International Labour Organization

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Research Brief

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Who moves and who stays?
Labour market transitions under automation and health-related restrictions

Key points

- This brief highlights the results of an ongoing research collaboration between the ILO Research Department, Eightfold.ai and researchers at the University of Oxford.
- Our aim is to evaluate data from individual CVs to better understand labour market adjustments in the light of shocks. Detailed results and analysis will be made available in a separate research paper.

Introduction

The world of work is changing. New technologies, demographic shifts and climate change are reshaping workplaces, jobs, organizations and enterprises. Labour market transitions during which people change their jobs or occupations, their work content, or simply their roles in an organization are likely to become more disruptive in the future (ILO, 2019).

This research brief examines the nature of such transitions in light of the recent COVID-19 shock on labour markets, as well as possible labour reallocation caused by automation. Specifically, this brief identifies groups of occupations (called "communities") within which workers tend to transition more easily. By understanding how exposed each community is to employment shocks, this work seeks to find groups of workers who may find it harder to find new employment opportunities outside their current occupations.

Some disruptions are temporary, for instance when workers are being furloughed following COVID-19-related restrictions. Others are permanent when jobs are being automated away. Regardless of the cause, however, such disruptions cause people in most cases to experience short spells of unemployment before returning to the same or a similar activity. In some instances, however, those affected by such shocks are at risk of being permanently detached from the labour market and becoming inactive. [1]

To a significant extent, the risk of dropping out of the labour market and ending up inactive depends on a person's opportunities to find another job, either in the same or a related sector. Indeed, recent research has demonstrated the importance of such occupational transitions in labour market adjustment dynamics (Del Rio-Chanona et al., 2021). This research also highlighted how unequal such transition probabilities are across occupations, with some being

[1] The probability of exiting the labour market following job disruption is particularly high for vulnerable groups such as older workers for whom activation programmes have been phased out in favour of pathways to early retirement (Yashiro *et al.*, 2020).

characterized as “dead-end jobs”, in other words, jobs that offer few opportunities to move elsewhere should they become obsolete.

But who can easily change jobs and who cannot? Which occupations open career pathways and which ones do not? These are questions for individuals, governments, and organizations that we raise in this research brief. To provide a granular analysis of occupational mobility, we illustrate these transitions in the form of a labour market network, where each node is an occupation and edges denote job transitions. The network is weighted and directed. Edges are directed from source to target occupation and weighted by the probability that an observed job transition in the Eightfold.ai dataset happens between the linked occupations. This network allows us to better understand which occupational transitions are possible and which ones happen more frequently than others.

A novel dataset

Historical information on individual career paths and (self-reported) competence profiles constitute a valuable alternative to national statistics or labour force surveys, or at least a complementary source of information. Eightfold.ai is a United States (US) based technology company specialized in deep-learning prediction models that extract and analyse data from CVs. We use a subset of the Eightfold.ai data to create a new occupational mobility network on the basis of more than 100 million observations. 2 Each observation is a career path for a US worker. Extracting this dataset from CVs is made possible through recent advances in natural language processing (NLP). We are using such data to build a labour market network that helps us in answering some of the above questions.

Eightfold.ai has grouped individually reported positions (job titles) into job clusters. We use the algorithm developed by Russ et al. (2016) to match the job titles and job clusters to US job titles in the O*NET database. 3 This crosswalk between Eightfold.ai jobs and official titles of the Standard Occupational Classification (SOC) system of the US Government allows us to compare our network and its characteristics with corresponding features from national labour statistics, for example, employment shares by occupation, average wages, gender and others).

Additionally, we incorporated occupation indexes related to automation and COVID-19-related restrictions into our network. In particular, we used the suitability for machine learning (SML) index that Brynjolfsson et al. (2018) developed at the occupation level to measure the potential effect of artificial intelligence (AI) on the demand for human labour. To capture the effects of restrictions related to the COVID-19 pandemic on different occupations, we utilize the remote labour index (RLI) that indicates the extent to which each of the occupations in the SOC can be carried out from home (Del Rio-Chanona et al., 2020). An RLI of 1 indicates that all activities associated with an occupation could be undertaken at home, while a zero indicates that none of the occupation's activities could be carried out from home. These two metrics as well as US national averages of employment statistics have been linked to the occupations in our network.

