What you do at work matters: New lenses on labour *

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Abstract

How is work distributed across individuals within society? And what can this tell us about career transition possibilities and job switching opportunities? This paper investigates the network structure of the division of labour by analysing discrete work activities that people undertake in different occupations. We find that what people do in their current job matters for their future job - people are significantly more likely to transition into occupations sharing similar work activities. Moreover, we find that our measure of occupational work-activity similarity is more predictive of job-to-job transitions than existing benchmark measures. We also highlight how our new networks-based lenses on labour can illuminate a range of labour market topics, including the gendered division of labour and the future of work.

*This project was supported by Partners for the New Economy and the Oxford Martin School project on the Post-Carbon Transition. We are also grateful to Mika Straka, Dominic Dent, Renaud Lambiotte and the INET Complexity Research Group for their valuable discussions and feedback. R. Maria del Rio-Chanona would also like to acknowledge funding from the Conacyt-Sener "Sustentabilidad Energética" doctoral scholarship.

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1 Introduction

How is work organised in society? And how might this influence people's future career options? Although more than two centuries have passed since Adam Smith famously articulated that wealth is linked to the division of labour, there has been relatively little effort to empirically investigate how discrete tasks are distributed across society. Even less is known how specialisation in particular types of work may influence an individual's future career transition possibilities. And yet many individuals are beginning to grapple with the implications of specialising in particular professions. While there is considerable debate about the likely impacts that automation (Frey and Osborne, 2017, Autor, 2015), offshoring (Blinder et al., 2009, Antràs et al., 2006) and even environmental policies (Greenstone, 2002, Walker, 2011, Morgenstern et al., 2002) may have on employment, there is a strong consensus that understanding career transition possibilities for displaced workers is likely to become increasingly important.

This paper provides a new lens on the labour force by investigating specific tasks that people working in different occupations undertake. By drawing on data from the Occupational Information Network (O*NET), which stipulates discrete work activities associated with given occupations, we measure the similarity between occupations in terms of the work activities they have in common. We find that people are significantly more likely to transition into occupations that involve similar work-activities to their current profession. We also find that our measure of occupational similarity is more predictive of job transitions than existing benchmarks, and is robust to the inclusion of a variety of control variables.

We then investigate the network structure of the division of labour. We create two related networks. The first is the 'Job Space' network, which is a network linking occupations together if they undertake a high degree of similar and specialised tasks. We find nine distinct clusters of occupations in Job Space, which highlight the relatedness in work activities within and across broad Standard Occupational Classification (SOC) 2-digit codes (often referred to as 'job families').

Unlike occupations, no standard classification (such as SOC) exists for classifying the nature of work undertaken by individuals. Therefore, we construct a 'Work Activity Space' - a network in which work activities are nodes connected to each other if they are frequently employed in the same occupation. We identify eleven communities of activities and name each cluster by examining the frequency of words in each work activity descriptions.

These network lenses provide a new way to investigate a range of labour market phenomena. Using data on the US labour force, we find stark divides relating to wage, education and gender. Highly skilled and well-paid occupations cluster in a particular region of the Job Space, and there are distinct differences in the work activities undertaken by males and females. While the clustering patterns are relatively stereotypical (for example, females are over-represented in office administration and healthcare, while males are over-represented in construction and engineering), the lack of overlapping work activities (and by extension career-transition possibilities) underscores the difficulty in overcoming social mobility and gender-segregated workforces.

We also demonstrate how this approach complements the task-based literature, which has focused on the extent to which occupations involve abstract, manual and routine tasks (Autor et al., 2003, Autor, 2013). By visualising each occupation's task intensity score[1] in the Job Space, we provide an additional perspective on the work activity similarity and job transition possibilities within and across abstract, manual and routine task intensity constructs.

Finally we show a very preliminary view into how our new lenses on labour could help address policy questions relating to the future of work. Drawing on estimates of each occupation's susceptibility to automation (Frey and Osborne, 2017), we find strongly segregated clustering of high and low risk occupations in the Job Space. Such divisions in labour not only reiterate current concerns about the distributional consequences of automation, it also highlights potential challenges for workers seeking to transition into jobs with lower automation risk. In contrast, visualising the position of pollution-intensive 'brown' occupations (Vona et al., 2017) in the Job Space paints a more positive picture for workers that may be adversely affected by the transition to a green economy.

2 Results

2.1 Predicting Job Transitions

While several studies have analysed career switching across industries (Neffke et al., 2017, Neffke and Henning, 2013, Chaparro et al., 2016) and firms (Guerrero and Axtell, 2013), comparably few studies have examined job transitions at the level of occupations. To characterise the empirical probability of transitioning from one occupation to another, we draw on monthly panel data from the US Current Population Survey (CPS) for the period January 2010-January 2017. By examining

[1] Abstract, manual and routine task intensity scores are based on continuous scale measures, while work activities are discrete activities either are or are not associated with a given occupation

the 4-digit occupation codes of surveyed respondents, we calculate the probability of transitioning from occupation i to occupation j as

$$P_{ij} = \frac{T_{ij}}{T_i} \tag{1}$$

where T_{ij} is the number of people that switched from occupation i to j, and T_i is the number of people that transitioned out of occupation i over the sampled time period.

We then develop a measure of each occupation i's similarity to every other occupation j in terms of the discrete work activities that occupation i and j have in common. While previous studies on the task-related occupations have employed *continuous-scale* task intensity scores from O*NET and the Dictionary of Occupational Titles (DOT) and (see for example Autor et al. (2003), Acemoglu and Autor (2011), Lin (2011), Michaels et al. (2013)) , here we draw on an alternative O*NET dataset that stipulates 332 *discrete* work activities that people working in different occupations undertake (see Figure 5).

Some work activities, such as 'direct organisational operations' are fairly general and undertaken by many occupations, while other activities, such as 'research healthcare issues' are quite specialised and only associated with a few occupations (see section 4.1). We note that O*NET has a wide range of other occupational descriptors, including more detailed work activities. However, as we show in Appendix A, O*NET's intermediate work activities explain the greatest variance in job transition probability. In addition, as O*NET occupations are more disaggregated than the American Community Survey (ACS) classification of occupations for which we calculate job transition probabilities, we aggregate O*NET occupations to the 4-digit ACS classification following a procedure outlined in section 4.2.

Our measure of occupational similarity exploits both the proportion of overlapping work activities between two occupations, and the extent to which these shared work activities are specialist (or scarce) in nature. Specifically, we organise the intermediate work activities for each occupation in a matrix A, where each of the i rows is associated with an occupation and each of the w columns is associated with an intermediate work activity. Letting $A_{iw} = 1$ if occupation i undertakes work activity w and 0 otherwise, we define an occupational similarity measure γ_{ij} as

$$\gamma_{ij} = min(\frac{\sum_w A_{iw} A_{jw} s_w}{\sum_w A_{iw}}, \frac{\sum_w A_{iw} A_{jw} s_w}{\sum_w A_{jw}}) \tag{2}$$

where s_w represents how scarce (or rare) each work activity is, and is given by

$$s_w = \frac{1}{\sum_i A_{iw}}. \tag{3}$$

Similar approaches have been taken to calculate the similarity between exports in terms of their co-exporting countries. In particular, our γ_{ij} functional form is identical to the approach taken by Zaccaria et al. (2014) to construct a 'taxonomy network' of traded products on the basis of countries that exported them. It also bears resemblance to the approach taken by (Hidalgo et al., 2007) to construct the 'product space', but differs in the inclusion of the s_w weight, which allows γ_{ij} to be increasing in the scarcity of work activities that two occupations share.

