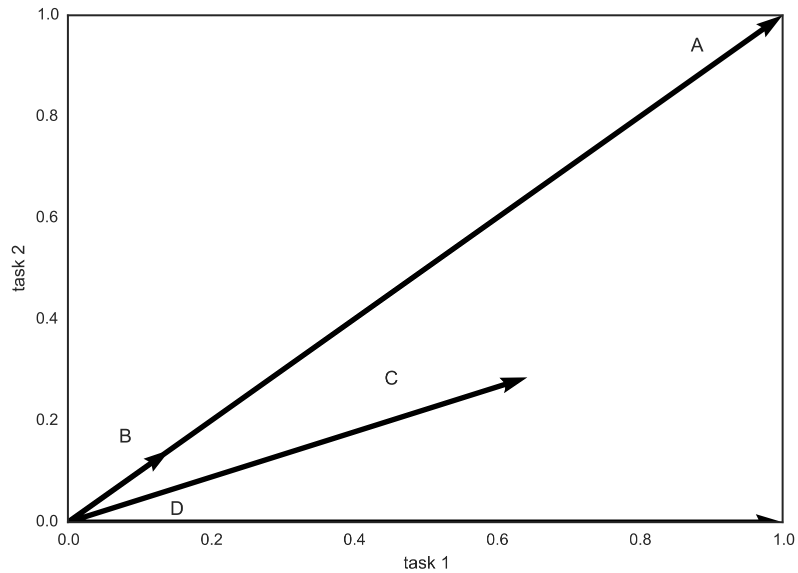
Figure 6 provides an illustration of how the ΔTask and ΔSkills measures can provide us with information about the content of occupational moves. We construct a basic example in which there are a total of four different occupations (A, B, C, D) which comprise two tasks: task 1 and task 2. Moving from occupation A, which is highly skilled in task 1 and task 2, to B, which is lowly skilled in both tasks gives a change in task composition of 0, since the tasks are still used in the same proportion. The $\Delta\text{Skills}_{o,o'}$ 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 tasks and upskilling, whereas the change in tasks from A to D constitutes downskilling. Finally, moving from and to the same occupation A results in zeros for both measures.

3.4. The Relationship between Skill Level and Wages

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

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

[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.



	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 6: An example of ΔTasks and ΔSkills with 2 tasks and 4 occupations

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:

$$\ln w_{it} = \alpha + \beta_1 \text{ Skill Level}_o + \sum_k \beta_k X_{k,it} + e_{it}, \tag{3}$$

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. Skill Level is standardised by subtracting its mean and dividing by its standard deviation to facilitate interpretation. We use the five quarter LFS and 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.

	$\ln w_{it}$
Skill Level	0.12***
	(0.00)
Age	0.08***
	(0.00)
Age^2	-0.84***
	(0.01)
Female	-0.22***
	(0.00)
High Education	0.66***
	(0.01)
Medium Education	0.25***
	(0.01)
Years Tenure	0.01***
	(0.00)
N	79155
R^2	0.377

Table 2: Estimated Returns to Skills

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

The estimation of Equation 3 can been seen in table 2. A one standard deviation increase in skill level is associated with an increase of 12% in weekly gross real wages. This result suggests that our measure of the length of the vector as a skill difficulty proxy is reasonable since it is strongly positively correlated with wages.

3.5. The Advantage of Using Disaggregated Task Data

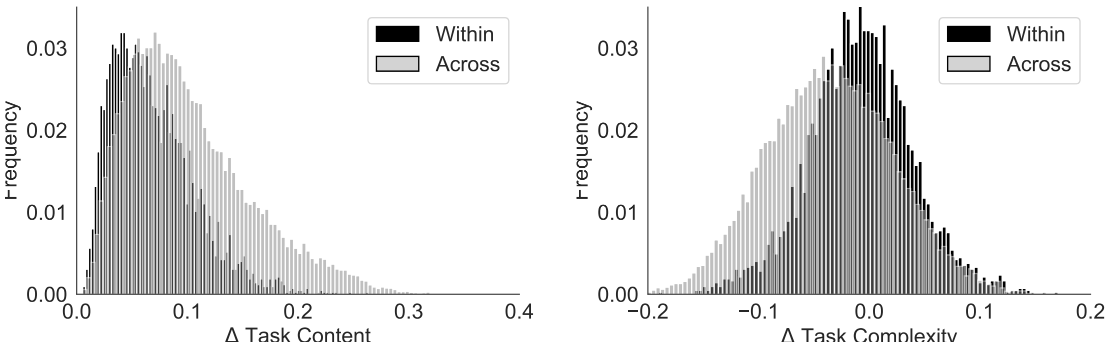
Before proceeding to apply the above measure in our analysis, we take a moment to highlight the way in which we use task data to characterise how the content of two occupations might be different. We differ from the mobility literature, which usually use highly aggregated occupational codes, as in Carrillo-Tudela 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 are a very rough proxy for capturing 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 7 shows the resulting theoretical distributions.[9] In both figures, we see that this 1-digit SOC code proxy does capture some of the differences between occupations. In the left-hand of figure 7, 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 'de-skilling' occupational moves. 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 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

Table 3 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-

[9]Note that these plotted distributions exclude zeros (i.e., no change in task or skill 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.



