Is Our Human Capital General Enough to Withstand the Current Wave of Technological Change?

Ljubica Nedelkoska, Dario Diodato and Frank Neffke

CID Research Fellow and Graduate Student

Working Paper No. 93
August 2018

Working Papers
Center for International Development
at Harvard University

Is our human capital general enough to withstand the current wave of technological change?

Ljubica Nedelkoska*, Dario Diodato* and Frank Neffke*

This version 1: August 10, 2018

Abstract

The degree to which modern technologies are able to substitute for groups of job tasks has renewed fears of near-future technological unemployment. We argue that our knowledge, skills and abilities (KSA) go beyond the specific tasks we do at the job, making us potentially more adaptable to technological change than feared. The disruptiveness of new technologies depends on the relationships between the job tasks susceptible to automation and our KSA. Here we first demonstrate that KSA are general human capital features while job tasks are not, suggesting that human capital is more transferrable across occupations than what job tasks would predict. In spite of this, we document a worrying pattern where automation is not randomly distributed across the KSA space – it is concentrated among occupations that share similar KSA. As a result, workers in these occupations are making longer skill transitions when changing occupations and have higher probability of unemployment.

* Center for International Development at Harvard University. Corresponding author: Ljubica Nedelkoska at Ljubica_nedelkoska@hks.harvard.edu

1. Introduction

Machines have come a long way in their ability to embed human tasks. Mechanization was behind much of the decline in the demand for routine manual tasks performed by unskilled workers in agriculture and industry in the nineteenth and the twentieth century.[2] Digital technologies expanded this impact to include routine cognitive tasks, while further automating routine manual ones (Autor, Levy and Murnane 2003). Most recently, machine learning and other AI-based technologies are becoming capable of outperforming humans in many cognitive non-routine tasks, while mobile robotics are perfecting the performance of non-routine manual tasks (Brynjolfsson and McAfee 2014; Brynjolfsson and Mitchell 2017; Frey and Osborne 2017). Both of these categories of tasks were considered beyond the reach of digital technologies just a decade ago.

While now few doubt the ability of novel technologies to significantly redesign, if not eliminate many occupations, the question arises if this time we are worse positioned to adjust to technological changes than we did in previous decades. Will the current technological change result in occupational restructuring, by moving workers from declining to growing occupations as it happened with previous waves of automation[3], or could it result in significant technological unemployment?

To answer this question, we need to understand the relationship between the tasks we perform at our jobs and the knowledge, skills and abilities (KSA) that enable us to perform these. In particular, we need to understand how the domains of job tasks affected by automation correspond to KSA domains. Automation as well as augmentation operate at the level of job tasks. It is our job tasks, not our KSA that are being replaced or amplified by technology. As workers we know more than what we do. We have a wider set of acquired KSA that enable us to perform job tasks beyond those we perform in a single job. Here we argue that if the KSA that underlay these tasks can be redeployed to perform other tasks that are less susceptible to automation, our adaptation to technological change may be easier than commonly feared[4], as it can allow for transitions from declining to growing occupations without a high cost of requalification. It is possible however that this time is different. The KSA requirements of the growing occupations might be significantly higher or qualitatively different from those in occupations susceptible to automation, making the adjustment through occupational change harder.

To study these issues, we use data from the O*NET, the primary source of occupational information for the United States, and the U.S. Current Population Survey (1997-2018). These two data sources allow us to combine detailed information on occupations' job tasks, KSA, and tools and technologies with individual-level information on occupational mobility, earnings and other economic and socio-demographic characteristics.

The paper makes a number of contributions. First, we provide evidence consistent with our view that KSA underlies the job tasks we are able to perform, making us potentially better able to adapt to

---

[2] During this period, the share of agricultural employment in the U.S. economy declined from 74 percent in 1800 to 40 percent in 1900, and then to eight percent by 1960 (Lebergott 1966).

[3] The mechanization of agriculture and industry, although rapid, resulted in reallocation of workers from shrinking to growing occupations, rather than in technological unemployment (Jerome 1934) even though the job tasks in the agricultural sector were quite different from the job tasks in industry.

[4] The generality of KSA vis-à-vis job tasks might be the reason why agricultural workers could transition to industry jobs without great difficulty: both sectors value abilities like stamina, and skills such as dexterity and multi-limb coordination, making their KSA transferable across occupations with otherwise distinct job tasks.

significant changes in our job task portfolios. Second, we test the predictability of KSA, job tasks and tools with respect to individual-level occupational mobility and earnings growth among those that change occupations. We find that similarities in the job tasks, KSA and tools between occupations are all independently highly predictive of occupational mobility. KSA is however the strongest predictor of earnings growth among occupational switchers. Third, we study how the risk of job automation is distributed across occupations that are similar in terms of KSA, tasks and tools. In all three cases, the risk is non-randomly distributed, affecting full domains of KSA, job tasks and tools. This is a troubling observation. It suggests that as general-purpose technologies (GPT) such as artificial intelligence (AI) diffuse, it may become increasingly difficult for certain workers to switch to jobs with different tasks, but similar KSA. In fact, we find that workers in occupations at high risk of automation make longer KSA transitions when switching occupations than workers in occupations at low risk of automation.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature and section 3 explains the data sources and the final samples. Section 4 explains our conceptual framework on the relationships between tasks, tools and KSA and introduces the measurement of human capital similarity. Section 5 tests the predictability of human capital similarity with respect to occupational mobility and earnings. Section 6 elaborates on the relationship between automatability, occupation-level labor market outcomes and human capital similarity. Section 7 concludes.

2. Literature review

We build our work on the grounds established by a few different research fronts. The first relevant research area is the so-called Task-Approach. In the literature on technological change and its impact on the labor market, this approach was introduced by Autor, Levy and Murnane (2003) and was further developed by Acemoglu and Autor (2011), Autor (2013), and Autor and Handel (2013). One key insight of this approach is that technology does not directly substitute or augment labor, but it can substitute or augment tasks that are performed by humans with certain skills. In Acemoglu and Autor (2011), people with different levels of skills (e.g., low, medium and high), as well as technologies, have comparative advantages in different tasks. In equilibrium, only the least-cost factor is assigned to a given task, affecting the relative employment and prices of people with different skills and that of technology.