We find that the similarity in two occupation's work activities γ_{ij} is significantly positively correlated with their corresponding job transition probability (Pearson $\rho = 0.301$, p-value $< 2.2 \times 10^{-}16$), suggesting that people are more likely to transition into occupations that involve similar work activities to their current occupation. While we find that γ_{ij} on its own only explains around 9% of the variation, it is important to note that there are a range of factors influencing job transitions that are not captured by work activity similarity (such as wages, education, location, supply and demand of labour). Moreover, as shown in Figure 1, γ_{ij} performs considerably better than the most relevant benchmark - the O*NET career changers matrix.

The O*NET's career changers matrix aims to identify jobs that people in a target occupation could pursue with minimal additional preparation (Allen et al., 2012). It matches each occupation to 10 related (or similar) occupations the basis of two procedures: (1) an analytical exercise, which considers each occupation's Euclidean distance to other occupations in terms of several O*NET occupational descriptors including work activities, knowledge, skills and work-context, and (2) a 'rational review' exercise, where analysts subjectively modify any inappropriately matched occupations. Despite only drawing on O*NET's intermediate work activities data, panel a) of Figure 1 shows that γ_{ij} can explain substantially more variance in job transition probability.

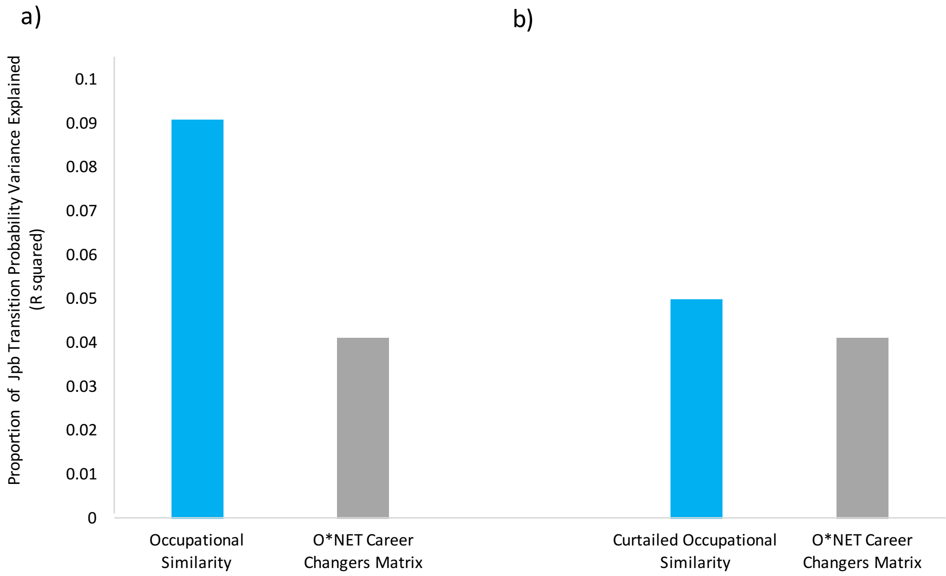

Figure 1: **Panel a):** Comparison in the variance in job transition probability explained by the occupational similarity measure γ_{ij} and the O*NET Career Changers matrix **Panel b):** Comparison in the variance in job transition probability explained by the curtailed occupational similarity measure $\widetilde{\gamma}_{ij}$ and the O*NET Career Changers matrix

However, this may not be a fair comparison as the O*NET career changers matrix (denoted CC_{ij}) is a binary matrix ($CC_{ij} = 1$ if occupation i is considered to be 'related' to occupation j and $CC_{ij} = 0$ otherwise), which only maps each occupation to 10 other occupations. In contrast, γ_{ij} is a non-binary measure that is defined across all i and j occupation combinations. As such, in Panel b) of Figure 1, we show a comparison between the O*NET career changers matrix and a binary $\widetilde{\gamma}_{ij}$, in which $\widetilde{\gamma}_{ij} = 1$ if occupation j is in the top 10 most proximate occupations to occupation i and 0 otherwise. Here we find that even the curtailed $\widetilde{\gamma}_{ij}$ still outperforms the O*NET career changers matrix. In Appendix A we make comparisons with measures based on other O*NET occupational descriptors (such as 'knowledge', 'abilities', 'skills', 'generalised work activities' and 'detailed work activities'). We find that the γ_{ij} of occupational similarity based on intermediate work activities consistently explains the highest proportion of variance in job transition probability by a considerable margin. Detailed work activities are able to explain at most, 3.8% of the variance, while all other measures fail to explain more than 0.05%.

To ensure the relationship between γ_{ij} and job transition probability is robust to the inclusion of relevant control variables, we undertake a regression analysis, shown in Table 1. For each of the regression models, we regress the log of job transition probability on different combinations of explanatory variables and compare their explanatory power. In all models, we also include a SOC 2 digit (job family) dummy to control for occupation-specific effects of job switching for particular job families.

Table 1: Job Transition Regression Results

	Dependent variable:					
	Log Job Transition Probability					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Occupational Similarity	1.045^{***}					1.015^{***}
	(0.033)					(0.032)
Average Education Attainment		-0.0001^{***}			-0.0002^{***}	-0.0001^{***}
		(0.00003)			(0.00004)	(0.00004)
Difference in Education Attainment		-0.00005^{***}			-0.0001^{***}	-0.0001^{***}
		(0.00001)			(0.00002)	(0.00002)
Average Earnings			-0.005^{***}		0.015^{***}	0.010^{***}
			(0.002)		(0.002)	(0.002)
Difference in Earnings			-0.002^{***}		0.008^{***}	0.007^{***}
			(0.001)		(0.001)	(0.001)
Average Employment				0.432^{***}	0.434^{***}	0.410^{***}
				(0.007)	(0.007)	(0.006)
Difference in Employment				0.215^{***}	0.216^{***}	0.218^{***}
				(0.004)	(0.004)	(0.003)
Constant	0.0003^{***}	0.003^{***}	0.002^{***}	0.0005^{***}	0.001^{***}	-0.0005
	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0003)
SOC 2-digit Dummy?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	215,296	215,296	215,296	215,296	215,296	215,296
Adjusted R^2	0.094	0.0002	0.00005	0.111	0.112	0.201

Note: *p<0.1; **p<0.05; ***p<0.01

Educational attainment, wage and employment data is for the year 2010 and sourced from the IPUMS-USA database (Ruggles et al., 2017).
Educational attainment is based on the IPUMS 'EDUC' variable, which relates to the highest year of school or degree completed by surveyed respondents. Responses are coded from 0= 'NA or no schooling' to 11 = '5 + years of college'. For each occupation, we calculate the average EDUC value of surveyed respondents in a given ACS occupation code. **Wage** is based on IPUMS 'INCWAGE' variable, which relates to the total pre-tax wage and salary income for the previous year. We calculate the average 'INCWAGE' value of surveyed respondents in given ACS occupation. **Employment** is based on the total number of respondents in each ACS occupation. Employment and wage variables are scaled to be in millions.