The Eightfold.ai occupational mobility network

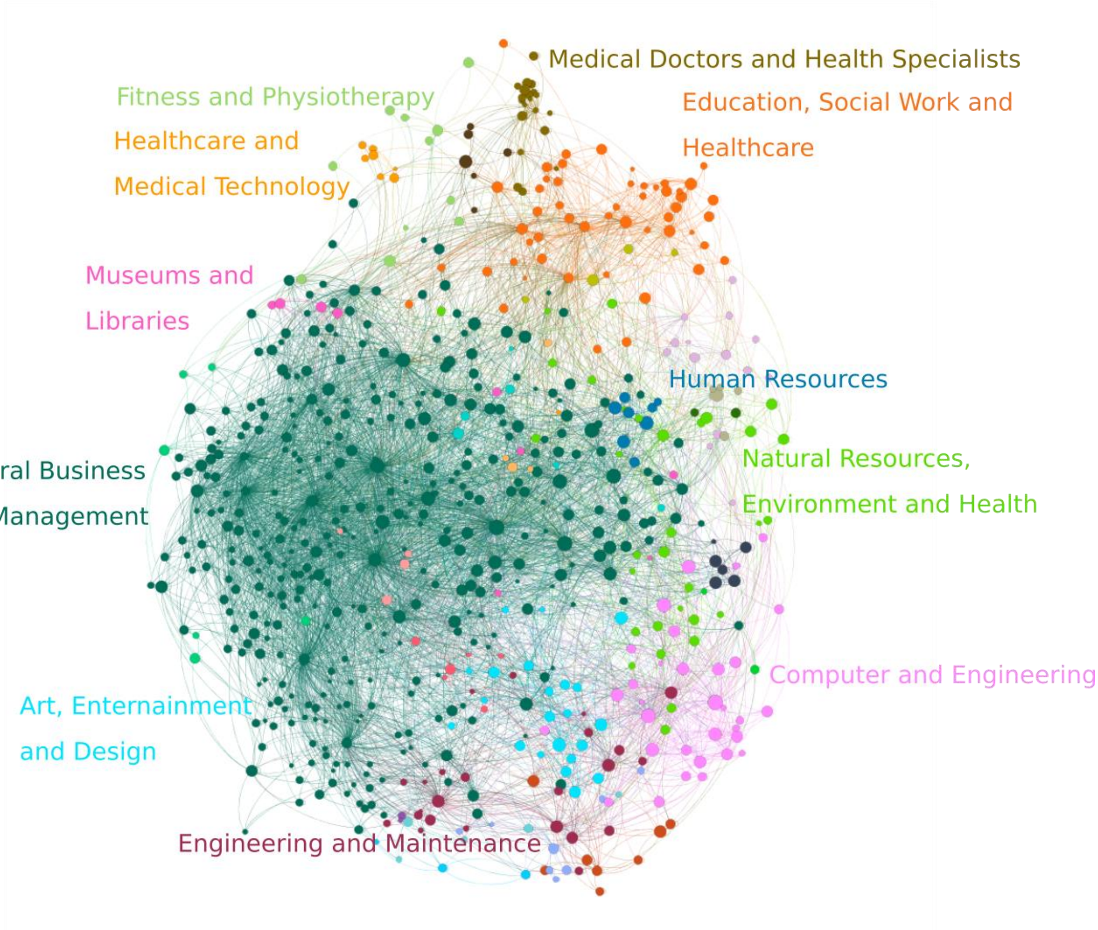
Figure 1 shows the resulting occupational network. The network consists of 674 occupations that are classified according to the SOC. Our analysis has subgrouped these occupations into 28 communities, using the map equation community detection algorithm with default parameters (Rosvall et al., 2008). The network plot was made with Gephi (Bastian et al., 2009) using the Force Atlas 2 layout algorithm (Jacomy et al., 2014). This algorithm tends to place nodes that are strongly connected closer together. In this regard, one expects that transitions occur more frequently between close communities than with those communities further away. In contrast, transitions between communities occur less frequently and hence boundaries between communities represent barriers. In this regard, communities provide additional information about the resilience of labour markets to shocks: A few, large communities indicate plenty of possibilities for occupational transitions. In contrast, many small communities may indicate adjustment barriers.

[2] Each observation is a CV in our dataset, so the evaluation covers more than 100 million transitions considering there are multiple job moves on each CV.
[3] The O*NET database is the US primary source of occupational information.

Our analysis does not indicate the underlying factors that facilitate or hamper occupational transitions. Most likely, similarity of skills required for an occupation or similarity of tasks can be expected to be among these factors. Moreover, people with certain characteristics that help facilitate transitions might self-select into certain occupations and hence end up in a specific community. For instance, people in occupations related to art, music and design – all occupations known for their difficulty to transit elsewhere – might possess certain artistic qualities that others do not. 4 Regulations and other institutional factors are also likely to facilitate or hinder transitions and will be subject to future research.

Comparing the 28 communities with the 23 major occupational groups available in O*NET shows that these occupational clusters often fall entirely into certain communities of our network. O*NET characterizes occupations according to tasks, skills, educational level and training credentials. This suggests that these factors jointly play an important role in determining how easy transitions are between those occupations, providing at least indirect evidence regarding the determinants of transitions.

▶ **Figure 1. The Eightfold.ai Occupational Mobility Network**



So*urce:* Authors' calculations.
The Eightfold.ai occupational mobility network consists of 674 different occupations (nodes). The size of the nodes represents the number of people working in this occupation. Occupations that experience many transitions and therefore have many connections (edges) are grouped as communities of the same colour. More than half of the occupations in the network (365) are in one large community (General Business and Management and in dark green), which means that most transitions occur across these occupations.

Additional insights derive from analysing those occupations that are either clustered together or split between different communities. Legal occupations, for instance, are split among two communities: Community 20, which consists of a group of legal occupations, such as lawyers and judges, together with educational occupations that are related to law

[4] See also the analysis regarding occupational transitions.