	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 7: 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.

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).

This motivates our 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 and skill change during employment transitions. The first hurdle is a Probit model, capturing whether an individual decides to change tasks or skills or not. If they do not change jobs, their Δ Tasks and Δ Skills will be always be zero. If the individual has changed jobs, they must decide whether to change occupations, resulting in Δ Tasks and Δ Skills being non-zero. If they do not change occupations, their Δ Tasks and Δ Skills will appear as zero in the data. This is illustrated in figure 8. For a large portion of the sample - approximately 40% of all job changers - the dependent variables are censored at zero. Individuals censored at zero are those who experience a job transition, but don't change their occupation code. Individuals that do not change codes may still change tasks since even the most detailed 4-digit SOC codes aggregate occupations into groups, as was shown in

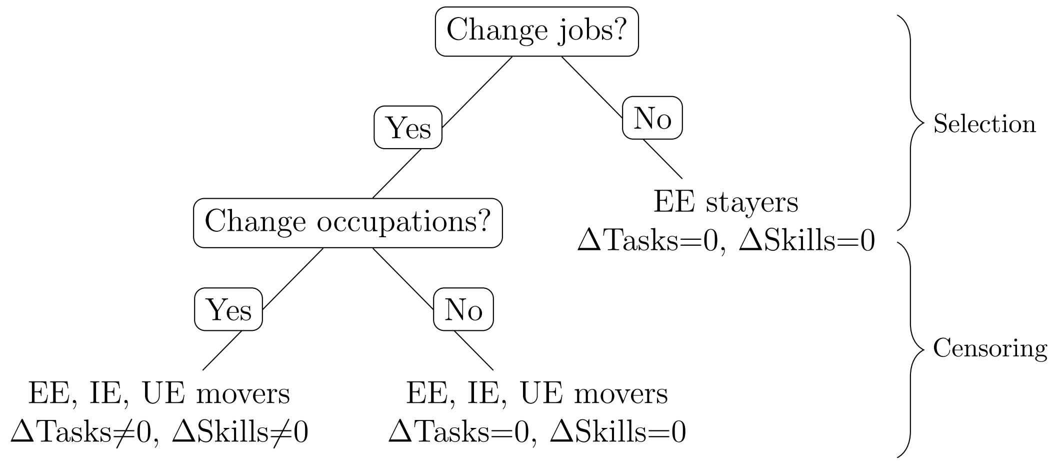


Figure 8: Illustration of Double Hurdle model

First step: whether an individual changes jobs. Second step: whether an individual changes occupations (whether they have a task and skill change.)

section 2.2. Hence the data is censored, and so a Tobit is the appropriate specification for the amount decision. Concretely, the equations of the Double Hurdle model are:

$$\mathrm{TSC}^*_{it,2} = \tilde{\beta}_0 + \tilde{\beta}_2 \mathrm{u}_{t,2} + \tilde{\beta}_2 \mathrm{Wait}_{t,1} + \sum_j \tilde{\beta}_j \hat{X}_{j,it,1} + \sum_k \tilde{\alpha}_k \mathrm{Q}_{k,2} + \sum_l \tilde{\gamma}_l \mathrm{R}_{l,1} + \sum_m \tilde{\delta}_m \mathrm{I}_{m,1} + \tilde{e}_{it} \tag{4a}$$

$$y^{**}_{it,2} = \check{\beta}_0 + \check{\beta}_1 u_t + \sum_j \check{\beta}_j X_{j,it,12} + \sum_k \check{\alpha}_k \mathrm{Q}_{k,1} + \sum_l \check{\gamma}_l \mathrm{R}_{l,1} + \sum_m \check{\delta}_m \mathrm{I}_{m,1} + \hat{\lambda}_{it} + \check{e}_{it} \tag{4b}$$

$$\mathrm{TSC}_{it,2} = \begin{cases} 1, & \text{if } \mathrm{TSC}^*_{it,2} > 0 \\ 0, & \text{if } \mathrm{TSC}^*_{it,2} \leq 0 \end{cases} \tag{4c}$$

$$y^*_{it,2} = \max(0, y^{**}_{it,2}) \tag{4d}$$

$$y_{it,2} = \mathrm{TSC}_{it,2} y^*_{it,2} \tag{4e}$$

Where subscripts refer to individual i, subscripts $_1$, $_2$ and $_{12}$ refer to data in the first quarter, second quarter, and both quarters of an individual transition at time t, respectively. Q are quarter, R region and I industry fixed effects; e_{it} is the error term.