Model 1 compares the explanatory power of γ_{ij} to the educational attainment of occupations (Model 2), wages (Model 3), and the number of people employed in occupations (Model 4) and all control variables combined (Model 5). In Model 6, we include all explanatory variables and show that γ_{ij} remains a very strong and significant predictor of job transition probability, and can explain variance that is not accounted for by wage, education or employment variables.

Our regression analysis also highlights additional findings relating to job switching in the US labour force. In Model (2), which includes the average education attainment of occupation i and j and the difference between occupations (occupation j's education minus occupation i's education), the negative and statistically significant coefficient on both variables suggests that job switching is more likely to occur within occupations requiring less education. Moreover, workers are less likely to transition into a job requiring higher education than their current occupation. A similar result is found for Model (3), which looks at occupational wages. Interestingly, the sign of the wage coefficient changes from negative to positive once we include education and employment variables (Model 5). This change suggests that once we account for the educational requirement and total employment in occupations, workers are more likely to switch to occupations that provide higher wages.

Model (4) shows that (not surprisingly) more switching takes place in occupations that employ a large number of people, and workers are more likely to transition into jobs that hire a larger number of people than their current occupation. In contrast to education and wage, total employment accounts for a comparably large proportion of the variance in job transition probability.

2.2 The Network Structure of the Division of Labour

To examine the structure and arrangement of the division of labour, we construct two related networks. The first is the *'Job Space'*, which is a network in which occupations are nodes linked to each other if they have a high degree of specialised work activities in common. The second is the *'Work Activity Space'*, which instead represents work activities as nodes linked to each other if they tend to be undertaken in the same occupation.[2]. In identifying key clusters within these networks, we shed light on how work tends to be divided amongst professions in society - and how professions relate to each other in terms of the similarity in activities that they undertake.

2.2.1 The Job Space

To visualise the Job Space network, we follow existing approaches (Hidalgo et al., 2007) and first construct a maximum spanning tree of the γ_{ij} adjacency matrix.

[2]These networks can be seen as one-mode projections of the weighted bipartite network associated with A_{iw}

We then add additional links with γ_{ij} greater than a given threshold τ. This approach ensures we only connect occupations that share a high degree of specialised occupations. In this case, $\tau = 0.005$ [3], however alternative values of τ give similar results.

We present the Job Space in Figure 3. In Panel a), we colour each node by their SOC 2-digit job families (also labelled in black). In Panel b), we use the Louvain community detection algorithm (Blondel et al., 2008, Bastian et al., 2009) to identify nine clusters of occupations that share similar work activities. Comparing panel a) and b) shows a close association between the job families and identified job clusters in the network. However, the Job Space network clusters provide additional information in providing insights into the occupational relatedness and career transition potential *across* job families.

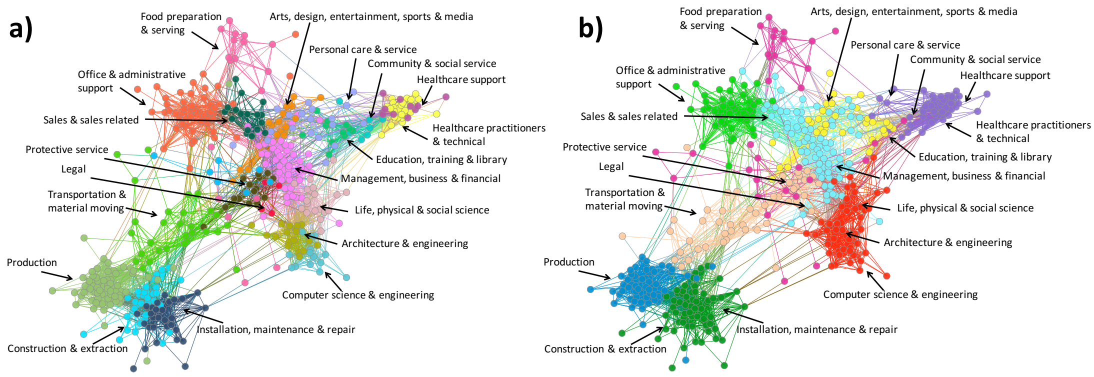

Figure 2: The Job Space: **Panel a)** Nodes are coloured by their 2-digit SOC job family. Job family titles are labelled in black. **Panel b)** Nodes are coloured in accordance with the nine job clusters identified with the Louvain algorithm.

2.2.2 The Work Activity Space

While standard classification schemes exist for occupations, no such codification currently exists for classifying the type of work undertaken by individuals. To this end, we construct the Work Activity Space, which is a network of work activities linked to each other if they are more likely to co-occur within occupations.

The Work Activity Space is closely related to the Job Space. We calculate links between work activities by applying the γ formula (equation 2) to the transpose of the A matrix.[4] We then construct the Work Activity Space network using the same

[3] $\tau = 0.005$ is approximately 1 standard deviation higher than the mean γ_{ij} value

[4] Effectively, we interchange the w and i indices in the γ formula

maximum spanning tree and thresholding approach that was used to construct the Job Space.[5]

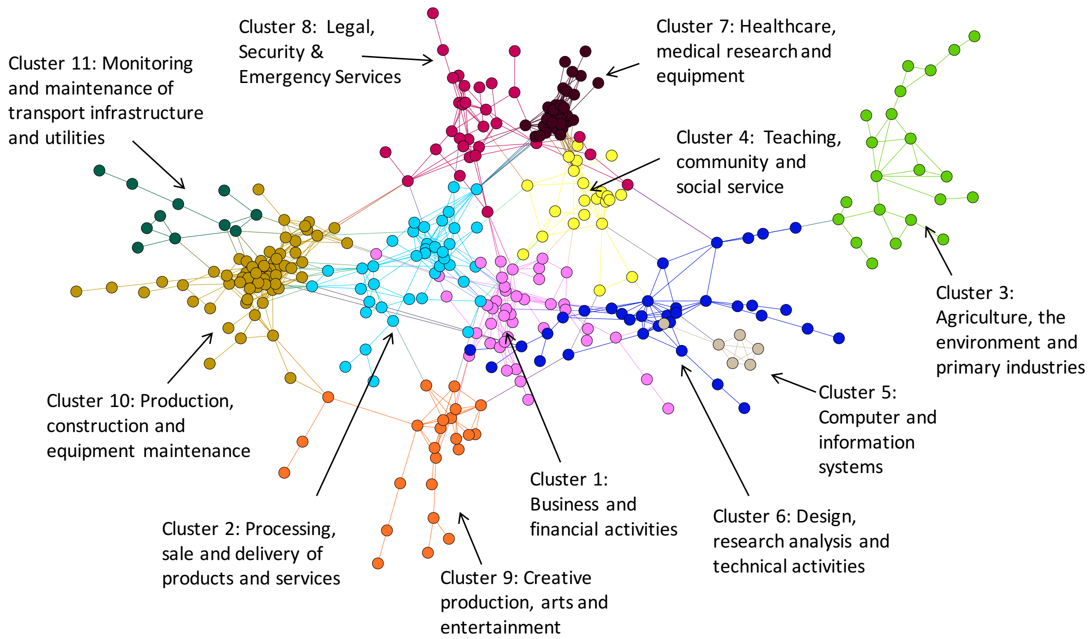

Figure 3: The Work Activity Space: Nodes are coloured in accordance with the 11 identified clusters. Labels are cluster names assigned by inspecting the frequency of words associated with work activity descriptions in each cluster (see section 4.3)

Like the Job Space, the Work Activity Space exhibits a high degree of community structure. In Panel b) of Figure 3, we again use the Louvain algorithm (Blondel et al., 2008, Bastian et al., 2009) to identify 11 clusters of work-activities that tend to be undertaken together. As no existing classification exists, we name each cluster by examining the relative word frequency in the work activity descriptions (see section 4.3). In showing how society tends to organise work-activities and allocate tasks to individual professions, this network provides a new way to visualise the structure and arrangement of the division of labour.