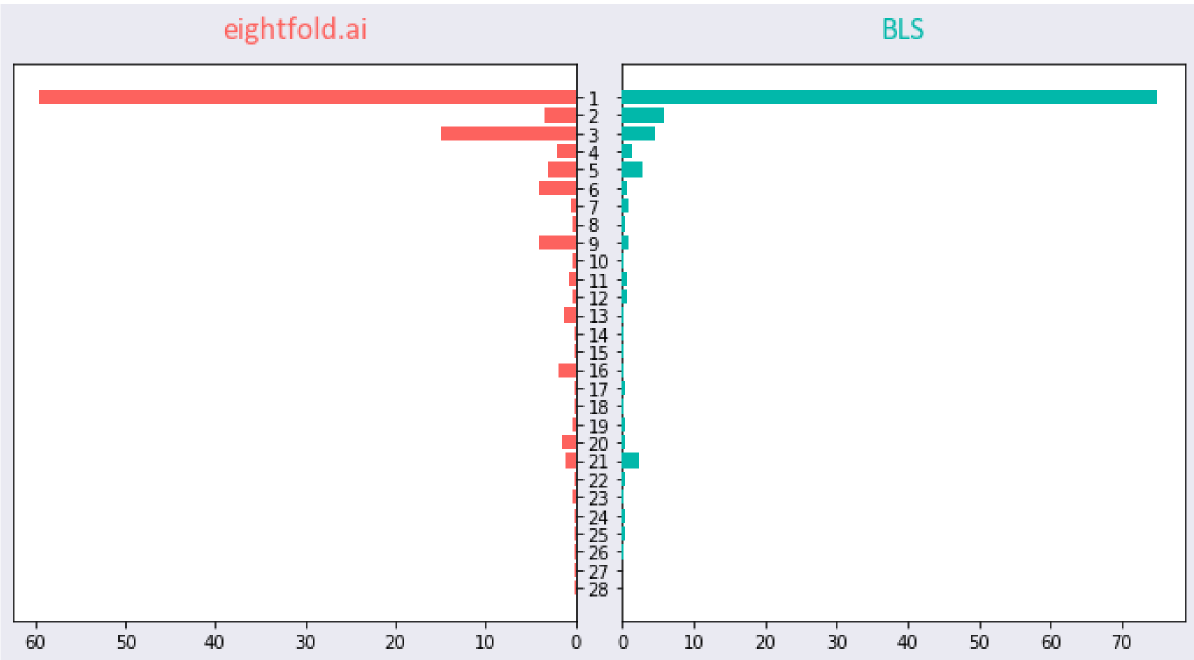
studies (for example, law professors); and all other legal occupations (for example, arbitrators, mediators, conciliators, paralegals, legal assistants) that are grouped into Community 1. Transitions across lawyers, judges and law educators can occur more frequently than across other legal occupations. This suggests a sharp segmentation of occupations even within the larger group of legal occupations.

In contrast, community and social service occupations fall entirely into Community 2, together with educational instructors and healthcare practitioners. Hence, this is an example of an SOC occupational group that is clustered exclusively within a larger Eightfold.ai community, suggesting that transitions both within these occupations and with respect to other, similar occupations in other areas are particularly prevalent. Further research is needed, however, to identify the exact factors influencing this clustering.

The distribution of occupations across the Eightfold.ai communities is highly skewed: About 54 per cent of all occupational titles are found in Community 1 (General Business and Management), as shown by figure 1 and table A1 in the appendix. The heterogeneity in the relative size of these communities is similarly striking. A comparison of employment shares in each community, with corresponding national data from the Bureau of Labour Statistics (BLS), shows that 58 per cent of employees in our sample work in Community 1. At the US national level, about 75 per cent of the workers fall into Community 1, suggesting that the sample of CVs in the Eightfold.ai database might not be fully representative (figure 2).

Such a skewed distribution of occupations across communities suggests that, while overall the US labour market is highly flexible – as indicated by the large size of Community 1 – it is also very vulnerable to asymmetric shocks, 5 affecting some of the smaller communities. Job disruptions in any of the other communities often lead employees to spend considerable time and resources to move to alternative occupations, possibly one of the factors explaining the recent increase in labour market mismatch observed over the past decade. 6

▶ Figure 2. Employment Shares by community



Source: Authors' calculations.
Figure 2 depicts the employment shares by community in the Eightfold.ai sample and the respective shares in the US economy as a share of total employment based on BLS data. For example, Community 1 consists of roughly 60 per cent of all workers in the sample, while in the US economy Community 1 comprises about 75 per cent of all workers. Short descriptions of the occupations in each of the 20 communities can be found in table A1 in the appendix.

[5] By asymmetric economic shock we mean an abrupt, exogenous change of economic conditions that is not affecting all sectors, regions or segments of the economy uniformly.

[6] The Beveridge Curve – in other words, the evolution of vacancies with respect to job seekers – provides a good indication of the extent of labour market mismatch: An outward movement of the curve indicates increased mismatch.

Community 1 consists of 18 SOC occupational groups and more than 350 individual occupations. We carried out several robustness checks that confirmed that this large community is indeed a statistical characteristic of the Eightfold.ai network. Digging deeper into why occupational transitions within this community occur more frequently suggests that possessing certain basic digital skills is certainly a requirement for successful labour market transitions: In fact, the Eightfold.ai sample is dominated by people who have written CVs in a digital format and are, therefore, more likely to apply for positions posted online. This could increase their chances of making successful transitions that show up in our dataset, while other occupations may be less prone to have online CVs.

Which are some of the occupations in the large Community 1 (General Business and Management) that allow for relatively easy cross-occupational transitions? We find a large number of management occupations as well as occupations in finance and business operations (close to 15 per cent of occupations). This could be an indicator of similarity in skills and tasks across occupations. About 20 per cent of the roles in Community 1 are in sales and related occupations, as well as in office and administrative support. There are similarities in the task descriptions of occupations in office and administrative support and the previous group of jobs in management and business operations, which may explain transitions across these occupations. It is less obvious how these latter occupations allow for easy transitions to jobs in arts, design, entertainment and media, or jobs as healthcare practitioners, which are also found in Community 1.

Proximity of communities in figure 1 indicate that transitions occur more frequently than with those communities further away. For instance, Community 1 (General Business and Management) is well connected with Community 9, covering human resources and labour specialists, but less well connected with technical occupations that are mainly found in Community 3, such as engineers and computer specialists. Certain communities such as Medical Doctors and Health Specialists are very isolated and have little connections with other communities. The specific and demanding skill set in medical occupations might be one reason for the relative isolation of this community. Considering the rising demand in (health) care workers in the future, this also calls for attention by labour market practitioners and policymakers regarding the importance of long-term planning of labour supply for this sector.