Equation 4a is the Probit participation model which has dependent variable TSC* (Task or Skill Change) equal to one if an individual changes both jobs and tasks or skills between the first and second quarter of interview, zero otherwise. Note that control variables $\hat{X}$ differ from those in the amount equation, 4b, since we include only first-period controls for characteristics of the respondent's previous job. We also omit search method as only those that changed jobs were asked which search method they used. Equation 4b and 4d are the Tobit structural model with dependent variables $y_{it,2}$ y_{it} is the dependent variable, which is either $\Delta\, Tasks_{it}$ when estimating the relationship between labour market conditions and the change in task composition of moves or $|\Delta Skills_{it}|$ when estimating the relationship with the absolute change in skill level. We take the absolute value of the change in skill level since we cannot have an upper and lower truncation limit for the Tobit equal to zero (as this would imply no truncated values). Equation 4e is the data actually observed, which captures the combined effect of the participation decision (equations 4a, 4c) and the amount decision (equation 4b). Equations 4b and 4d are a Tobit model with the addition of the estimated inverse Mills ratio, $\hat{\lambda}$, obtained from estimating equation 4a to control for selection. Our independent variable of interest is u_t, the aggregate unemployment rate. We add 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.

The Double Hurdle model has the advantage of allowing the extensive (participation) and intensive (amount) margins to be governed by distinct stochastic processes. That is, unlike a simple Tobit model, it allows different processes to determine the value of the continuous (non-zero) observations and the discrete switch at zero. This is important for our purposes since there is no reason to expect that the relationship between the unemployment rate and the extensive margin (the decision to change task/skills) to be the same as the intensive margin (the amount to change task/skills).

[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.

This modelling approach is also related to the control function advanced by Heckman (1979), but whereas the Heckit model assumes first hurdle dominance - ie. that in the second stage there will be no zero observations, the Double Hurdle model allows zero observations to arise, important in this case as a zero task/skills move is a valid choice. As in a Heckman model, we allow the errors of the first and second hurdles to be correlated.

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 or skill 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 3: Difference in Means of E2E Sample In and Outside Recession

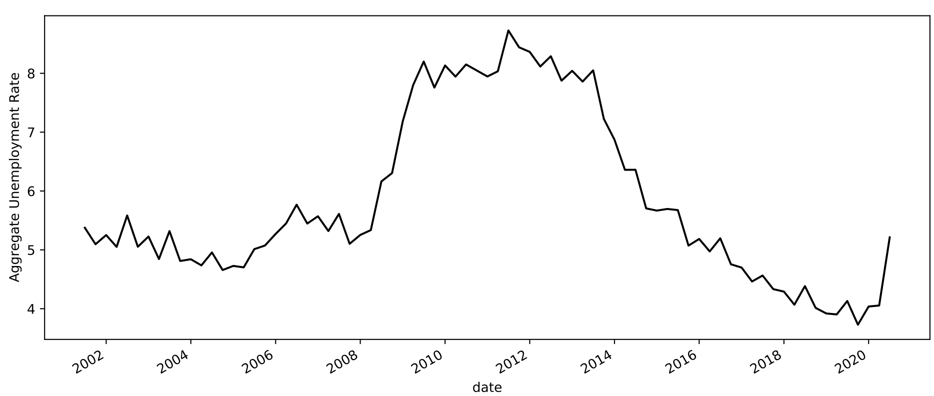
Recession	0	1	Difference
Female	0·51	0·51	0·000
	(0·00)	(0·01)	(0·008)
Age	34·36	36·18	1·820***
	(0·08)	(0·20)	(0·209)
Married	0·41	0·44	0·027***
	(0·00)	(0·01)	(0·008)
Tenure (months)	40·99	46·80	5·809***
	(0·42)	(1·10)	(1·103)
Full Time in Previous Job	0·68	0·68	0·007
	(0·00)	(0·01)	(0·008)
Full Time in Current Job	0·71	0·71	−0·001
	(0·00)	(0·01)	(0·007)
Temporary in Previous Job	0·18	0·17	−0·015**
	(0·00)	(0·01)	(0·006)
Temporary in Current Job	0·21	0·21	−0·002
	(0·00)	(0·01)	(0·007)
Self Employed in Previous Job	0·07	0·08	0·014***
	(0·00)	(0·00)	(0·004)
Self Employed in Current Job	0·09	0·10	0·008*
	(0·00)	(0·00)	(0·005)
Public Sector in Previous Job	0·14	0·16	0·023***
	(0·00)	(0·01)	(0·006)
Public Sector in Current Job	0·16	0·19	0·026***
	(0·00)	(0·01)	(0·006)
High Education	0·16	0·17	0·012**
	(0·00)	(0·01)	(0·006)
Medium Education	0·60	0·46	−0·135***
	(0·00)	(0·01)	(0·008)
Low Education	0·24	0·37	0·123***
	(0·00)	(0·01)	(0·007)
Search Method: Not Looking	0·91	0·90	−0·005
	(0·00)	(0·00)	(0·005)
Search Method: Job Centre	0·02	0·01	−0·003
	(0·00)	(0·00)	(0·002)
Search Method: Applying to Ads	0·06	0·06	0·007*
	(0·00)	(0·00)	(0·004)
Search Method: Direct Application to Employers	0·01	0·01	−0·001
	(0·00)	(0·00)	(0·001)
Search Method: Ask Friends/Relatives	0·01	0·01	0·001
	(0·00)	(0·00)	(0·001)
Other Job Search Method	0·01	0·01	0·002
	(0·00)	(0·00)	(0·001)
Involuntary Separation	0·48	0·43	−0·052***
	(0·00)	(0·01)	(0·008)
Voluntary Separation	0·15	0·17	0·020***
	(0·00)	(0·01)	(0·006)
Other Separation	0·30	0·29	−0·013*
	(0·00)	(0·01)	(0·008)
N	25027	4294	29321

Notes: Difference in longitudinal-weighted means inside=1 and outside=0 of recession for all transitions in the synthetic 2Q sample. Recession periods defined using UK ECRI indicator. Significance levels: $^{*} < 10\%$ $^{**} < 5\%$ $^{***} < 1\%$. Standard errors in parentheses. Source: author's calculations.