Following the Task-Approach, several studies have tried to identify which job tasks are susceptible to technological automation and augmentation. The seminal work by Autor, Levy and Murnane (2003) argued that the tasks prone to automation by computer capital are routine manual and routine cognitive, while non-routine manual and non-routine analytical and interactive tasks are complemented by computer capital. Brynjolfsson and McAfee (2014) and Frey and Osborne (2017) later argued that the fast developments of new technologies such as machine learning and mobile robotics are expanding the range of automatable tasks and now include tasks that are non-routine in nature: car driving, translation, fraud detection, medical diagnostics, pre-trail research in legal services, personnel recruitment, financial advice and software programming among others. They proposed that thinking of current engineering bottlenecks to automation, such as social intelligence and creativity is a fruitful way of identifying the limits to the impact of technologies on the labor market. More recently, Brynjolfsson and Mitchell (2017) designed a task-level measure of suitability to machine learning, while Grace et al. (2017) using a survey of AI experts evaluated the time until certain human tasks will be conducted more cost-effectively by machines. Felten, Raj and Seamans (2018) used the data from Electronic Frontier Foundation AI Progress Measurement to measure the AI performance progress on different tasks (e.g., image recognition, reading comprehension, speech recognition) and mapped these to O*NET abilities in order to estimate which occupations are likely to be affected by the advances in AI.

The second research area relevant to this study is the economics of human capital transferability. A key proposition in our paper is that individuals' human capital (our knowledge, skills and abilities in particular) is more general that what one would guess by only looking at the job tasks individuals perform in any given job. In other words, our human capital is highly transferable across jobs and occupations. This was most prominently shown by Gathmann and Schönberg (2010), who concluded that human capital is more portable across occupations than previous thought. Similarly, Poletaev and Robinson (2008) found that our human capital is skill-specific rather than occupation or industry specific. Nedelkoska, Neffke and Wiederhold (2015) studied the asymmetric nature of human capital transferability and showed that a major source of the well-documented earnings losses after job displacement is due to down-skilling, or the fact that after being displaced, many workers are matched to jobs with lower skill requirements than the ones characterizing their pre-displacement jobs. Approaches using actual job transitions either between occupations or between industries have also been in use in the labor economics literature and the literature of economic geography (Shaw 1987; Neffke and Henning 2013; Neffke, Otto, and Weyh 2017). In these approaches, excess labor flows, i.e., labor flows that cannot be explained by the size of the two occupations or industries, are considered to signal skill-relatedness or human capital similarity between those occupations or industries. Our approach here is the closest to the one of Gathmann and Schönberg (2010).

A number of recent studies have used the O*NET and similar data to map the space of human tasks and skills using network analysis.[5] Mealy, del Rio-Chanona and Farmer (2018) used O*NET's job tasks to create a matrix of occupational similarities, as well as a matrix showing which tasks co-occur at the level of occupations. Similar to our work, the matrices are analyzed using network analysis and they show that the tasks-based occupational space is predictive of how we change occupations. Anderson (2017) used online freelance website data on the skill requirements in job postings and the reported skills by job applicants to create two co-occurrence matrices that she analyzes using network analysis: one representing the skills that workers have and the other representing the skills that employers require. She then analyzes how these skills correlate with workers' earnings. Frank et al. (2018) use several different O*NET modules (skills, interests, education, work context etc.) and translate these into raw skill values by occupation. With the help of this, they study the distribution of automation across U.S. cities. Alabdulkareem et al. (2018) use the O*NET data on tasks, skills, knowledge and abilities to map what they refer to as skill-complementarity. Then they demonstrate that the resulting network is polarized between two skill clusters: socio-cognitive skills and sensory-physical skills. They put forward the idea that this polarization is what constraints the mobility of workers between physical and cognitive occupations. Although very close to the network approach taken in this study, what clearly distinguishes these previous articles from ours, is that they either focus on one specific aspect of human capital (e.g., job tasks in Mealy et al. 2018 or worker skills in Anderson 2017) or they bunch several aspects of human capital together, disregarding the causal relationships between tasks, tools, and KSA we propose here (e.g., Frank et al 2018; Alabdulkareem et al. 2018).

[5] A few studies also use the O*NET data for developing methodological contributions in network analysis (Yildirim and Coscia 2014; Coscia and Neffke 2017).

3. Data and final samples

Our data come from two sources: O*NET and the Current Population Survey.

The O*NET is the most comprehensive online resource on occupation-level data for the U.S. (National Center for O*NET Development 2018a). Most importantly, for over 970 occupational categories it offers detailed descriptions of the occupational knowledge, skills, abilities, work activities, tools and technologies among other occupational characteristics. The data is collected by interviewing occupational experts and surveying employees. O*NET updates its data by interviewing incumbents and occupational experts from about 100 occupations at a time. The data used here were updated between 2004 and 2017 using a schedule available on O*NET's website (National Center for O*NET Development 2018b).

The second dataset is the Current Population Survey (CPS), a monthly survey of about 60,000 U.S. households conducted by the U.S. Census Bureau for the Bureau of Labor Statistics (BLS). It is the primary data used for calculating the U.S. unemployment rate and other key labor market indicators. We use the CPS version as available on IPUMS USA (Flood et al. 2017). We use the CPS January 1996-March 2018. Although it has been collected for over seven decades, we focus our analysis starting in 1996 because we see a sharp discontinuity in the monthly rates of occupational change between the period before and after 1996 – monthly mobility doubles in 1996. Among others, the CPS contains individual-level information on one's occupation, industry, and extensive list of demographic and economic characteristics.

Our final data is a subset of the data available in the CPS and O*NET. Following Kambourov and Manovskii (2008), from the CPS we only include male, not self-employed workers, age 23-61, who do not work for the government. Unlike Kambourov and Manovskii (2008), we do not exclude those with more than one employment/job because this share decreases over time in the time period we cover and could induce spurious trend in occupational mobility.

We merge the CPS data with O*NET and Frey and Osborne's measure of the risk of automation (Frey and Osborne 2017), which was calculated using O*NET data, at the level of occupations. Frey and Osborne calculate this measure for about 700 O*NET occupations, which reduces our sample to that set of occupations. The CPS uses the American Community Survey (ACS) occupational classification, which has 450 occupational categories. IPUMS provides a crosswalk between the SOC and ACS which we apply in order to merge the two datasets. After merging all datasets, we are left with 368 occupations that are consistently surveyed over time.

We then create two final datasets. The *mobility* dataset is a dyadic dataset, where the dyads are all possible pairs of the 368 occupations. Mobility refers to job switching between two occupations over time, which later will be one of our main variables of interest. We first estimate occupational mobility at the individual level for individuals that we can follow in two consecutive months, and then we aggregate the number of switches between any two occupations at the annual level.[6]

[6] We choose to aggregate monthly mobility estimates at the annual level for two reasons. First, as discussed in Kambourov and Manovskii (2013), what seems to look like annual occupational mobility in the CPS is actually mobility over 2-3 months. Second, to generate a stronger signal of occupational mobility, we'd like to maximize the

The *earnings* dataset uses the weekly earnings reported in the Outgoing Rotation/Earner Study. These are reported for about a quarter of the CPS[7] sample but are available throughout the whole period of our analysis. We deflate them to real 2000 earnings using the CPS-provided Consumer Price Index. This dataset is individual-month level dataset limited to individuals that have made an occupational switch.