Barriers across communities might also be linked to occupational licensing and the provision of firm-specific skills, preventing a more rapid transition to such occupations. In this regard, the recent increase in labour market power 7 and the resulting decline in transitions should be reason for concern (see Eeckhout, 2021; Davalos and Ernst, 2021). Skill shortages, for instance, which in principle should lead to higher wages for occupations in high demand, so far do not seem to have created wage pressures, partly because of enterprises preventing employee poaching through the provision of firm-specific skills (Murali, 2021). This differentiation of general versus specialized skills is an important area of future research for us.

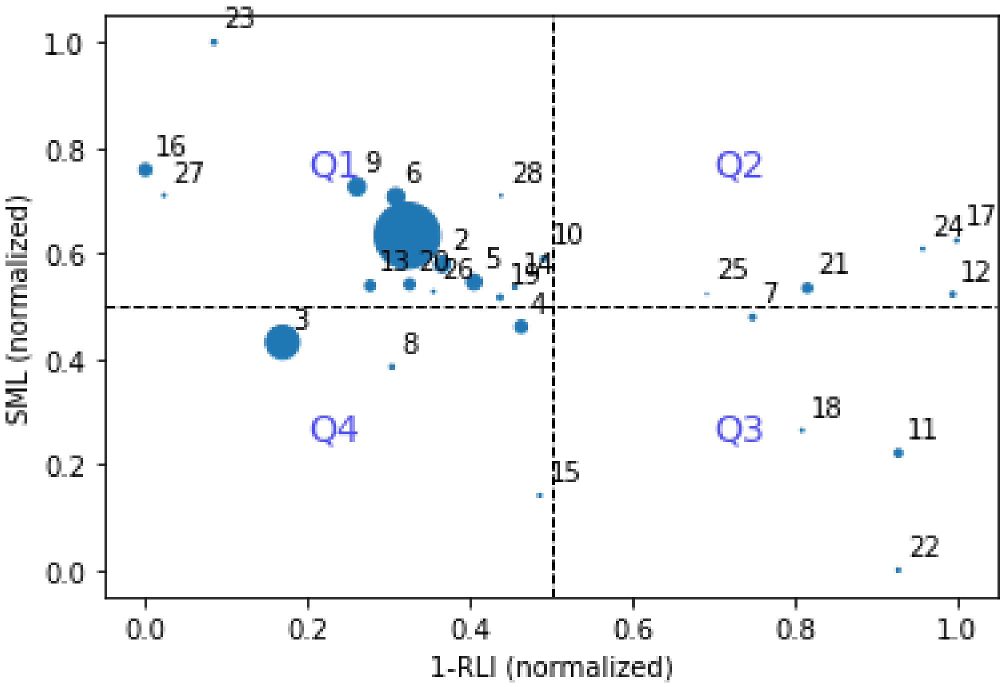
New Insights, conclusions and outlook

Automation and COVID-19

In this section, we further examine the characteristics of the Eightfold.ai communities. We capture labour market exposures to COVID-19 policies and to potential automation with the two metrics introduced above, the RLI and the SML. As both measures exist only on the occupational level, we use the employment shares of each occupation in its community as a weight to compute an average for the community: The sizes of the nodes in the Eightfold.ai network correspond to the (imputed) employment numbers per occupation. Based on the actual employment shares per occupation in the Eightfold.ai sample, we impute the absolute employment number that would be expected at the US national level, given total employment in all listed occupations as reported by the BLS. The Eightfold.ai network then represents a US workforce of 136 million workers.

[7] Labour market power in this context refers to monopsony power of firms in certain market segments (regional or sectoral) in which they can strongly influence hiring patterns and working conditions.

▶ **Figure 3. Community exposure to COVID-19 Measures and Automation Risk**



Source: Authors' calculations.
Figure 3 depicts the 28 communities in Eightfold.ai occupational mobility network according to their SML scores and the RLI. The SML score measures the effects of machine learning technologies on occupations, including the potential automation of tasks. The RLI measures to what extent typical work tasks of an occupation can be performed remotely. Both scores have been calculated on the community level as weighted averages of the occupations in each community and then been normalized to a score between 0 and 1. This means that the scores show only relative exposure (the communities relative to each other) to automation risk and to COVID-19 measures, like social distancing. Since an RLI of 1 is defined for occupations in which virtually all tasks could be performed remotely, the x-axis of figure 3 uses (1-RLI) as units, so that an increasing x-value indicates fewer possibilities to work remotely.

Figure 3 shows all 28 communities on an x-y plane whereby exposure to automation is depicted on the vertical axis and exposure to COVID-19 measures is on the horizontal axis. The size of each dot corresponds to the employment share of each community. We use the SML score developed by Brynjolfsson et al. (2018) in the following paragraphs rather loosely as a metric for "automation risk". Yet, the authors point out that the interpretation of this measure is a bit more complex than mere replacement of humans through machines, which is only one aspect of a high SML score. Occupations are perceived as a bundle of tasks, some of which can be taken over by machines through new capabilities of machine learning as they "currently exist". Only technical feasibility is taken into consideration, not economic, organizational, legal, cultural, and societal factors influencing machine learning adoption. 8

In our more simplified interpretation of figure 3, we can group the communities into the four quadrants Q1–Q4. The occupations in the communities located in the second quadrant, Q2, have a high risk of automation (in other words, high SML scores) and consist of tasks that cannot be performed remotely. Occupational tasks of communities in Quadrant 4 (Q4) are neither easily automatable, nor do they require physical presence in an office or other workspace, and are in this sense at a lower risk. Most communities and also most workers from the Eightfold.ai sample, including Community 1, are in the first quadrant, experiencing an elevated automation risk but by and large being able to perform at least parts of their work remotely.