5. Results

(a)

(b)



(c)

Figure 9: Five quarter moving average of the (a) Δ Tasks and (b) Δ Skills within-quarter for EE, IE transitions.(c) Aggregate Unemployment Rate.

Results are shown in model (1) of table 4. We see that an increase in the unemployment rate of one percentage point is associated with .01 of a standard deviation reduction in task change.[11] The magnitude of this relationship is very small. To put this into context, we estimate that the conditional average of ΔTask Change is .03 [12]. An example of a move with ΔTask composition equal to .03 is from 4159 'Fraud Inspector' to 3533 'Insurance Underwriter'. During the 2008 recession, the unemployment rate increased by approximately 2.5 percentage points. The estimated standard deviation of ΔTask composition, conditional on the controls listed in section 4, is .04. An increase in the unemployment rate by 2.5 percentage points would therefore correspond to an approximate change of:

$$\underbrace{2.5}_{\Delta Xu} * \underbrace{0}_{\frac{\widehat{\partial E(y|X)}}{\partial Xu}} * \underbrace{.04}_{\widehat{E(\sigma|X)}} = .001$$

In our example, this would be an occupational move with ΔTasks=.03 .001 = .041. An example of such a task move is 3532 'Insurance Broker' to 4132 'Administrative Officer, Insurance'. Both of these examples are small occupational moves, and there seems to be minimal difference between the two types of moves.

In terms of the absolute change in skill level (i.e. when $y_i = |\Delta Skills_i|$), the estimate is in the same direction and of a similar magnitude. An increase in the aggregate unemployment rate corresponds to a 0 change in skill level.[13] This estimated relationship is similarly economically insignificant.

[11].01 times the APE factor, .48

[12]Conditional on the compositional controls listed in table 4.