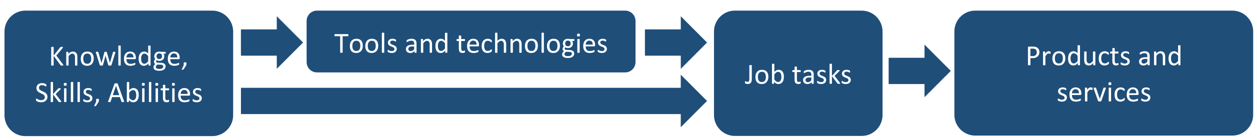
From both datasets we exclude occupational mobility taking place in 2003. The CPS conducted a major reclassification in that year (U.S. Census Bureau 2006), creating a large number of artefactual occupational moves. Appendix A provides the descriptive statistics of the final datasets and shows the trends in occupational mobility, earnings growth and skill similarity over time.

4. Human capital and human capital similarity

We analyze human capital from three aspects: the tasks we perform at the job, the tools and technologies we employ when performing those tasks, and the knowledge, skills and abilities that enable us to use the tools and perform the tasks.

Figure 1 illustrates how we see the relationships between job tasks, tools and KSA. Job tasks are the direct inputs in the production of products and services. Tools help us perform these tasks. KSA is what makes us capable of using tools and performing tasks.

Figure 1. Hypothesized relationships between KSA, tools and job tasks



Source: Own illustration.

More specifically, job tasks are work activities such as conduct market research, review customer information, conduct legal analysis or repair a machine. They are our direct inputs in the production of goods and services. KSA are a mix of more general and more permanent attributes of our human capital.[8] O*NET defines knowledge as "organized sets of principles and facts applying in general domains".[9] Skills, on the other hand, are defined as "developed capacities that facilitate learning or the more rapid acquisition of knowledge".[10] Abilities are considered to be "enduring attributes of the

---

number of observed occupational moves per occupation-occupation-time cell. Even after annualizing the occupational flows, only 5% of all possible occupational dyads contain non-zero flows.

[7] According to Minnesota Population Center (2018) individuals eligible for the earner study are civilians age 15 and older in rotation groups 4 or 8 who are not self-employed. In any given month, approximately 1/4 of the CPS sample is in the earner study and each household should appear in the earner study exactly twice. The Outgoing Rotation/Earner Study also reports hourly wages which would have been our preferred choice. However, these are more often missing than are the weekly earnings.

[8] They are defined at different levels of detail in O*NET. We use the Intermediate Work Activities following Mealy (2018) which include 332 different tasks.

[9] They survey 36 domains of knowledge, such as biology, design, English language or transportation (National Center for O*NET Development 2018c).

[10] O*NET distinguishes among the categories of basic, complex problem solving, resource management, social, systems and technical skills. Overall, O*NET surveys 35 skills for each occupation. (National Center for O*NET Development 2018d).

individual that influence performance".[11] Tools include machines, equipment, tools, information technology, and software used at the job.

Our view on the relationships between KSA and job tasks is very much in line with the one proposed by Autor and Handel (2013) and Acemoglu and Autor (2011). In their work they make a clear distinction between tasks, which are units of work activities that produce output, and skills, which are workers' endowments of capabilities for performing various tasks. Skills are applied to tasks to produce output and skills do not directly produce output. While skills are created through durable investments (e.g., in education) and can be thought of as relatively stable worker attributes, tasks are not fixed worker attributes – they can change in response to task supplies or technological change. However, different from Acemoglu and Autor (2011) who map tasks to three skill levels (low, medium and high), we allow for KSA to not only vary in the level of complexity, but also by domain.

Human capital similarity

We calculate measures of human capital similarity for any given pair of occupations along the three aspects of human capital. In the case of tasks and tools, O*NET reports the presence (or absence) of these at the occupational level. This structure is well suited for calculating the Jaccard similarity index[12], which is the intersection of tasks (tools) over the union of tasks (tools) between any two occupations. In the case of KSA, O*NET assigns importance and level weights to each element. The importance and the level weights are almost perfectly correlated although they are measured on somewhat different scales and although they are supposed to reflect different qualities of KSA. The importance weights are measured on a 1-5 Likert scale, with 1 being "not important" and 5 being "extremely important". We dichotomize the Likert scale variables, such that a KSA variable gets a value of one if the original variable has a value of 2.5 or higher. Otherwise, it gets a value of zero. The dichotomization allows us to calculate Jaccard similarity in the case of KSA as well:

$$JSimi'_{oo} = \frac{HC_o \cap HC_{o'}}{HC_o \cup HC_{o'}}$$

Where: $HC = \{Tools, Tasks, KSA\}$

$$Tasks = \{1, \dots, 332\}$$

$$Tools = \{1, \dots, 4302\}$$

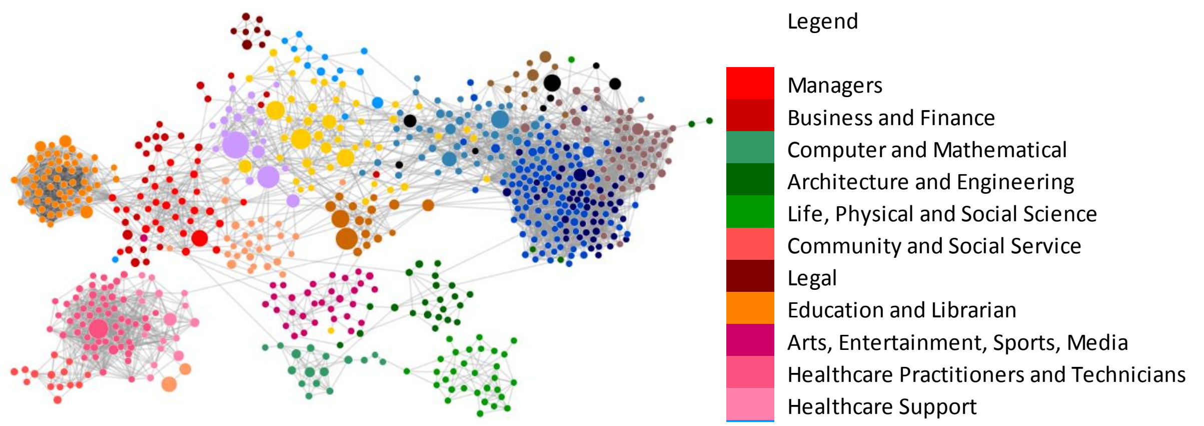
$$KSA = \{1, \dots, 123\}$$

[11] O*NET distinguishes among cognitive, physical, psychomotor and sensory abilities and surveys a total of 52 abilities. (National Center for O*NET Development 2018d).