A closer look at the particular communities shows that communities such as Writing and Reporting (16), Human Resources and Labour Specialists (9), Mapping Technicians (27), and Actuaries and Bioinformatics (28) are among the communities that will be mostly affected by machine learning technologies (relatively high SML scores). On the other

[8] Brynjolfsson *et al.* (2018) create a survey of 23 questions on SML of work tasks to which respondents can reply with a score between 1 (strongly disagree), which corresponds to low SML, and a 5 (strongly agree), which corresponds to high SML. Neutral exposure corresponds to a score of 3 (neither agree nor disagree). The occupational level SML is then calculated by using the SML score associated with each occupational task and then weighting each task by its O*NET importance data value. The result is an average SML for each occupation.

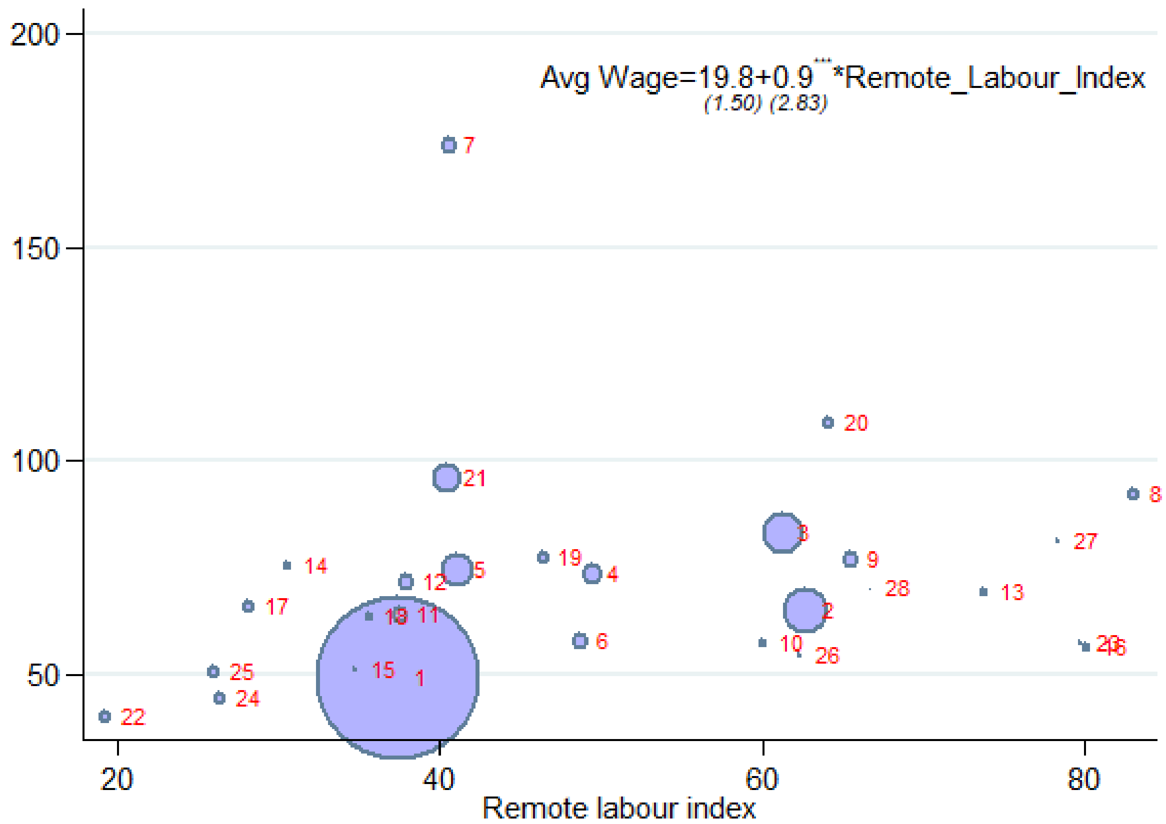
hand, communities like Personal Care (22), Apparel and Fashion (15), Fitness and Physiotherapy (11) and Higher Education (8) are among the communities with low SML scores.

Communities that may deserve special attention are found in Quadrant 2 of figure 3: These are communities with a high automation potential that cannot be performed remotely, hence the pressure to automate work activities in these communities or even entire occupation might be particularly high. The communities in Q2 are the following: Production and Machine Operations (24), Electricity and Maintenance (25) Law Enforcement (12), Nursing (21) Healthcare and Medical Technology (17).

Wages

The wage estimates for each of the 28 communities are national US averages (means) and lie between about US$29,000 per annum (Personal Care) and around US$170,000 per annum (Medical Doctors and Health Specialists). High salaries are also paid in Community 20 (Lawyers and Judges). The data for the wage estimations stem from BLS, not from the Eightfold.ai sample.