2.3 New Lenses on Labour

What can our new network lenses tell us about labour and the way work is distributed across society? In Figure 4, we highlight several insights arising from the

[5] The threshold t used for the Work Activity Space network is 0.005

Job Space network.

Panel a) and b) colour nodes in accordance with the average occupational wage and educational requirements. Here we have drawn on US census data from the Integrated Public Use Microdata Series (IPUMS) for the year 2010 (Ruggles et al., 2017). Highly skilled occupations are fairly tightly clustered in a particular region of the Job Space, suggesting that the type of work highly skilled professions undertake tends to involve fairly similar work activities. Given the well documented positive relationship between education and wages, it is not surprising to see highly paid occupations also clustering in similar locations of the Job Space. However, there are some interesting exceptions, such as the tendency for some mining-related occupations located in the bottom cluster (e.g. derrick, rotary drill, and service unit operators, rustabouts, earth drillers and extraction workers) to receive a comparatively high wage in relation to their average education level.

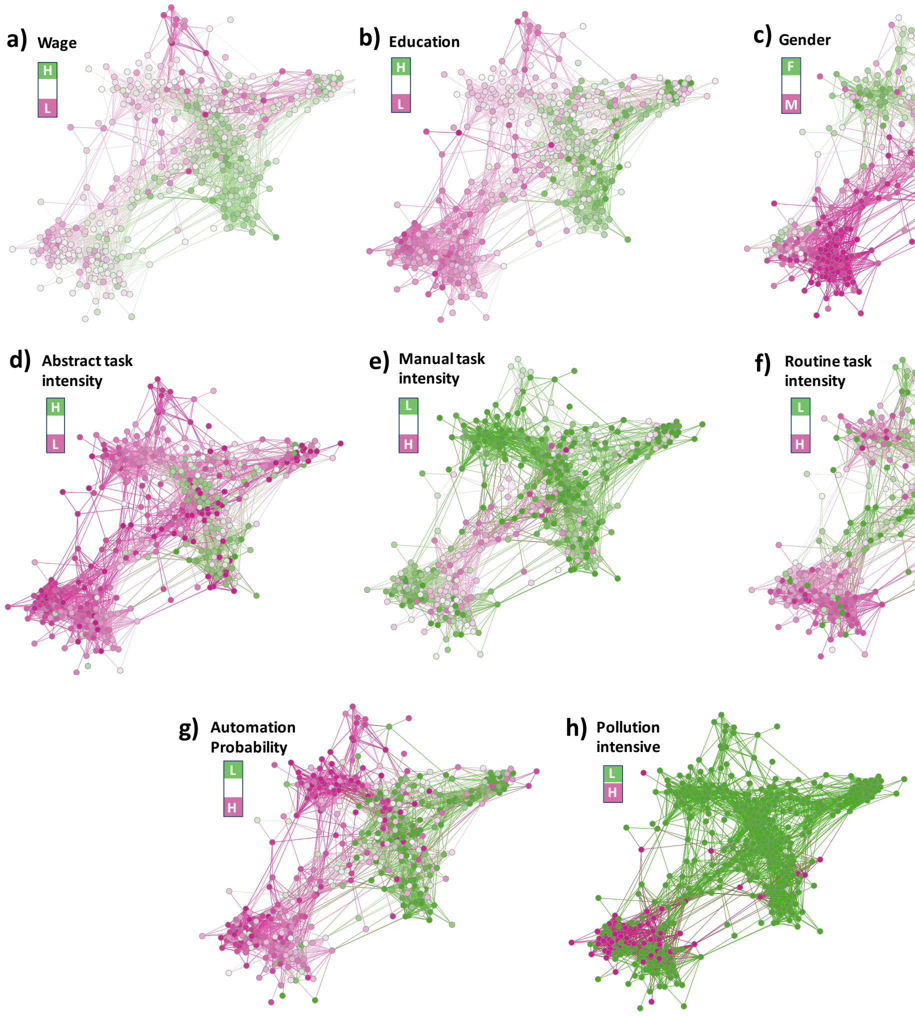

Figure 4: The Job Space provides a new lens on labour. **Panel a, b and c:** Occupation nodes are coloured in accordance with their average wage, educational requirements and gendered proportions. Data is drawn from the US census data (available from IPUMS (Ruggles et al., 2017)) in 2010. **Panel d, e and f:** Nodes are coloured by their abstract, manual and routine task intensity, based on DOT task measures made available by Autor and Dorn (2013). **Panel g:** Nodes are coloured by their susceptibility of computerisation as estimated by Frey and Osborne (2017). **Panel h:** Node colours denote the set of pollution-intensive ('brown') jobs, which were identified by (Vona et al., 2017) as occupations that are seven times more likely to work in industries in the 95th percentile of pollution intensity.

Panel c), which shows the gendered proportion of US workers in each occupation, highlights the distinct gender-based division of labour in the US workforce. The plot reflects stereotypical divides in work across the sexes. Females are concentrated in occupations relating to office and administrative support, food preparation and serving, healthcare and community service, while males are concentrated in construction, manufacturing and engineering professions. Although sex-based occupational segregation is known to be a persistent phenomenon in many labour markets (Blau et al., 1998, Blau and Kahn, 2000, Preston and Whitehouse, 204, Seron et al., 2016), the marked gendered clustering *across job families* in the Job Space highlights the endemic divisions in the nature of work activities undertaken by males and females. Such divides also suggest that career paths are likely to be fairly male and female-centric, underscoring the systemic difficulties in achieving more gender-balanced work places.

Since we know which work activities are performed by each occupation, we can explore the type of work undertaken at the top and bottom ends of the wage, education and gender spectra in more detail. In Table 2 we rank work activities by calculating the average wage, educational requirement or female proportion of the occupations it is associated with. So for example, if a work activity is undertaken by two occupations i and j, which are paid \$30,000 and \$50,000 respectively, the average wage of the work activity will be \$40,000.

In each column, we find work activities that align closely with expectations about the nature of work at the top and bottom of each spectrum. Highly paid activities relate to legal, analytical managerial work, while low paid activities involve less sophisticated tasks like preparing and providing food an beverages. A similar pattern is evident for educational attainment, although activities associated with highly educated workers have a stronger slant towards medicine and healthcare.

The gender spectrum of work activities is particularly interesting as it gives us clues for understanding and addressing the persistent gender imbalance across professions. Tasks most commonly undertaken by males tend to relate to work requiring physical strength, where on average, males may have traditionally held a comparative advantage. However, automation and the increasing integration of robots within industry could substantially lower this barrier. On the other end of the spectrum, tasks currently dominated by females tend to relate to healthcare, administration and teaching. The fact that there is no physical barrier to males performing these roles highlights the importance of addressing long-held gendered stereotypes and other socio-cultural factors that exacerbate sex-segregations in the division of labour (England and Li, 2006, Cotter et al., 2011, Seron et al., 2016).