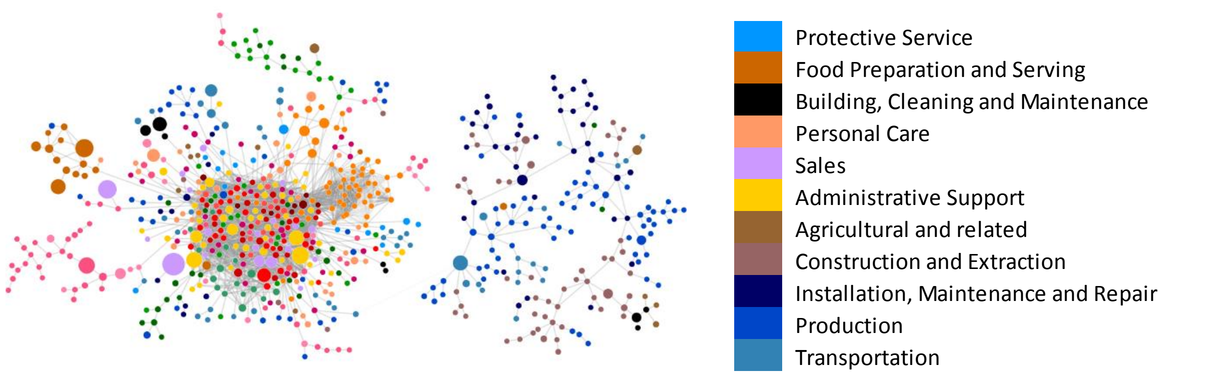
[12] To check how sensitive our results are to the choice of similarity measure we also estimated the raw co-occurrence (which is simply the intersection of tasks/KSA/tools) and the Pearson correlations. We prefer the use of Jaccard compared to the other two measures. Unlike co-occurrence, the Jaccard is not affected by the breadth of tasks/KSA/tools in each occupation. Moreover, unlike correlations which are heavily impacted by the "absence" of tasks/KSA/tools, Jaccard similarity depends on the presence of these, which is more informative.

Figure 2. Visualizations of occupational similarity based on tasks, tools and KSA

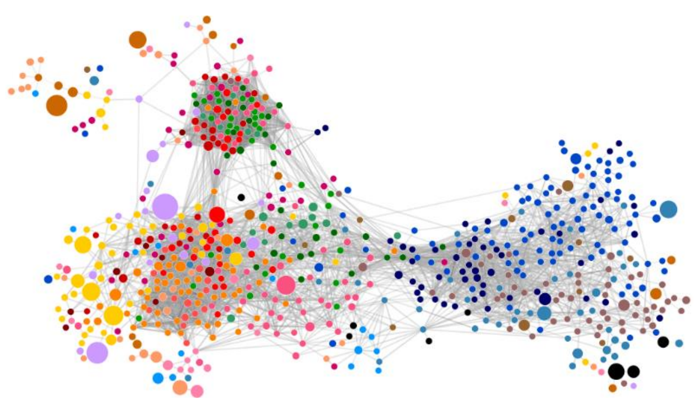
a. Occupational similarity using job tasks (Tasks-based occupational space)



b. Occupational similarity using tools (Tools-based occupational space)



c. Occupational similarity using knowledge, skills, abilities (KSA-based occupational space)



Source: Own calculations using O*NET.

Using the O*NET data only but limiting it to the occupations for which Frey and Osborne's measure of job automatability is available, we calculate the Jaccard similarity for $701^2 - 701$ $(490{,}700)$

occupational dyads (oo')[13]. Figure 2 a-c shows the strongest $10 * N$ links in each of the similarity matrices, where N is the number of occupations (or nodes).[14] In the Figure, each node represents an occupation and each link is a Jaccard score. The node colors correspond to the 22 job families in the SOC, as indicated in the legend.

The visualizations reveal important differences in the human capital similarity estimated using the three different human capital aspects. When occupational similarity is estimated using job tasks, we see very strong clustering of occupations that coincide with the 22 job families (Figure 2a). Almost all job families form strong clusters, meaning that job tasks are similar within job families, but dissimilar across them. This strongly supports the idea that occupations can be seen as bundles of tasks (Acemoglu and Autor 2011; Yamaguchi 2012).

When occupational similarity is estimated using tools, we see a very different pattern: there is one big component which core is composed of many job families that roughly coincide with what we would call white-collar workers, and a second component composed of mainly blue-collar occupations (Figure 2b). The white-collar component has in common the use of office machinery by many occupations, while the blue-collar component has in common the use of transportation machinery and various industrial equipment. Some notable exceptions to the two big components are education occupations; part of the medical occupations; life, physical and social sciences; and food preparation and service. Each of these three job families seems to use tools that are more unique to the jobs within the job family. With the exception of these three job families, the tools-based similarity matrix suggests that we use the same tools to perform many different tasks across many different job families.

Finally, when occupational similarity is estimated using KSA, we observe three big components (Figure 2c). The first one clusters various blue-collar jobs together: construction, transportation, production, repair and the majority of building cleaning and maintenance services. The second component clusters various computational, engineering, managerial, business and finance, arts, media and even a number of medical occupations together. What these occupations have in common is that they require strong analytical and problem-solving skills. The third large component is extremely diverse and it includes administrative occupations; education; lawyers; community and social service; managerial occupations; sales; life, physical and social sciences; some engineering; computational; and medical occupations. In addition to analytical skills, these occupations strongly rely on social, interpersonal skills. In comparison to the tasks space, the KSA space reveals that occupations across different job families share similar KSA. The same KSA (e.g., cognitive problem-solving skills) can give rise to different job tasks employed across many job families (engineering, arts, management, health etc.). The differences in the topology of the KSA-based occupational space and the tasks-based occupational space demonstrate the more general character of our KSA and the job-specific character of our tasks.