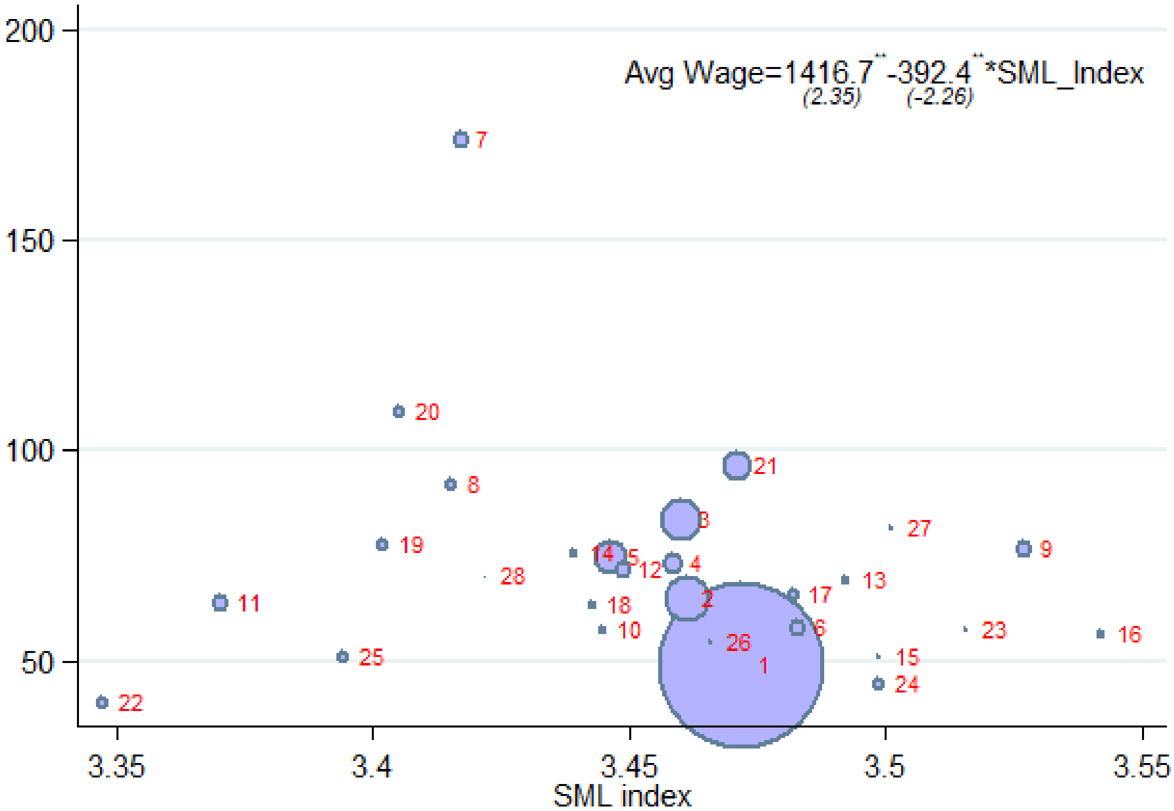
▶ **Figure 4. Average wage in US$1,000 by Community and the Remote Labour Index**



Source: Authors' calculations.
Figure 4 depicts the relationship between the RLI and the average annual wage for each of the 28 communities. The size of the bubbles represents the employment share of each of the communities in total employment (BLS). The percentage of the RLI on the x-axis shows the extent to which the tasks of the occupations can be performed remotely. Numbers indicate the communities (see also table A1 in the appendix).

We can see that many communities earn slightly more than the US mean wage of about US$50,000 per annum, but only the two communities mentioned above, Lawyers and Medical Doctors, earn more than US$100,000 on average. The lowest income community is 22, Personal Care. There is a (strong) positive correlation in the data between the RLI of the community and the average wage (as indicated by the regression equation in the chart). Communities that consist of occupations in which work can be performed remotely tend to earn higher wages.

▶ **Figure 5. Average wage in US$1,000 by Community and the SML Index**



Source: Authors' calculations.
Figure 5 depicts the relationship between the SML index and the average annual wage for each of the 28 communities. The size of the bubbles represents the employment share of each of the communities in total employment (BLS). The SML index on the x-axis shows the extent to which the tasks of the occupations can be programmed in a machine. Numbers indicate the communities (see also table A1 in the appendix).

Figure 5 shows the same average wages as in figure 4 but instead of the RLI, the SML index is shown on the horizontal axis. Here, a negative correlation between the SML score and the average wage appears, albeit less significant than in the case of the RLI score and driven mainly by Community 7, which is highly non-automatable while commanding high average wages.