[13]0 times the APE factor,.48, table 4

Table 4: Double-Hurdle Regression Output

	Δ Tasks						ΔSkills					
	ALL		EE		IE & UE		ALL		EE		IE & UE	
	Above	Hurdle	Above	Hurdle	Above	Hurdle	Above	Hurdle	Above	Hurdle	Above	Hurdle
Aggregate Unemployment Rate	0.23***	0.059***	0.23***	0.055***	0.014	-0.074***	0.24***	-0.022	0.25***	-0.037***	-0.044**	-0.0052
	(0.0080)	(0.0066)	(0.0076)	(0.0069)	(0.027)	(0.026)	(0.0092)	(0.015)	(0.0090)	(0.014)	(0.022)	(0.080)
Regional-Aggregate Unemployment Rate	0.0027	0.019*	0.00032	0.018*	-0.0025	-0.00023	-0.0026	0.0092	-0.00032	-0.0038	-0.020	0.017
	(0.011)	(0.0097)	(0.011)	(0.010)	(0.032)	(0.036)	(0.012)	(0.019)	(0.012)	(0.019)	(0.028)	(0.11)
Female	-0.25***	0.20***	-0.26***	0.14***	-0.22***	0.19***	0.12***	-0.66***	0.053*	-0.45***	0.016	0.50**
	(0.028)	(0.024)	(0.025)	(0.025)	(0.068)	(0.058)	(0.030)	(0.12)	(0.031)	(0.074)	(0.058)	(0.21)
Age	-0.030***	-0.0010	-0.028***	0.0056	-0.047***	-0.0019	-0.037***	0.037***	-0.031***	0.024**	-0.042***	-0.075
	(0.0056)	(0.0061)	(0.0055)	(0.0064)	(0.013)	(0.015)	(0.0065)	(0.010)	(0.0070)	(0.011)	(0.012)	(0.052)
Age^2	0.21***	0.11	0.17**	0.050	0.51***	-0.071	0.31***	-0.54***	0.21**	-0.34**	0.51***	0.58
	(0.069)	(0.070)	(0.068)	(0.073)	(0.17)	(0.19)	(0.079)	(0.13)	(0.086)	(0.14)	(0.16)	(0.60)
Married/Cohabitating	0.020	-0.059***	0.020	-0.049**	-0.019	-0.046	0.049*	-0.057	0.065**	-0.087*	-0.15**	0.37
	(0.024)	(0.021)	(0.024)	(0.022)	(0.076)	(0.076)	(0.026)	(0.045)	(0.027)	(0.046)	(0.068)	(0.26)
Number of Children	-0.071***	0.025***	-0.077***	0.026***	-0.020	-0.042	-0.049***	-0.023	-0.046***	-0.039**	-0.0058	0.0041
	(0.011)	(0.0096)	(0.011)	(0.010)	(0.028)	(0.031)	(0.012)	(0.020)	(0.013)	(0.020)	(0.027)	(0.12)
High Education	-0.10***	-0.21***	-0.12***	-0.18***	-0.024	0.18*	-0.33***	0.54***	-0.27***	0.37***	-0.11	2.02**
	(0.036)	(0.028)	(0.034)	(0.030)	(0.095)	(0.11)	(0.036)	(0.12)	(0.038)	(0.068)	(0.089)	(1.01)
Medium Education	-0.30***	-0.089***	-0.33***	-0.059***	0.13*	0.075	-0.49***	0.38***	-0.51***	0.41***	0.024	0.44*
	(0.023)	(0.020)	(0.022)	(0.021)	(0.070)	(0.073)	(0.027)	(0.044)	(0.026)	(0.045)	(0.068)	(0.26)
Previous Employment Duration	0.0012	-0.096***	0.019***	-0.11***	0.015	-0.061***	-0.029***	0.068***	-0.037***	0.11***	0.014	-0.058
	(0.0061)	(0.0058)	(0.0062)	(0.0065)	(0.014)	(0.014)	(0.0078)	(0.013)	(0.0077)	(0.014)	(0.012)	(0.041)
Full time, Previous Job	0.016	-0.51***	0.0056	-0.46***	-0.054	0.10	-0.060	0.41***	-0.012	0.31***	-0.10*	0.012
	(0.049)	(0.034)	(0.049)	(0.035)	(0.064)	(0.070)	(0.052)	(0.069)	(0.054)	(0.051)	(0.061)	(0.20)
Full time, Current Job	0.57***		0.64***		-0.017		0.41***		0.50***		-0.029	
	(0.044)		(0.047)		(0.054)		(0.045)		(0.047)		(0.054)	
Temporary, Previous Job	0.043	-0.24***	0.091	-0.30***	0.037	-0.19**	-0.071	0.28***	-0.023	0.24***	-0.034	-0.52
	(0.056)	(0.065)	(0.058)	(0.073)	(0.075)	(0.083)	(0.058)	(0.071)	(0.063)	(0.067)	(0.081)	(0.40)
Temporary, Current Job	0.83***		0.91***		-0.12**		0.75***		0.83***		-0.098*	
	(0.049)		(0.053)		(0.052)		(0.050)		(0.054)		(0.052)	
public1	-0.58***	-1.13***	-0.45***	-1.66***	-0.094	-0.21**	0.44***	-0.40***	0.58***	-0.69***	0.056	0.89*
	(0.076)	(0.11)	(0.080)	(0.34)	(0.095)	(0.089)	(0.089)	(0.081)	(0.086)	(0.068)	(0.084)	(0.51)
public2	0.31***		0.28***		0.20***		0.32***		0.32***		0.15**	
	(0.060)		(0.064)		(0.067)		(0.061)		(0.065)		(0.067)	
Self-employed, Previous Job	-0.46**	-2.31***	0.21	-2.95***	0.27	-0.66***	0.18**	4.88	0.49***	1.85	-0.64***	-0.19
	(0.20)	(0.12)	(0.21)	(0.36)	(0.17)	(0.087)	(0.084)	(113.9)	(0.091)	(1.47)	(0.086)	(0.32)
Self-employed, Current Job	0.37***		0.30***		0.19**		-0.38***		-0.42***		-0.21***	
	(0.071)		(0.076)		(0.079)		(0.062)		(0.067)		(0.074)	
Looking for Job	0.97***	1.13***	0.85***	1.03***	-0.11	0.55***	0.51***	2.67	0.43***	1.34***	0.072	1.09***
	(0.049)	(0.081)	(0.044)	(0.085)	(0.089)	(0.071)	(0.049)	(1.64)	(0.044)	(0.23)	(0.060)	(0.24)
Job Mover	6.16***		6.04***				6.12***		6.08***			
	(0.043)		(0.048)				(0.047)		(0.052)			
Separation: Involuntary	1.50***		1.90***		0.079		1.49***		1.80***		0.17**	
	(0.087)		(0.095)		(0.079)		(0.090)		(0.098)		(0.082)	
Separation: Voluntary	2.02***		2.43***		-0.087		2.00***		2.32***		-0.080	
	(0.067)		(0.072)		(0.10)		(0.070)		(0.079)		(0.10)	
Separation: Other	1.49***		1.91***		-0.022		1.57***		1.93***		0.096	
	(0.11)		(0.12)		(0.12)		(0.11)		(0.12)		(0.12)	
Method of seeking: Job Centre	-0.030		-0.0011		0.066		0.0076		0.025		0.034	
	(0.11)		(0.11)		(0.14)		(0.11)		(0.11)		(0.15)	
Method of seeking: Ads	-0.028		-0.011		0.29***		-0.039		-0.016		0.13*	
	(0.044)		(0.047)		(0.080)		(0.045)		(0.047)		(0.079)	
Method of seeking:Direct application	0.12		0.15		0.085		0.054		0.082		-0.10	
	(0.13)		(0.14)		(0.22)		(0.13)		(0.14)		(0.20)	
Method of seeking: Family/Friend	0.013		0.042		-0.14		0.065		0.092		-0.054	
	(0.12)		(0.13)		(0.22)		(0.12)		(0.13)		(0.22)	
Method of seeking: Other	0.39***		0.42***		0.29		0.39***		0.42***		0.21	
	(0.11)		(0.12)		(0.23)		(0.11)		(0.11)		(0.22)	
Wait		1.14		-0.48		0.27***		1.96		3.98		1.14**
		(0.75)		(18.3)		(0.10)		(1.54)		(148.5)		(0.57)
λ	3.23***		2.25***		-0.021		-2.33***		-2.73***		-2.69***	
	(0.30)		(0.30)		(0.60)		(0.13)		(0.14)		(0.30)	
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	1525310		1518538		6772		1525310		1518538		6772	
pseudo R^2	0.0537		0.0503		0.0231		0.0508		0.0482		0.0240	
Log llik.	-635952.5		-625239.1		-9059.8		-634805.7		-623783.4		-8987.3	