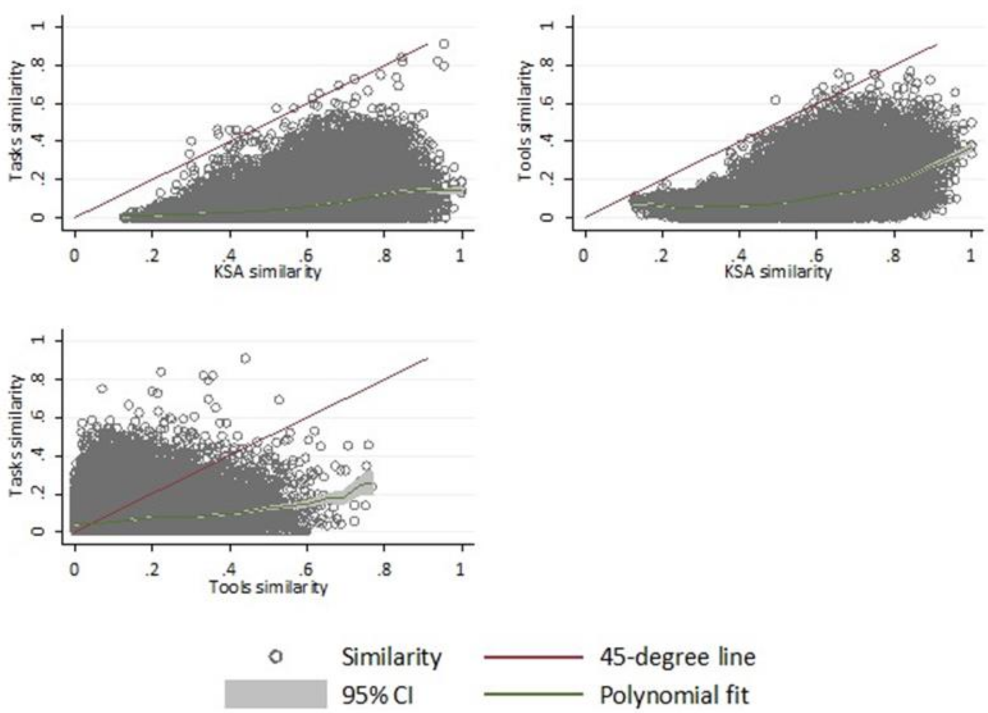
---

[13] Note that Jaccard similarity produces symmetric oo' matrices, but we will relate these similarity measures to asymmetric quantities, such as job switches between o and o'.

[14] More specifically, we show the $N * 10$ strongest links, where 10 is a rank of the strength of the link and $N = 701$. It is possible to have more than 7,010 strongest links when multiple occupational dyads have the same Jaccard score. Moreover, to make sure that all 701 occupations in the visualization are connected by a link, we calculate the maximum spanning tree (MST) and additionally include links that may not be among the 7,010 strongest ones but are on the MST. See Hidalgo et al. (2007) for this approach to network visualization.

Figure 3 shows the empirical relationships between KSA similarity and tasks similarity, KSA similarity and tools similarity, and tools similarity and tasks similarity. All relationships are positive, but not very strong, as illustrated by the moderately upward sloping median splines. The figure however reveals something more important. The scatter plot in the case of the KSA and tasks similarity, as well as KSA and tools similarity has a triangular shape: occupational pairs that are highly similar in terms of tasks are highly similar in terms of KSA, but not the other way around: occupations that are highly similar in terms of KSA are not necessarily similar in terms of tasks. The same pattern holds for the relationship between KSA and tools similarity. This supports our claim that we know more than what we do, i.e., same KSA can give rise to many different tasks and tools, but the opposite does not hold. The relationship between tools similarity and tasks similarity does not exhibit the pattern that the relationships with KSA do.

Figure 3. Correlations between tasks, tools and KSA-based occupational similarities



Source: Own calculations using O*NET.

Note: Each circle corresponds to an occupational dyad. The red line shows the 45-degree line. The green line is a fitted median spline, showing the correlations between the variables and its 95% confidence interval.

5. Human capital similarity, occupational change and the growth of earnings

Human capital similarity and occupational change

Using job tasks data, previous studies have demonstrated that human capital similarity between occupations is predictive of the probability of job switching between those occupations (Gathmann and Schönberg 2010; Nedelkoska, Neffke and Wiederhold 2015; Mealy 2018). Here we study how the predictability of KSA-based and tools-based occupational similarity compares to that of job tasks-based similarity.

The outcome variable we are interested in is the flow of workers between any two occupations. A suitable econometric model for our goal is a Gravity model (Mátyás 1997; Anderson 2011), or more specifically, its econometric representation. Here, the flow of workers between two occupations F_{ijt} at time t depends on human capital similarity S_{ij}^{HC}, and economic factors that vary by occupation and time O_{it} and O_{jt}. G is a constant, and ν_{ijt} is an error term with a mean of 1:

$$F_{ijt} = G\,\frac{O_{it}^{\beta_2} O_{jt}^{\beta_3}}{S_{ij}^{\beta_1}}\,\nu_{ijt}$$

Taking logs on both sides of the equation, we estimate:

$$ln\left(F_{ijt}\right) = \alpha + \beta_1\, ln\left(S_{ij}^{HC}\right) + \boldsymbol{O_i T}_t + \boldsymbol{O}_j\boldsymbol{T}_t + \varepsilon_{ijt}$$

We estimate the above equation for $HC = \{Tasks, Tools, KSA\}$. There are 368 occupations over 21 years and hence $(368^2 - 368) \times 21$ occupational combinations in the sample. $\beta_2 \ln(O_{it})$ and $\beta_3 \ln\left(O_{jt}\right)$ are translated to $\boldsymbol{O_i T}_t$ and $\boldsymbol{O_j T}_t$, which are occupation-time dummies for the occupation of origin and the occupation of destination. They control for any occupational aspects and potential confounders that also vary over time (e.g., occupation-specific earnings, gender distributions and educational distributions).

Given that we strongly believe that KSA, tools and tasks are causally related, it would be statistically unsound to include them simultaneously in one regression model, and hence we do not. Doing so would introduce the problem of bad controls (Angrist and Pischke 2009). Hence, at this point we will simply compare three different regressions where occupational mobility is modelled as a function of one aspect of human capital similarity and control variables. However, if we include all three simultaneously, all three remain highly significant and economically relevant. KSA and job tasks have about the same coefficient, while the coefficient of tools is about half that of KSA or job tasks.

From the three separate regressions, we find that KSA similarity, tasks similarity and tools similarity are all predictive of occupational switching (Table 1). Other factors equal, occupational moves are 2.6 times larger[15] between occupations at the 95th percentile of the tasks-based similarity than between occupations at the 5th percentile of this similarity. Occupational moves are 3.5 times larger between occupations at the 95th percentile of the tools-based similarity than between those at the 5th percentile. They are 2.3 times larger between occupations at the 95th percentile of the KSA-based similarity than between occupations at the 5th percentile of KSA similarity.

We also estimate the same regressions, but now for three time periods of 6-7 years (1997-2002, 2004-2011 and 2012-2018) to see if these patterns change over time. The ranking of the coefficients of KSA,

[15] Task similarity: $(\exp(2.61) - 1) \times 0.204 = 2.57$, where 0.204 is the difference between the 95th percentile and 5th percentile of the tasks Jaccard distribution. Tools similarity: $(\exp(2.648) - 1) \times 0.269 = 3.53$. KSA similarity: $(\exp(1.911) - 1) \times 0.403 = 2.32$.