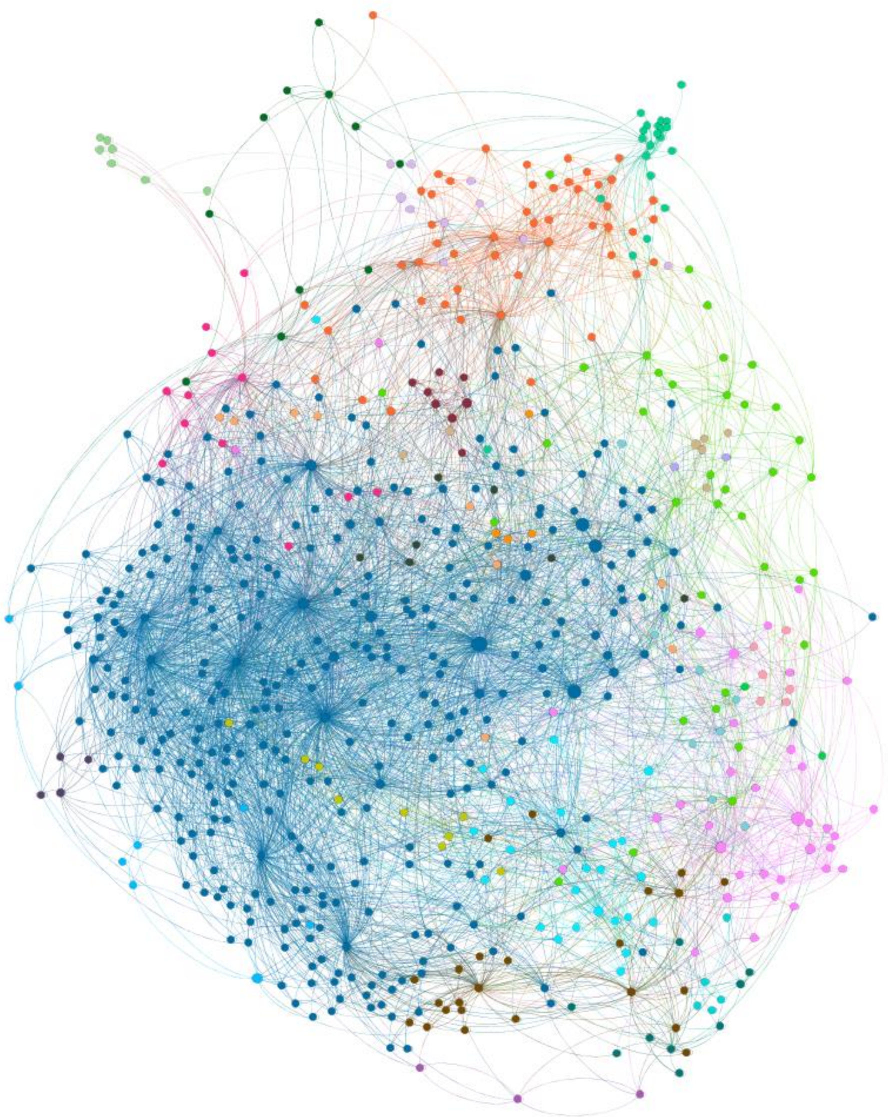
This research brief has shown how a new database created from CVs can be transformed into a network model of occupations. With the help of this network, we can study job-to-job-transitions and the characteristics of workers who easily make transitions and those who do not. Managing transitions successfully is an important challenge for the future of work for policymakers, corporate leaders and workers alike (ILO, 2019). We have shown that the data are by and large representative of the US economy and can therefore complement the analysis of national labour force surveys (LFS), which are not available at the same frequency as online CVs. This brief serves as an outlook for upcoming research in which we will address the gender dimensions of the network further, in other words differences in transitions made men versus transitions made by women. Other areas concern generalized and specialized skills as barriers or facilitators of transitions. Finally, this dataset also allows for an analysis of career paths, something that cannot be addressed with labour force surveys. Based on the results, the research paper will also support the formulation of policies that can facilitate successful transitions.

▶ Table A1: The Eightfold ai Occupational Communities

Community	Name	Frequency	SOC Major Groups
1	General Business and Management	54.2	MISC.
2	Education, Social Work, and Counselling	7.7	21, 25, 29
3	Computer and Engineering	4.7	15, 17, 47, 49, 51
4	Natural Resources and Environment	4.7	17, 19, 21, 29, 45, 51
5	Engineering Operations and Maintenance	3.6	11, 17, 49, 51
6	Art, Entertainment, and Design	3.3	17, 25
7	Medical Doctors and Healthcare Specialists	3.0	19, 25
8	Higher Education	2.1	19, 25
9	Human Resources and Labour Specialists	1.2	11, 13
10	Museums and Librarians	1.3	19, 25, 27, 43
11	Fitness and Physiotherapy	1.6	11, 29, 31
12	Law Enforcement	0.9	19, 25, 33
13	Architecture, Landscaping, and Design	1.2	11, 27
14	Resource Extraction and Production	1.2	17, 19, 47, 51
15	Apparel and Fashion	0.9	27, 39, 51
16	Writing and Reporting	0.9	27, 43
17	Healthcare and Medical Technology	1.2	29
18	Emergency and Disaster Management	0.6	11, 29, 33
19	Transportation	0.9	25, 27, 53
20	Lawyers and Judges	0.7	23, 25
21	Nursing	0.9	25, 29
22	Personal Care	0.6	39
23	Clergy and Religious Work	0.6	21, 25
24	Production and Machine Operations	0.7	51
25	Electricity and Maintenance	0.3	47, 49
27	Mapping Technicians	0.4	15, 43
28	Actuaries and Bioinformatics	0.3	17, 19