Rank	Wage	Educational Attainment	Female Proportion
1	Draft legislation or regulations.	Make legal decisions.	Assess student capabilities, needs, or performance.
2	Make legal decisions.	Research laws, precedents, or other legal data.	Transport patients or clients.
3	Analyze scientific or applied data using mathematical princi	Diagnose health conditions or disorders.	Prepare health or medical documents.
4	Manage control systems or activities.	Evaluate scholarly work.	Assist individuals with special needs.
5	Design structures or facilities.	Draft legislation or regulations.	Serve on organizational committees.
6	Evaluate project feasibility.	Develop health assessment methods or programs.	Teach life skills.
7	Develop scientific or mathematical theories or models.	Develop scientific or mathematical theories or models.	Prepare medical equipment or work areas for use.
8	Analyze business or financial risks.	Order medical tests or procedures.	Clean medical equipment or facilities.
9	Research laws, precedents, or other legal data.	Advise others on healthcare or wellness issues.	Schedule appointments.
10	Assess characteristics or impacts of regulations or policies.	Teach academic or vocational subjects.	Set up classrooms, facilities, educational materials, or equipment.
[...]	[...]	[...]	[...]
323	Take physical measurements of patients or clients.	Perform general construction or extraction activities.	Operate construction or excavation equipment.
324	Process animal carcasses.	Dispose of waste or debris.	Install energy or heating equipment.
325	Sew garments or materials.	Remove workpieces from production equipment.	Install plumbing or piping equipment or systems.
326	Develop recipes or menus.	Set up protective structures or coverings near work areas.	Repair vehicle components.
327	Hunt animals.	Operate construction or excavation equipment.	Repair electrical or electronic equipment.
328	Train animals.	Cut trees or other vegetation.	Set up protective structures or coverings near work areas.
329	Apply hygienic or cosmetic agents to skin or hair.	Sew garments or materials.	Fabricate devices or components.
330	Prepare foods or beverages.	Operate agricultural or forestry equipment.	Perform general construction or extraction activities.
331	Groom or style hair.	Process animal carcasses.	Climb equipment or structures.
332	Provide food or beverage services.	Hunt animals.	Install commercial or production equipment.

Table 2: Work activities ranked in accordance with the average wage, educational attainment and female proportion of occupations that undertake them

The Job and Work Activity Spaces also complement the growing literature on tasks. Introduced by Autor et al. (2003), the 'task framework' focuses on how skills are allocated tasks, and has been used to investigate a wide range of labour market questions relating to the impact of automation and technological change (Autor et al., 2003, Spitz-Oener, 2006, Autor, 2015, Berger and Frey, 2016), off-shoring (Antràs et al., 2006, Grossman and Rossi-Hansberg, 2008, Blinder et al., 2009, Blinder and Krueger, 2013)), immigration (Peri and Sparber, 2009, Basso et al., 2017), structural employment shifts (Autor et al., 2006, Goos and Manning, 2007) and the evolution of wages (Acemoglu and Autor, 2011, Autor et al., 2008). While our methodology employs O*NET's dataset on *discrete* work activities, the task-approach literature usually draws on continuous scale task intensity scores from the DOT or O*NET to quantify occupations in terms of the extent they involve manual, routine and abstract (or cognitive) tasks. As shown in panel d), e) and f) of Figure 4, our networks-based approach offers a new way to visualise the distribution of manual, routine and abstract tasks across the professions. Moreover, it has the added advantage of providing additional information on task similarity and job transition possibilities.

Finally, we briefly highlight the potential value of our new lens on labour for addressing policy questions relating to future labour transitions. While it is beyond the scope of this paper to delve into labour market impacts in any detail, we provide a cursory view of two phenomena that will likely affect workers in coming years. The first is automation, and the potential impact that the widespread adoption of computers and robots will have on the labour force. The second is climate policy, and the potential impact that transitioning to a carbon-constrained world may have on jobs in pollution-intensive industries.

There is currently a healthy debate on the potential impact of automation on employment. Using an innovative method based on machine learning, Frey and Osborne (2017) estimate that 47% of employment in the US workforce has high susceptibility to computerisation, and could be at risk of being automated over the next decade or two. Other studies using related methodologies have arrived at estimates of 9% (Arntz et al., 2016) and 45% (McKinsey, 2015). Since Frey and Osborne (2017)'s estimates are publicly available, we draw on this work to colour each occupation by its estimated probability of computerisation in Panel g) of Figure 4 (see section 4.1.4 for more detail about how these probabilities were calculated). It is important to emphasise that an occupation's susceptibility to computerisation does not mean its workers will be necessarily displaced (Autor, 2015, Arntz et al., 2016). Further, Frey and Osborne (2017)'s analysis is silent on the possibilities for new job creation. However, the segregated clustering of highly susceptible occupations in the Job Space underscores existing concerns about the adverse distributional impacts of automation (Autor et al., 2003, Goos and Manning, 2007, Michaels et al., 2014, Hémous and Olsen, 2016). Moreover, the fact that there are such distinct differences in the type of work undertaken by high and low risk occupations highlights the potential difficulties displaced workers may find in transitioning into roles with a lower automation risk.

The impact of environmental policies on employment has also been a subject of debate. Some studies have found environmental regulations have had negative impacts on jobs (Greenstone, 2002, Liu et al., 2017) and wages (Walker, 2011), while others document small positive (Morgenstern et al., 2002) or negligible impacts (Berman and Bui, 2001, Gray et al., 2014). In Panel g) of Figure 4 we preview a different way to look at this question. We draw on the set of 'brown jobs' identified by Vona et al. (2017), which relate to occupations that have a high probability of being employed in pollution intensive industries. These include occupations like petroleum pump system operators, dredge operators and well pumpers (see section 4.1.5 for more detail on how these occupations were identified). Interestingly, we find that most jobs that could be threatened by pollution-reduction policies occupy a relatively localised region of the Job Space. While the geographical concentration of brown jobs could mean that job losses are amplified by local multiplier effects, it is encouraging to see that there appears to be a number of nearby non-brown jobs that share similar work-activities. Further analysis could examine whether these nearby occupations could provide alternative employment for displaced workers.

3 Discussion

This paper has advanced a new lens on labour by investigating the network structure of activities that people working in different occupations undertake. We find that the Job Space and Work Activity Space both have informative community structures that highlight similarities (and divisions) in the nature of work undertaken by different professions. Moreover, we find that our measure of occupational similarity is more predictive of job transitions than existing benchmark measures.

Our network lenses provide a new way to analyse a range of labour market topics. In addition to demonstrating how the Job Space can offer a complementary perspective on the the growing literature on tasks (Autor et al., 2003, Autor, 2013), we also highlighted the value of our approach for investigating issues ranging from gender to environmental policy to automation. Future work could explore each of these areas - and others - in more detail.

Beyond labour markets, our work also contributes to the broader literature on path-dependence. A commonly documented finding is that a place (countries, cities and regions) is more likely to develop new specialisations in industries products, technologies or occupations that are similar to what already exists in that place (Hidalgo et al., 2007, Hausmann et al., 2014, Neffke and Henning, 2008, Delgado et al., 2014, Neffke et al., 2017, Neffke and Henning, 2013, Chaparro et al., 2016, Muneepeerakul et al., 2013, Boschma et al., 2013). This study provides empirical evidence to show that this phenomenon also operates on the level of people - individuals are more likely to transition into new jobs that undertake activities that are similar to what people have done in the past.