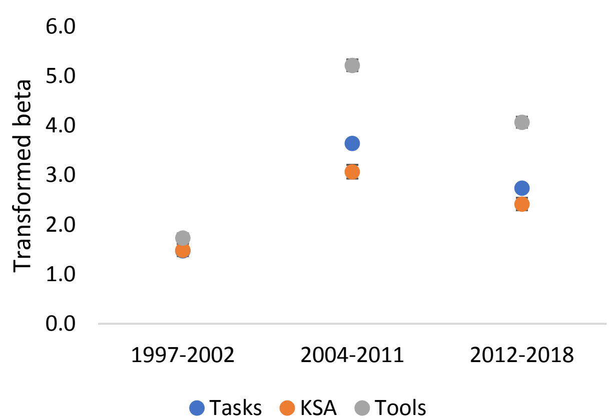
tools and tasks remains stable over time. The coefficients in all three cases are the highest in the second period, which coincides with the great recession and lowest for the first period (Figure 4).

Table 1. Human capital similarity and occupational change

VARIABLES	(1)	(2) $ln(F_{ijt})$	(3)
Tasks similarity	2.610***		
	(0.156)		
KSA similarity		1.911***	
		(0.145)	
Tools similarity			2.648***
			(0.172)
Observations	2,843,904	2,843,904	2,843,904
R-squared	0.198	0.199	0.196
Adj. R-sq	0.194	0.194	0.192
Within R-sq	0.0167	0.0174	0.0141

Standard errors clustered two-way by occupation of origin and occupation of destination in parentheses. All models include occupation*year dummies, one set for the occupation of origin and one set for the occupation of destination. Significant at: *** p<0.01, ** p<0.05, * p<0.1

Figure 4. Human capital similarity and occupational change over time



Note: As in the regression results in Table 1, we transform the betas: $(\exp(\beta) - 1) \times \Delta Jacc_{95^{th}-5^{th}}$

Human capital similarity and the growth of earnings

Previous studies have demonstrated that human capital similarity, as measured by the job tasks overlap among occupations, is predictive of the growth in earnings between our past and current occupation (Gathmann and Schönberg 2010; Nedelkoska, Neffke and Wiederhold 2015). Here we compare the predictability of KSA-based and tools-based similarity with the one of tasks-based similarity. For this exercise we follow Gathmann and Schönberg (2010). They hypothesized that among occupational switchers, the correlation between the wage in the current occupation and the wage in the previous occupation is stronger for higher levels of human capital similarity. We estimate[16]:

$$lne_{pjt} = \alpha + \beta_1 lne_{pi,t-1} + \beta_2 \, ln\left(S_{ij}^{HC}\right) + \beta_3 \, ln\left(S_{ij}^{HC}\right) * lne_{pi,t-1} + \boldsymbol{X}'_{pt}\boldsymbol{\beta} + \boldsymbol{O_i T}_t + \boldsymbol{O}_j\boldsymbol{T}_t + \varepsilon_{pijt}$$

Where e_{pjt} are the person-level weekly earnings in period t in occupation j, while $e_{pj,t-1}$ are the person-level weekly earnings in period $t-1$ in occupation i. $\boldsymbol{X}_{pt}$ are a set of person-level characteristics such as potential work experience and education measured at time t. $\boldsymbol{O_i T}_t$ and $\boldsymbol{O_j T}_t$ are occupation-time dummies for the occupation of origin and the occupation of destination.

At the individual level, past occupational earnings are a strong predictor of current occupational earnings. In our estimates (Table 2, column 1), past earnings explain 61% of current earnings among occupational switchers, ceteris paribus. Gathmann and Schönberg (2010) demonstrated that the past wages predict current wages better if the current and the past occupation are more similar in terms of job tasks. Here we show that this is the case with task similarity and with KSA similarity, but it is not the case with tools similarity. KSA similarity, it turns out, is particularly predictive. Past earnings explain 6% more of the current earnings when people change occupations at the 95th percentile of KSA similarity than when they change between occupations at the 5th percentile of KSA similarity. This estimate is 2% in the case of tasks similarity and it is not different from zero when it comes to tools similarity.

We also study if this pattern changes over time, by dividing our data into three periods: 1997-2002, 2004-2011 and 2012-2018. We find that the estimated coefficients are quite stable over time. The interaction term between past earnings and KSA similarity is higher than the interaction term between past earnings and tasks similarity in all three periods, but the differences are not statistically significant (Figure 5).

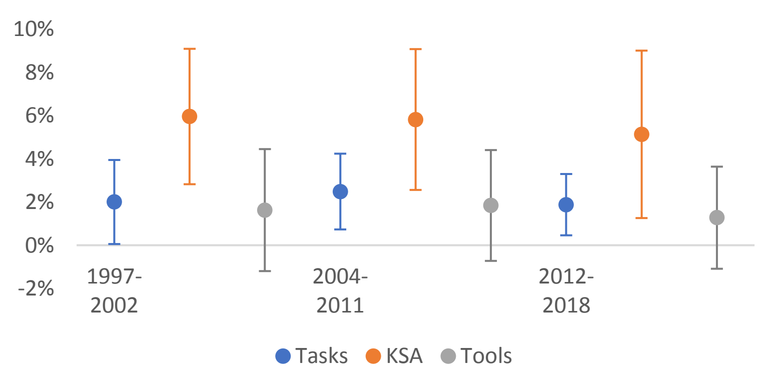
[16] One difference between ours and Gathmann and Schönberg's specification is that we do not use person fixed effects - we have one observation per individual in the dataset. Instead, we use a more stringent set of controls at the occupational-time level than those used in Gathmann and Schönberg.