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.

Regression specification (2) in table 4, which estimates equation **??** at the one-digit level of SOC codes, shows further that our results are not driven by our use of more granular occupational codes. Model (2) shows the same Tobit model as (1) but with task and skill moves aggregated to 1-digit occupational categories. As expected the coefficient on the unemployment rate is larger in magnitude, however it remains economically insignificant.

Regression specification (3) in table 4, which estimates equation 4, further controls for selection using a Double Hurdle model. Controlling for the selection of those who move occupations in recessions, we see that the coefficient on the unemployment rate is smaller in magnitude for both task and skill moves and is now statistically insignificant. The coefficient on the unemployment rate in the Probit equation 4a is negative and highly significant, suggesting that negative relationship between recessions and job transitions works entirely through the extensive margin of whether to change employers or not. This suggests that the types of people that move employers in a recession are less likely to make large task and skill moves.

In each specification control variables are, for the most part, significant; in a number of cases they are a magnitude larger than the estimated coefficient on the unemployment rate. Older individuals (*Age*) tend to make smaller task and skill moves, consistent with the idea that individuals tend to specialise over their careers. For the same reasons, those with a higher relative to lower education level (*High Education*), and those with greater tenure (*Tenure*) tend to make smaller task and skill moves. Being full time relative to part time in a previous job (*Full Time in Previous Job*) is associated with much lower task and skill moves in all specifications, and at a magnitude of approximately ten times that of recessions. This suggests that full time workers are much less flexible in changing the content of their jobs when moving employers than part time workers are. Similarly, being fired from a first quarter job (*Involuntary Separation*) is associated with much smaller task and skill moves than quits. If an individuals' second quarter recorded occupation is temporary rather than permanent (*Temporary in Current Job*), this is associated with much larger task and skill moves. Again this association is an order of magnitude greater than that of recessions. The same is true for having a public sector rather than private sector job in the second quarter (*Public Sector in Current Job*), being self employed in either the first or second quarter of interview (*Self Employed in Previous/Current Job*) and applying to jobs via Job Centres (*Search Method: Job Centre*) and Advertisements (*Search Method: Advertisements*) relative to not searching for a job.

6. Concluding Remarks

We study the extent to which the occupational content of job transitions is sensitive to cyclical fluctuations. Using the UK Labour Force Survey matched with the O*NET dictionary of tasks for the period 2001q3-2020q4, we find little evidence for an economically significant relationship. Unlike previous research, we focus on observed changes in the task content and skill level of job transitions, not only on changes in occupational category.

Our first econometric specification sits closest to the existing literature; we use a Tobit model to estimate the relationship between business cycles and the propensity to make occupational changes. Novel to our paper is the addition of task and skills data. This captures not only the extensive margin of whether people make occupational transitions in recessions, but also the intensive margin of the extent of task and skill change. We find a relationship in the same direction as existing studies: task and skill distances decrease in recessions. However the economic significance of the result is small, and by using a McDonald-Moffit decomposition we show that this is because the intensive margin of the extent of occupational change comprises over 43% of the total relationship. Furthermore, we aggregate the tasks and skills data to the one-digit SOC code level, and show that our result is not simply a result of using more disaggregated data. These results, along with evidence of selection effects in the types of people that change jobs in a recession, suggests a need to capture both the decision to change employers and the decision to make an occupational change. Our final specification, which uses a Double Hurdle model, captures this two-stage decision process and allows for selection. We show that the estimates under this specification show an insignificant relationship between recessions and the intensive margin of occupational change. In recessions, individuals make smaller occupational changes - but this is driven entirely by a slowing down in the rate of employer change, along with selection effects: the types of people that make employer changes in recessions also tend to make smaller occupational task and skill moves.

7. Acknowledgements

An earlier version of this paper formed part of both authors' PhD theses, and as such would like to thank our supervisors Liang Bai, Mike Elsby, Maia Güell, and Ludo Visschers for their guidance. We also thank Carlos Carrillo-Tudela, Cristina Lafuente, Eva Pocher, Jean-Marc Robin, Tuomas Pekkarinen, Anna Salomons, Mark Schaffer and Jonathan Thomas as well as participants from conferences at Economics at Panmure House, EEA-ESEM, EALE, ESPE, RES, SaM, SGPE, SMYE, SGPE; from seminars at Aalto University, The University of Edinburgh, ETLA, IAB, Scottish Government and VATT.