4 Methods

4.1 Data

4.1.1 Work Activities

O*NET work activities database is constructed on the basis of 19,450 unique task descriptions, which are each associated with one of the 974 SOC occupations classified at the 8-digit level. O*NET have aggregated these tasks into two levels of activities: 2,071 'Detailed Work Activities' (DWA) and the more aggregated 332 'Intermediate Work Activities' (IWAs). Examples of tasks, DWAs and IWAs are given in Table 3.

Element	Description
IWA	• Direct organizational operations, activities, or procedures.
DWA	• Direct sales, marketing, or customer service activities. • Direct organizational operations, projects, or services.
Task	• Appoint department heads or managers and assign or delegate responsibilities to them. • Direct or coordinate activities of businesses or departments concerned with production, pricing, sales, or distribution of products. • Direct non-merchandising departments, such as advertising, purchasing, credit, or accounting.

Table 3: Example of task, detailed work activity (DWA) and intermediate work activity (IWA) descriptions.

While tasks are occupation-specific (each task is associated with exactly one occupation), DWAs and IWAs have some degree of overlap across occupations. Figure 5 shows an example of the intermediate work activities (in green) associated with different occupations. More general work activities, (such as ‘direct organisational operations’) overlap across many occupations, while other specialised work activities (such as ‘research healthcare issues’) only relate to a few occupations. As we show in Figure 6, the number of work activities that occupations undertake is also reasonably heterogeneous, with some occupations such as engineering technicians linked to 78 IWAs, while other occupations such as medical transcriptionists are only linked to 5 IWAs.

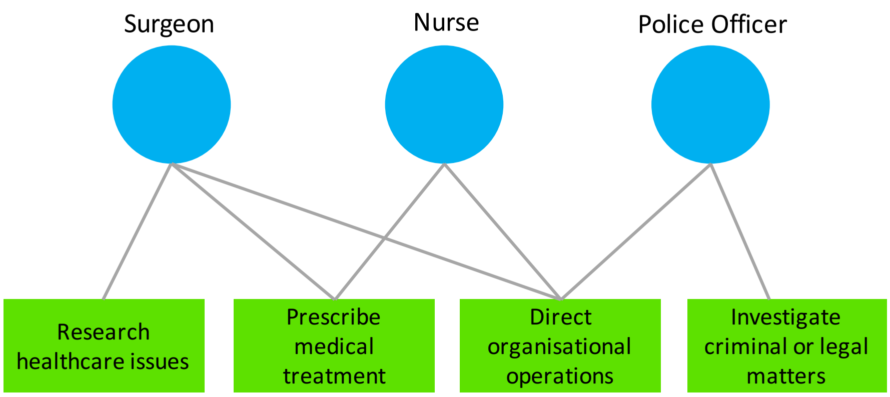

Figure 5: Illustration of intermediate work activities associated with different occupations

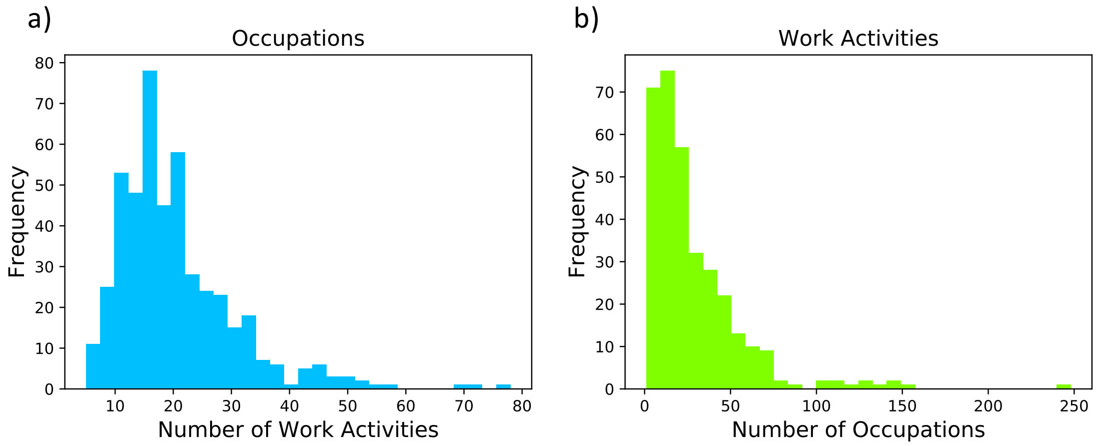

Figure 6: **Panel a):** Distribution of the number of work activities associated with occupations. **Panel b):** Distribution of the number of occupations associated with work activities

4.1.2 Job Transitions Data

Data on job transitions are drawn from the US Current Population Survey (CPS), which is available from IPUMS-CPS. We use monthly panel data on the occupations of surveyed respondents over the period January 2010-January 2017. The CPS surveys around 60,000 US households every month in a 4-8-4 sampling scheme. This means that households participate in the survey for four consecutive months, are removed from the sample for eight months, and then return for four months before being removed from the sample permanently.

4.1.3 Abstract, Manual and Routine Task Intensity Data

Data on abstract, manual and routine task intensity scores for each occupation (shown in Panel d, e and f of Figure 4) is drawn from Autor and Dorn (2013)'s analysis of the Dictionary of Occupational Title (DOT) task constructs. Abstract task intensity scores are based on the simple average of the DOT task variables DCP (Direction, control and planning of activities) and GED-MATH (quantitative reasoning requirements). Routine task intensity is calculated as the average of STS (adaptability to work requiring set limits, tolerances, or standards) and FINDEX (finger dexterity). Manual task intensity is captured by EYEHAND (eye, hand and foot coordination).

4.1.4 Automation Probability Data

Data on automation probability is sourced from Frey and Osborne (2017) estimates of each occupation's susceptibility of computerisation. These were calculated by first subjectively hand-labelling 70 occupations as 1 if automatable and 0 if not. They then drew on machine learning to classify the automatability of 702 occupations using the assigned labels and several feature vectors based on continuous-scale O*NET variables corresponding to bottlenecks to computerisation (variables related to perception and manipulation, creativity and social intelligence).

4.1.5 Brown Jobs Data

Data on pollution intensive jobs is drawn from Vona et al. (2017). They first identified 62 4-digit NAICS industries in the 95th percentile of pollution intensity (measured in terms of emissions per worker) for at east three of the following pollutants: CO_2, CO, VOC NO_x, SO_2, PM10, PM2.5 and lead. They then identify 'brown' jobs as occupations that have a probability of working in polluting industries seven times higher than other sectors.

4.2 Aggregation Procedure

The IPUMS CPS data on job transitions are available at the American Community Survey (ACS) 4-digit occupational level, while the O*NET data is available at the SOC 8-digit level. To examine the relationship between ONET occupational descriptors and job transition probability, we map the O*NET 8-digit occupations to the more aggregate ACS 4-digit occupations.