Table 2. Human capital similarity and the growth in earnings among occupational switchers

VARIABLES	(1)	(2)	(3)	(4)
	Current earnings			
Past earnings	0.479***	0.462***	0.394***	0.469***
	(0.00806)	(0.0104)	(0.0250)	(0.0134)
Tasks similarity		-0.507**		
		(0.217)		
Past earnings*Tasks similarity		0.101***		
		(0.0342)		
KSA similarity			-0.751***	
			(0.231)	
Past earnings*KSA similarity			0.132***	
			(0.0357)	
Tools similarity				-0.232
				(0.290)
Past earnings*Tools similarity				0.0539
				(0.0453)
Potential experience	0.0133***	0.0133***	0.0133***	0.0132***
	(0.000974)	(0.000979)	(0.000969)	(0.000972)
Potential experience sq	-0.000225***	-0.000225***	-0.000225***	-0.000224***
	(2.09e-05)	(2.10e-05)	(2.08e-05)	(2.08e-05)
Years of education	0.0244***	0.0243***	0.0243***	0.0244***
	(0.00185)	(0.00185)	(0.00182)	(0.00186)
Observations	123,431	123,431	123,431	123,431
R-squared	0.596	0.597	0.597	0.596
Adj. R-sq	0.556	0.557	0.557	0.557

Standard errors clustered two-way by occupation of origin and occupation of destination in parentheses. All models include occupation*year dummies, one set for the occupation of origin and one set for the occupation of destination. Significant at: *** p<0.01, ** p<0.05, * p<0.1

Figure 5. Human capital similarity and the growth in earnings among occupational switchers over time

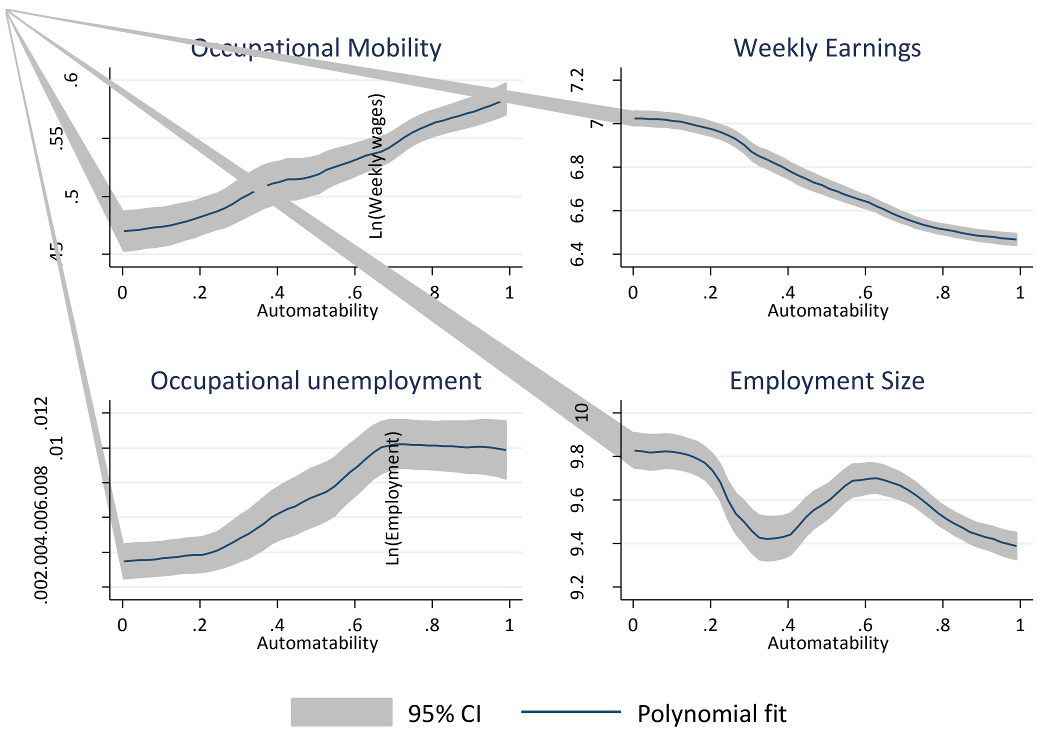


Note: The error bars correspond to the 90% confidence intervals.

6. Automatability, occupational characteristics and human capital similarity

The degree of occupational automatability as estimated by Frey and Osborne (2017)[17] is positively correlated with the probability of becoming unemployed and with the probability of leaving the current occupation. It is negatively correlated with weekly earnings and with the employment size of the occupation (Figure 6). However, it is not correlated with the changes in these labor market outcomes over time (not shown).[18] Hence, while we cannot claim that any of these correlations imply causality, it is clear that the same occupations which are at high risk of automation, have many unfavorable labor market characteristics: they are small, poorly paid, and workers in these occupations are more likely to either leave for another occupation, or undergo unemployment.

Figure 6. Automatability and occupational labor market outcomes



Note: The figures are based on bivariate correlations without controls and are averages over the period 2004-2018. Occupational unemployment is measured as the share of workers in an occupation i who were employed in that occupation in month t-1, but are unemployed in month t.

[17] We choose to work with this measure of automatability for a number of reasons: it claims to capture not only the degree of routineness of occupations, but also their susceptibility to advances in AI and mobile robotics; it is created using the same O*NET data; it is publicly available and meanwhile widely used by other scholars.

[18] Occupational mobility has been on the rise in the U.S. (Kambourov and Manovskii 2008), but the growth in mobility is uncorrelated with the risk of automation as measured by Frey and Osborne (2017). Wage and earnings growth have been stagnating in the U.S. since 2000 (Hahn et al. 2017). However, we find no correlation between these trends and the risk of automation.

Automatability and human capital similarity

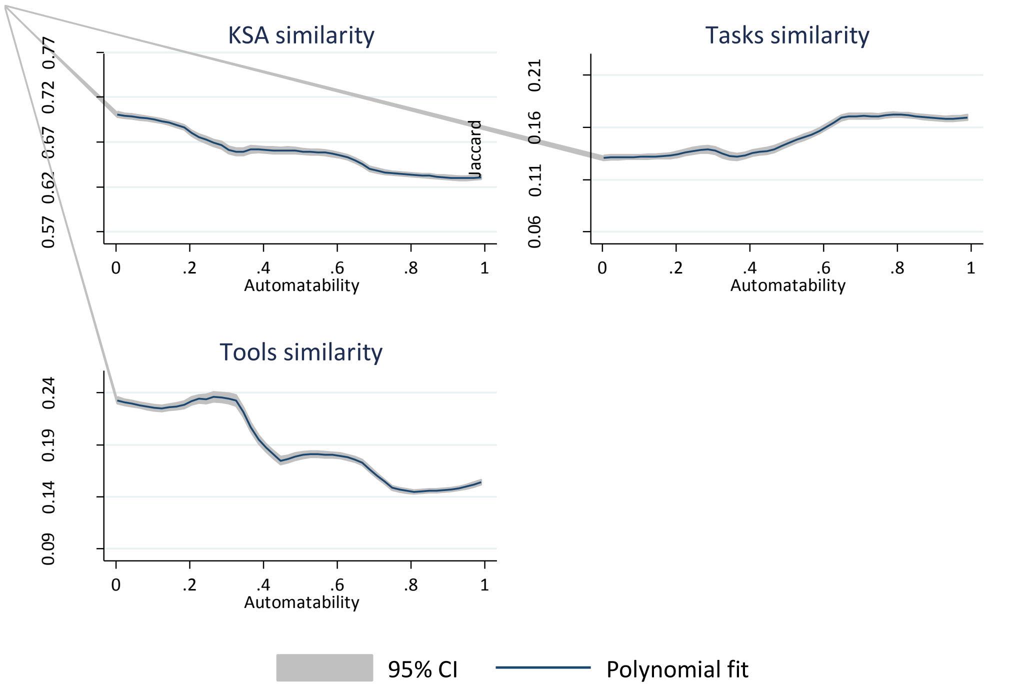
Among those who switch occupations, occupational automatability is negatively correlated with KSA similarity and tools similarity, meaning that those switching from more automatable occupations are making longer human capital transitions in terms of KSA and tools. Surprisingly, they are not making longer job tasks transitions – if anything the relationship between occupational automatability and task similarity is positive (Figure 7). These relationships remain sturdy once we control for individual (education, experience, past earnings) and occupation-level factors[19] (Table 3). The patterns are stable over time and are not affected by additional controls related to the topology of the occupational similarity networks (not shown here).