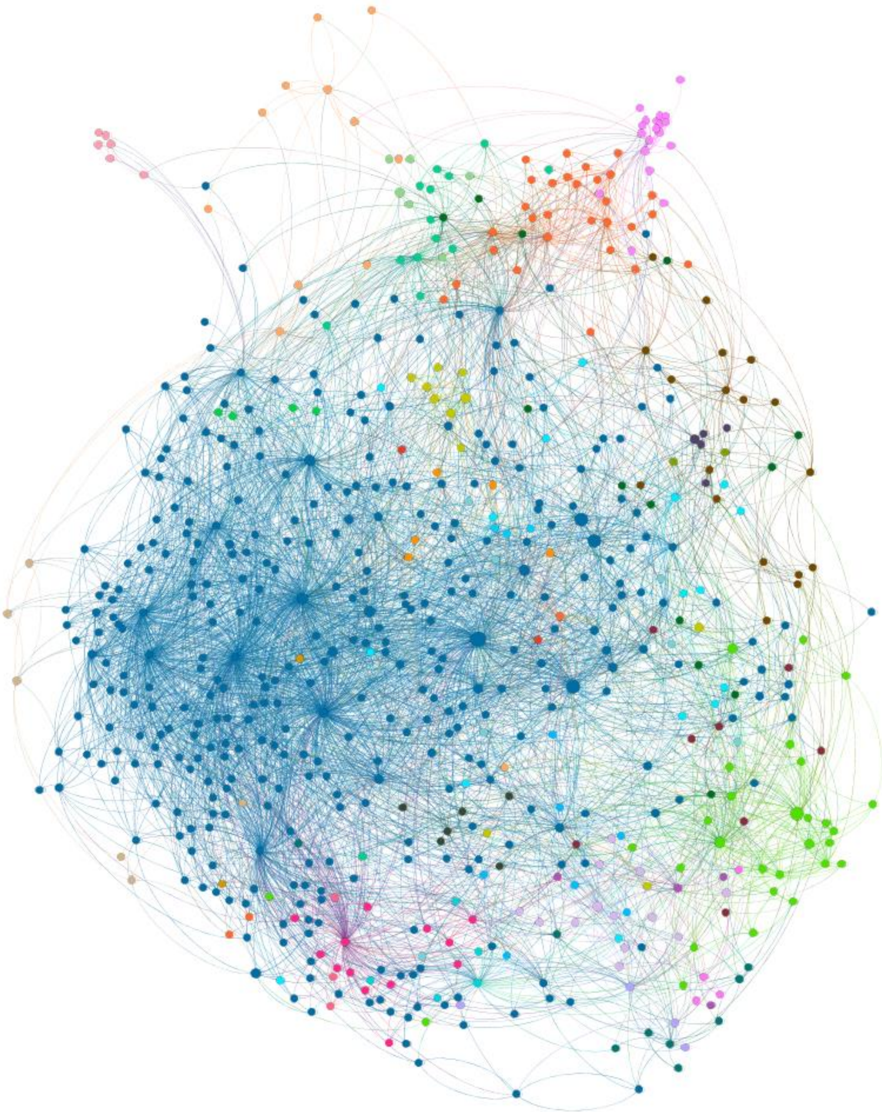
Source: Authors' calculations
Table A1 describes the 28 communities of the Eightfold.ai Occupational Network, as well as the relative frequency of the occupations in each community as a share of the total. The last column provides the major classification code of the occupations (2-digits) according to the United States Standard Occupational Classification (SOC) system that occur in each of the communities.

▶ **Figure A1. The Eightfold.ai Occupational Mobility Network (Males only)**



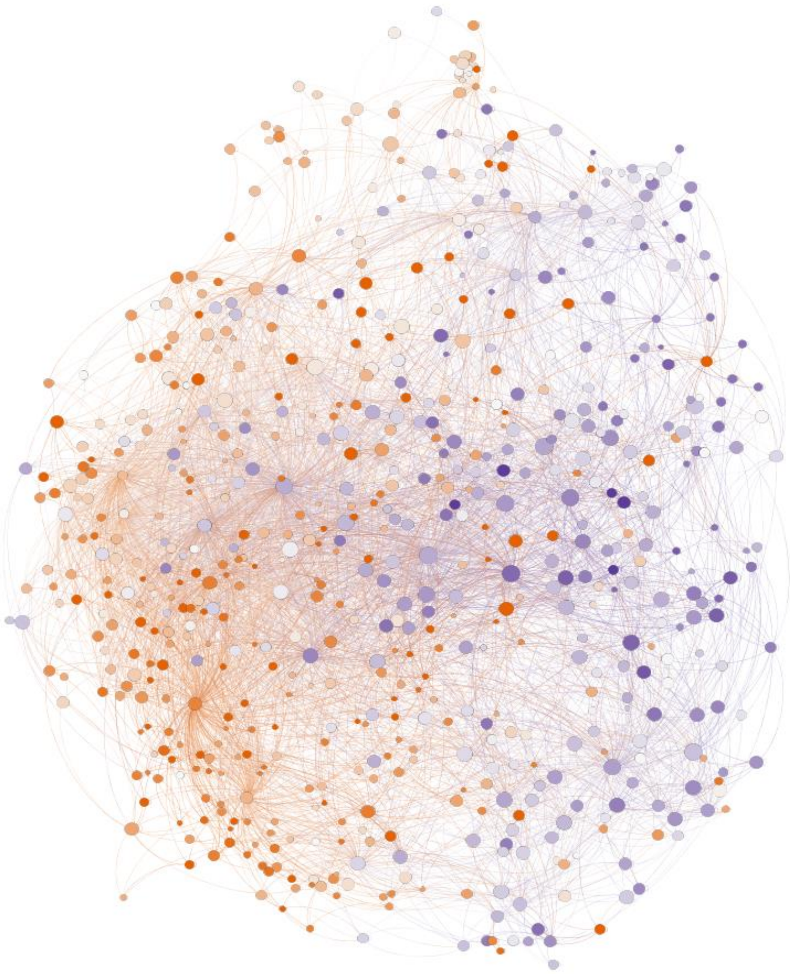
Source: Authors' calculations.
The Eightfold.ai occupational mobility network constructed using only males:

▶ **Figure A2. The Eightfold.ai Occupational Mobility Network (Females only)**



Source: Authors' calculations.
The Eightfold.ai occupational mobility network constructed using only females:

▶ **Figure A3. The Eightfold.ai Occupational Mobility and Exposure to COVID**



Source: Authors' calculations.
Figure 4 depicts the Eightfold.ai occupational mobility network with 674 different occupations and the Remote Labour index (RLI). Orange and red nodes are occupations with a low RLI, hence cannot be performed remotely and are therefore negatively exposed to COVID measures. Violet and dark violet nodes are occupations with a relative high RLI and can be carried our remotely, for example from home. These occupations and communities are at a lower risk to be disrupted by strict COVID social distancing measures,

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Authors

- R. Maria del Rio-Chanona, Oxford University
- Ekkehard Ernst, ILO Research Department
- Steve Feyer, Eightfold.ai
- Daniel Samaan, ILO Research Department
- Shruti Trivedi, Eightfold.ai

Contact details

International Labour Organization
Route des Morillons 4
CH-1211 Geneva 22
Switzerland

T: +41 22 799 6530
E: research@ilo.org