We first aggregate SOC 8-digit codes (974 occupations) to 6-digit codes (775 occupations) using the O*NET-SOC2010 occupations to 2010 SOC occupations available from `https://www.onetcenter.org/crosswalks.html`. We then use the 2016 National Employment Matrix/SOC to ACS Crosswalk available from `https://www.bls.gov/emp/ep_crosswalks.htm` to map each O*NET 6-digit occupation to the ACS 4-digit occupation. Each 6 digit SOC occupation is linked to exactly one 4-digit ACS occupation.

We specify intermediate work activities associated with each ACS occupation as the union of intermediate work activities associated with its corresponding SOC occupations in the SOC-ACS occupation mapping. That is, we assume that a 4-digit ACS occupation undertakes all the work activities associated with its corresponding 8-digit SOC occupations.

We use a similar approach when aggregating the automation probability and brown jobs data to the IPUMS 4-digit level. As (Frey and Osborne, 2017)'s automation probability estimates are available at the SOC 6-digit level, we use the 2016 National Employment Matrix/SOC to ACS Crosswalk and assign an automation probability to each ACS 4-digit occupation based on the simple average of the SOC 6-digit occupation automation probabilities it is linked to. Similarly, as Vona et al. (2017)'s brown job identification is available for 6-digit SOC occupations, we also use the 2016 National Employment Matrix/SOC to ACS Crosswalk and identify a ACS 4-digit occupation as brown if it is linked to at least one brown 6-digit SOC occupation. (Assigning the status on the basis of the majority of the 6-digit SOC occupations has very little impact on our results).

4.3 Naming Work Activity Clusters

O*NET Intermediate work activities are a one-line description containing a single verb (see Table 3 for example). To name the Work Activity Space clusters, we examine the frequency of words in the description of work activities associated with each identified cluster. Specifically, we remove all stop-words, and consider the top five most frequent words arising in each cluster. While no classification currently exists for tasks undertaken by individuals in occupations, our approach provides one possible methodology for providing a taxonomy of work undertaken by society.

A Comparison of Alternative Functional Forms and Different O*NET Descriptors for Predicting Job Transitions

In constructing the measure of occupational similarity used in this paper, we also considered different functional forms and alternative occupational descriptors available on the O*NET database. Here we compare how each functional form, applied to alternative O*NET occupational descriptors, performs in explaining variance in job transition probability. We show that the occupational similarity measure (γ_{ij}) based on intermediate work activities has a much higher ability to predict job transitions than the considered alternatives.

A.1 O*NET Occupational Descriptors

O*NET is an online database providing a vast amount of information on occupational characteristics. It collects and maintains its database surveying expert analysts and job incumbents across a sample of US firms. We explored to types of O*NET occupational descriptors: (1) discrete descriptors, which describe the activities undertaken by each occupation and (2) continuous scale descriptors, which assign an importance rating on a continuous scale indicating how important the given element to a given occupation.

A.1.1 O*NET Discrete Descriptors on Tasks and Work Activities

O*NET maintains a list of $19,450$ specific task descriptions which are uniquely associated with a particular 8-digit SOC occupation. As part of the O*NET Work Activities project (Hansen et al., 2014), these tasks were aggregated into two higher level descriptions of $2,071$ 'detailed work activities' (DWAs) and '372' intermediate activities (IWAs). Unlike task descriptions, DWAs and IWAs are not unique to each occupation, but have some overlap - so occupations can have DWAs and IWAs in common with other occupations.

A.1.2 O*NET Continuous Scale Occupational Descriptors

We also examined O*NET's 'knowledge', 'abilities', 'skills' and 'generalised work activities' occupational descriptors. These descriptors each contain a unique set of elements (for example, knowledge encompasses elements such as 'Economics and accounting' or 'Sales and marketing', while abilities include elements such as 'Deductive reasoning' and 'Number facility'). For each occupation, continuous scale importance ratings are assigned to each element, signifying how important it is to a given occupation. Importance ratings range from (1-5).

A.2 Occupational Similarity Measures

We experiment with three different functional forms for measuring the similarity between occupation i and j.

- ω_{ij} Scaled Pearson correlation measure (used in Hausmann et al. (2014))
- ϕ_{ij} Proximity measure (used in Hidalgo et al. (2007)), which considers the proportion of elements that two occupations have in common

- γ_{ij} Scarcity-adjusted proximity measure (used in Zaccaria et al. (2014)) which is similar to ϕ_{ij}, but includes an additional weight reflecting the scarcity of elements that two occupations have in common.

A.2.1 Scaled Pearson Correlation Measure

The scaled Pearson correlation measure is given by

$$\omega_{ij} = \frac{(1 + corr(Y_i Y_j)}{2}). \tag{4}$$

For continuous-scale descriptors, Y_i represents the vector of importance values assigned to occupation i across all descriptor elements, while for discrete descriptors, Y_i is a binary vector of activities which $= 1$ if an occupation undertakes the activity and 0 otherwise.

This metric is scaled so that characteristic vectors that are perfectly negatively correlated will have a value of 0, and perfectly positively correlated vectors will have a value of 1.

A.2.2 Proximity measure

For discrete descriptors the Proximity measure is given by

$$\phi_{ij} = min(\frac{\sum_w A_{wi} A_{wj}}{\sum_w A_{wi}}, \frac{\sum_w A_{wi} A_{wj}}{\sum_w A_{wj}}) \tag{5}$$

where the A_i column of the matrix can be seen as a binary vector of w work activities in which elements $= 1$ if occupation i undertakes work activity w and 0 otherwise.

To apply the Proximity measure to the set of continuous-scale descriptors, we create binary versions of the continuous scale importance ratings. Here, we introduce a 'relative importance indicator' (RII_{ie}) which represents the ratio of the importance of descriptor element e compared to the average importance ratings given to all descriptor elements for a given occupation i and the average importance ratings given to the descriptor element e compared to the average importance ratings across all occupations and elements of that descriptor.

$$RII_{ie} = \frac{M_{ie}/\langle M_i \rangle}{\langle M_e \rangle / \langle M \rangle} \tag{6}$$

where M_{ie} is the importance rating assigned to descriptor element e for occupation i, $\langle M_i \rangle$ is the average importance rating across all elements of a given descriptor for an occupation i, $\langle M_e \rangle$ is the average importance rating across all occupations for the descriptor element e and $\langle M \rangle$ is the average importance rating assigned across all occupations and elements within a given descriptor (like knowledge).

We then create binary descriptor vectors for a given occupation i by assigning a 1 to the occupation-element pair if $RII_{ie} > 1$ and 0 otherwise. On the basis of these binary descriptors, we can then apply the ϕ_{ij} measure described in equation 5.

A.2.3 Scarcity-Adjusted Proximity Measure

While the Proximity measure is relatively straight-forward and intuitive, it is limited in that it does not account for the heterogeneous prevalence of particular work activities (or the relative importance of continuous-scale descriptors). For example, some 'generalist' work activities, such as 'maintain operational records' or 'direct organizational operations' are undertaken by a large number of occupations, other 'specialist' work activities, such as 'draft legislation or regulations' are only taken by a small number of occupations. As two occupations having a 'specialist' work activity in common may be considered to be more closely related than two occupations having a 'generalist' work activity in common, we propose an alternative scarcity-adjusted proximity measure, which weights the proximity between two occupations by the scarcity of the work activities that they share in common.