Appendix A. Summary Statistics

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

	Job Mover=0	Job Mover=1
EE	1471755	46783
IE		3096
UE		3676
N	1471755	53555

Table A.3: Mean and sd of Δ tasks and Δ skills by job move, 0 = did not move jobs, 1= moved jobs

	Job Mover=0		Job Mover=1	
	mean	sd	mean	sd
Δ Tasks	.0031451	.0147789	.0286688	.04092
Δ Skills	.0025851	.0126701	.0215183	.0325527
Observations	1471755		53555	

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

	Skill/Task Mover=0	Skill/Task Mover=1
EE	1400165	118373
IE	1700	1396
UE	1432	2244
N	1403297	122013

Table A.5: Mean and sd of Δ tasks and Δ skills by task/skill move

	Task/skill mover=0		Task/skill mover=1	
	mean	sd	mean	sd
Δ Tasks	0	0	.0505202	.0360182
Δ Skills	0	0	.0406277	.0321674
Observations	1403297		122013	

Table A.6: Mean and sd of job mover by task/skill move, 0 = did not move task/skills, 1= moved task/skills

	Task/skill mover=0		Task/skill mover=1	
	mean	sd	mean	sd
Job Mover	.0199879	.1399587	.2090433	.406627
Observations	1403297		122013	

Table A.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	.4974456	.4999936	.5094949	.4999145
Age	42.06688	12.08511	34.91777	13.00206
Married	.5856233	.4926143	.4129213	.4923635
Tenure	6.363783	2.139122	3.059882	2.669587
Full time	.7344184	.4416425	.6560919	.4750153
Temporary	.0383929	.192143	.1865932	.3895883
Public	.2581965	.4376428	.1529642	.3599564
Self-employed	.1357468	.3425196	.0862851	.2807872
Education	2.242116	.6891855	2.162356	.6666321
Region	10.8174	4.916284	10.51104	4.672623
Reason left last job	2.72e-06	.0023315	.7593502	1.019184
Industry	2.746894	.4695046	2.767921	.4493731
Number of Children	.768085	1.020599	.8049855	1.035531
Time between jobs	0	0	.1658482	.4808957
Whether looking	.049303	.2165001	.2854822	.451648
N	1471755		53555	

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

	EE		IE		UE	
	mean	sd	mean	sd	mean	sd
Job Mover	.0308079	.172797	1	0	1	0
N	1518538		3096		3676	

Table A.9: Mean values of Δ tasks and Δ skills for EE transitions by whether waited to start new job, 1= yes , 0=no

Variable	0	1	Diff
Δ Tasks	0·03	0·02	−0·007
	(0·00)	(0·01)	(0·008)
Δ Skills	0·02	0·02	0·000
	(0·00)	(0·01)	(0·006)
N	46756	27	46783

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

Table A.10: Mean values of Δ tasks and Δ skills for IE transitions by whether waited to start new job, 1= yes , 0=no

Variable	0	1	Diff
Δ Tasks	0·03	0·03	0·004
	(0·00)	(0·00)	(0·003)
Δ Skills	0·02	0·02	0·002
	(0·00)	(0·00)	(0·002)
N	2883	213	3096

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

Table A.11: Mean values of Δ tasks and Δ skills for UE transitions by whether waited to start new job, 1= yes , 0=no

Variable	0	1	Diff
Δ Tasks	0·04	0·04	0·001
	(0·00)	(0·00)	(0·003)
Δ Skills	0·03	0·03	−0·002
	(0·00)	(0·00)	(0·002)
N	3376	300	3676

[1] Significance levels: $^{*} < 10\%$ $^{**} < 5\%$ $^{***} < 1\%$
[2] Standard errors in parentheses

Table A.12: Likelihood of job move for EE transitions by whether waiting to start job, 1= yes , 0=no

Variable	0	1	Diff
JobMover	0·03	0·41	0·378***
	(0·00)	(0·06)	(0·021)
N	1518472	66	1518538

[1] Significance levels: $^{*} < 10\%$ $^{**} < 5\%$ $^{***} < 1\%$
[2] Standard errors in parentheses

Appendix B. Robustness Checks

Table B.13: Changes in Tasks and Skills 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 2001q3-2020q4 and employed

References

Acemoglu, D., Autor, D., 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings, in: Ashenfelter, O., Card, D. (Eds.), Handbook of Labor Economics. Elsevier. volume 4 of *Handbook of Labor Economics*. chapter 12, pp. 1043–1171. URL: https://ideas.repec.org/h/eee/labchp/5-12.html.

Autor, D.H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the us labor market. American Economic Review 103, 1553–97. URL: https://www.aeaweb.org/articles?id=10.1257/aer.103.5.1553, doi:10.1257/aer.103.5.1553.

Autor, D.H., Levy, F., Murnane, R.J., 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. The Quarterly Journal of Economics 118, 1279–1333. URL: https://ideas.repec.org/a/oup/qjecon/v118y2003i4p1279-1333..html.