Specifically γ_{ij}, which represents the weighted occupational relatedness between occupations i and j is given by:

$$\gamma_{ij} = min(\frac{\sum_w A_{iw} A_{jw} s_w}{\sum_w A_{iw}}, \frac{\sum_w A_{iw} A_{jw} s_w}{\sum_w A_{jw}}) \tag{7}$$

where s_w represents how scarce (or rare) each work activity is, and is given by

$$s_w = \frac{1}{\sum_i A_{iw}}. \tag{8}$$

To apply this scarcity-adjusted proximity measure to the scale-continuous descriptors, we apply the same methodology of converting the descriptors into binary values as discussed in the previous section.

A.3 Correlation with Job Transition Probability

Applying each of the three functional forms to DWAs, IWAs, skills, abilities, knowledge, generalised work activities and an '*all* continuous descriptor' variable which encompasses all of the continuous scale variables (skills, abilities, knowledge and generalised work activities) gives 21 possible occupational similarity metrics. In this section, we test which measure has the greatest ability to explain the variance in job transition probability.

As discussed in the main paper, we characterise the empirical probability of job switching by drawing on monthly panel data from the US Current Population Survey (CPS) for the period January 2010-January 2017. By examining the 4-digit occupation codes of surveyed respondents, we calculate the probability of transitioning from occupation i to occupation j as

$$P_{ij} = \frac{T_{ij}}{T_i} \tag{9}$$

where T_{ij} is the number of people that switched from occupation i to j, and T_i is the number of people that transitioned out of occupation i over the sampled time period.

Table 4 shows that the intermediate work activities descriptor has the highest correlation with the job transition probability variable - across all three measures. Applying the Scarcity Adjusted Proximity measure to IWAs gives the highest correlation, with a Pearson R of 0.3. Detailed work activities give the next highest set of correlations, while the continuous scale variables - including the variable including *all* continuous scale descriptors tend to correlate fairly weakly across all measures. All variables are statistically significant at the 1% level.

Table 4: Correlation of each metric with job transition probability

Metric	Pearson R
Intermediate Work Activities	
Scaled Pearson Measure	0.234
Proximity Measure	0.240
Scarcity Adjusted Proximity Measure	0.301
Detailed Work Activities	
Scaled Pearson Measure	0.165
Proximity Measure	0.176
Scarcity Adjusted Proximity Measure	0.196
Skills	
Scaled Pearson Measure	0.041
Proximity Measure	0.012
Scarcity Adjusted Proximity Measure	0.027
Abilities	
Scaled Pearson Measure	0.031
Proximity Measure	0.026
Scarcity Adjusted Proximity Measure	0.034
Knowledge	
Scaled Pearson Measure	0.060
Proximity Measure	0.036
Scarcity Adjusted Proximity Measure	0.060
Generalised Work Activities	
Scaled Pearson Measure	0.063
Proximity Measure	0.010
Scarcity Adjusted Proximity Measure	0.022
All Continuous Scale Descriptors combined	
Scaled Pearson Measure	0.044
Proximity Measureh	0.015
Scarcity Adjusted Proximity Measure	0.036

A.4 Correlation within Occupation Similarity Metrics

In Figure 7, we show the Pearson correlation between all occupational similarity metrics. Three things are worth mentioning. Firstly and not surprisingly, each descriptor tends to have high internal correlation across the three different proximity functional forms. Secondly, the occupation similarity metrics based on continuous scale descriptors tend to have fairly high correlation with each other. This means that occupations that have similar knowledge will also have similar abilities and skills etc. Thirdly, the occupation similarity metrics based on detailed and intermediate work activities descriptors are not very strongly correlated to the continuous scale proximity metrics. This result suggests that these detailed and intermediate work activity descriptors capture different information that, as shown by Table 4, is particularly relevant for predicting job transitions.

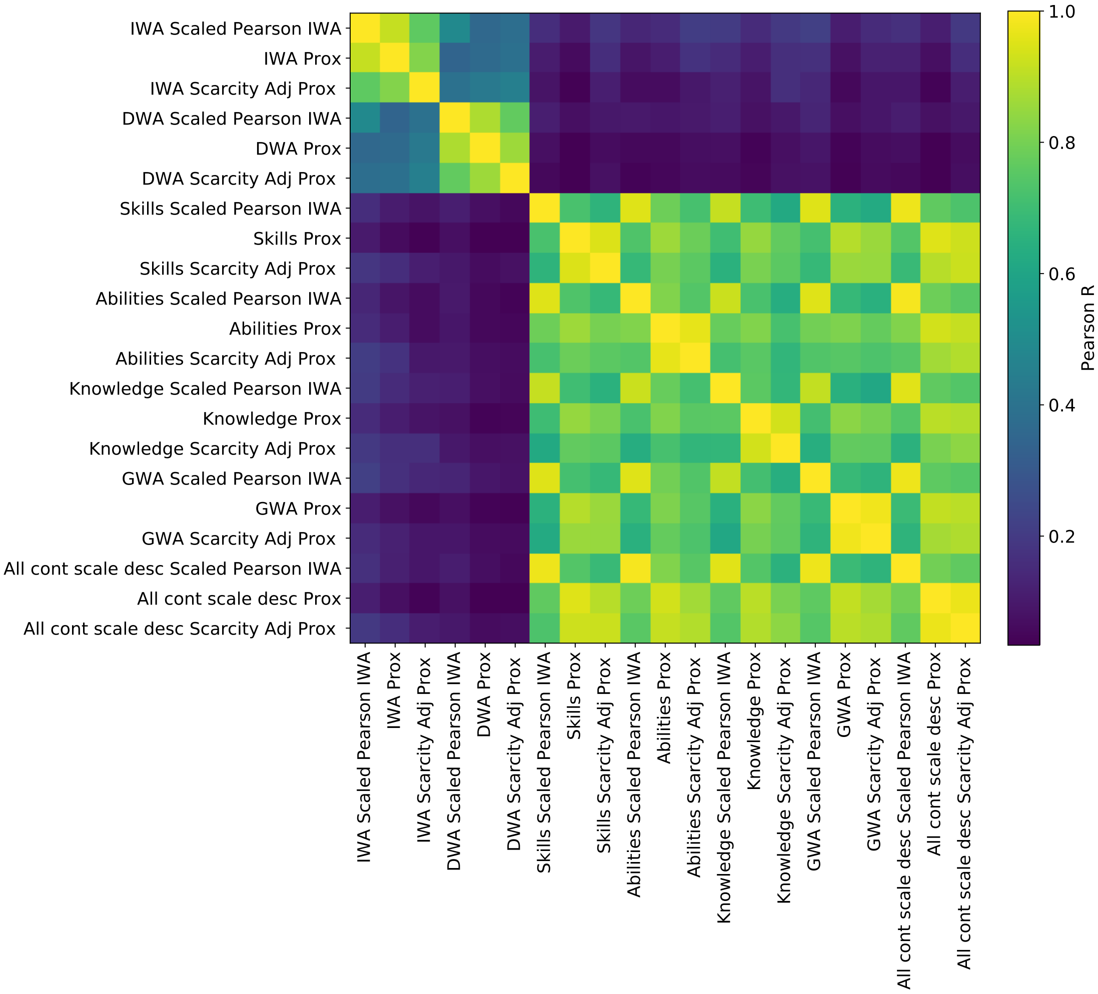

Figure 7: Heatmap showing Pearson R correlation between all occupation proximity descriptor metrics

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