Blundell, R., Ham, J., Meghir, C., 1989. Unemployment and Female Labour Supply. Palgrave Macmillan US, New York. pp. 9–36. URL: https://doi.org/10.1007/978-1-349-19795-8, doi:10.1007/978-1-349-19795-8.

Blundell, R., Meghir, C., 1987. Bivariate alternatives to the tobit model. Journal of Econometrics 34, 179–200. URL: https://EconPapers.repec.org/RePEc:eee:econom:v:34:y:1987:i:1-2:p:179-200.

Carrillo-Tudela, C., Hobijn, B., She, P., Visschers, L., 2016. The extent and cyclicality of **career** changes: Evidence for the U.K. European Economic Review 84, 18 – 41. URL: http://www.sciencedirect.com/science/article/pii/S0014292115001464, doi:https://doi.org/10.1016/j.euroecorev.2015.09.008. european Labor Market Issues.

Carrillo-Tudela, C., Hobjin, B., Visschers, L., 2014. Career changes decline during recessions. FRBSF Economic Letters 2014-09 , 2–5URL: http://www.frbsf.org/economic-research/files/el1995-39.pdf.

Cortes, G.M., Gallipoli, G., 2017. The Costs of Occupational Mobility: An Aggregate Analysis. Journal of the European Economic Association 16, 275–315. URL: https://doi.org/10.1093/jeea/jvx006, doi:10.1093/jeea/jvx006, arXiv:https://academic.oup.com/jeea/article-pdf/16/2/275/25441061/jvx006.pdf.

Cragg, J.G., 1971. Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. Econometrica 39, 829–844. URL: https://ideas.repec.org/a/ecm/emetrp/v39y1971i5p829-44.html.

Devereux, P.J., 2000. Task assignment over the business cycle. Journal of Labor Economics 18, 98–124.

Gathmann, C., Schönberg, U., 2010. How General Is Human Capital? A Task-Based Approach. Journal of Labor Economics 28, 1–49. URL: http://www.jstor.org/stable/10.1086/649786 papers2://publication/doi/10.1086/649786.

Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review 104, 2509–26. URL: https://www.aeaweb.org/articles?id=10.1257/aer.104.8.2509, doi:10.1257/aer.104.8.2509.

Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica 47, 153–161. URL: http://www.jstor.org/stable/1912352.

Hillage, J., Cross, M., 2015. Exploring the value of an O*NET resource for the UK. 2015 Workshop Meeting Papers. Institute for Employment Studies. URL: https://www.gatsby.org.uk/.

Jaffe, A., 1986. Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. American Economic Review 76, 984–1001. URL: http://EconPapers.repec.org/RePEc:aea:aecrev:v:76:y:1986:i:5:p:984-1001.

Kambourov, G., Manovskii, I., 2008. Rising occupational and industry mobility in the united states: 1968–97. International Economic Review 49, 41–79.

Kambourov, G., Manovskii, I., 2009. Occupational specificity of human capital. International Economic Review 50, 63–115.

McDonald, J.F., Moffitt, R.A., 1980. The Uses of Tobit Analysis. The Review of Economics and Statistics 62, 318–321.

Moscarini, G., Postel-Vinay, F., 2016. Wage posting and business cycles. American Economic Review 106, 208–13. URL: http://www.aeaweb.org/articles?id=10.1257/aer.p20161051, doi:10.1257/aer.p20161051.

Moscarini, G., Thomsson, K., 2007. Occupational and job mobility in the us. scandinavian Journal of Economics 109, 807–836.

Murphy, K.M., Topel, R.H., 1987. The Evolution of Unemployment in the United States: 1968 – 1985, in: NBER Macroeconomics Annual 1987, Volume 2. National Bureau of Economic Research, Inc. NBER Chapters, pp. 11–68. URL: https://ideas.repec.org/h/nbr/nberch/11098.html.

Office for National Statistics, 2020a. Labour force survey five-quarter longitudinal dataset [data collection]. URL: http://doi.org/10.5255/UKDA-SN-8959-1, doi:10.5255/UKDA-SN-8959-1.

Office for National Statistics, 2020b. Labour force survey two-quarter longitudinal dataset [data collection]. URL: http://doi.org/10.5255/UKDA-SN-8586-2, doi:10.5255/UKDA-SN-8586-2.

O*NET 25.1 Database, 2020. U.S. department of labor, employment and training administration (usdol/eta)[data collection]. URL: https://www.onetcenter.org/database.html.

Poletaev, M., Robinson, C., 2008. Human Capital Specificity : Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000. Journal of Labor Economics 26, 387–420.

Robinson, C., 2018. Occupational mobility, occupation distance, and specific human capital. Journal of Human Resources 53, 513–551.

Summerfield, F., 2016. Matching Skills and Tasks: Cyclical Fluctuations in the Overqualification of New Hires.

Yamaguchi, S., 2010. The effect of match quality and specific experience on career decisions and wage growth. Labour Economics 17, 407–423. URL: http://linkinghub.elsevier.com/retrieve/pii/S0927537109000748, doi:10.1016/j.labeco.2009.07.002.