A look at the distribution of the probability of automation by similarity matrix is informative of why we observe these patterns. Figure 8 shows the visualizations of the occupational networks in black and white mode, with the node transparency increasing in proportion to the risk of automation. What we see is that in the case of KSA and tools similarity, the occupations at high risk of automation tend to be located more peripherally, while the occupations at low risk of automation are located more centrally, with many neighboring (i.e., similar) occupations to move to. In the case of tasks similarity however, a significant number of occupations (mainly administrative and sales) are located more centrally in the network. Contrasting tasks and KSA in particular, highly automatable occupations (where automatability is over 70%), have 19 neighbors[20] on average and less automatable occupations have 32 neighbors on average when occupational similarity is measured using KSA. When similarity is measured in terms of tasks, highly automatable occupations have 26 neighbors on average and less automatable occupations have 24 neighbors. This might explain why we see a negative relation between automatability and KSA similarity, but a positive one between automatability and task similarity. Importantly however, if we further distinguish between neighbors that are highly automatable and those that are less automatable using the 70% risk of automation as a cutoff point, we find that in the KSA-based occupational space, highly automatable occupations have 9 neighbors that are less automatable on average, while less automatable occupations have 27 neighbors that are less automatable on average. In the case of the tasks-based space, highly automatable occupations have only 5 less automatable neighbors and less automatable occupations have 18 less automatable neighbors on average.

[19] We estimate: $Jacc_{ij}^{HC} = \alpha + \beta_1 Auto_{ij} + \boldsymbol{X'_{pt}\beta} + \boldsymbol{T_t} + \varepsilon_{pijt}$, where $Auto_{ij}$ is the risk of automation as estimated by Frey and Osborne (2017) and $\boldsymbol{X'_{pt}\beta}$ are individual-level variables: years of education, potential work experience and weekly earnings in the past occupation. $\boldsymbol{T_t}$ is a set of time dummies.

[20] The cutoff for being a neighbor is being at the 97th percentile of the Jaccard similarity or higher. Using different thresholds does not affect these findings.

Figure 7. Automatability and human capital similarity among occupational switchers



Note: The y-axes scale for each sub-figure starts at the 25th percentile of Jaccard similarity and ends at its 75th percentile.

Table 3. Automatability and human capital similarity among occupational switchers

	(1)	(2)	(3)
VARIABLES	Tasks similarity	Tools similarity	KSA similarity
Automatability	0.0494***	-0.0603***	-0.0312**
	(0.0111)	(0.0177)	(0.0144)
Potential experience	0.00112***	-0.000632**	0.000543**
	(0.000236)	(0.000282)	(0.000254)
Potential experience sq.	-1.49e-05***	1.28e-05**	-5.82e-06
	(4.64e-06)	(5.32e-06)	(5.10e-06)
Years of education	-0.00239***	0.00545***	0.00372***
	(0.000719)	(0.00110)	(0.00107)
Weekly earnings	0.00358	0.0181***	0.0396***
	(0.00293)	(0.00502)	(0.00428)
Year dummies			
	124,928	124,928	124,928
Observations	0.027	0.087	0.072
R-squared	0.0266	0.0871	0.0720
Adj. R-sq	0.0266	0.0870	0.0720

Standard errors clustered by occupation of origin. We use weekly earnings for the occupation of origin. Significant at: *** p<0.01, ** p<0.05, * p<0.1

Figure 8. Non-random distribution of automatability across the human capital similarity matrices

a. Task-similarity of occupations and occupational risk of automation

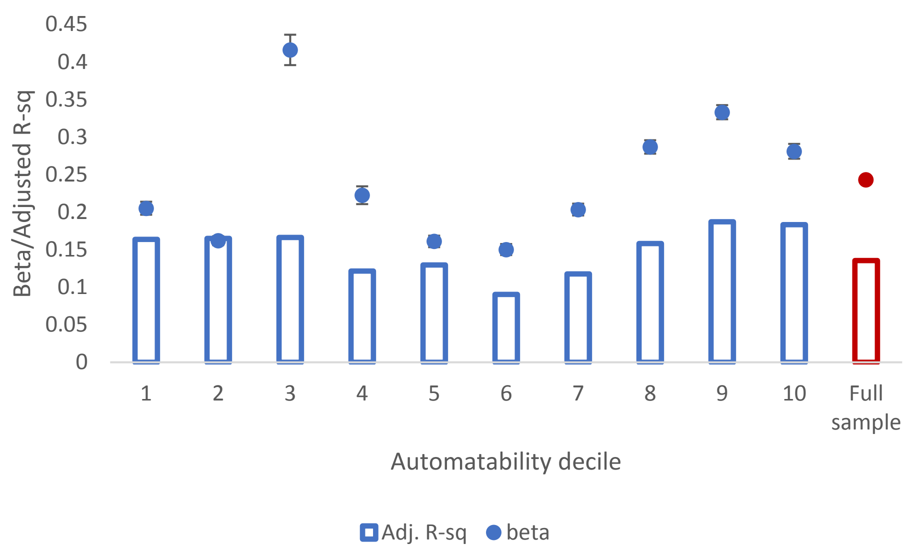
b. Tools-similarity of occupations and occupational risk of automation

c. KSA-similarity of occupations and occupational risk of automation

Tasks-similarity, KSA-similarity and automatability

We have argued that the degree to which we may be able to easily adapt to the current wave of automation by moving from declining to growing occupations depends on how closely the job tasks which are being automated map to our knowledge, skills and abilities. The more general our KSA are relative to our tasks, the smoother we can transition between jobs. The correlation we observe between tasks similarity and KSA similarity in the data is modest. Overall, a simple regression where we explain tasks similarity as a function of KSA similarity gives us a coefficient of 0.24 and an adjusted R-squared of 0.135. However, if we divide the sample in 10 deciles along the measure of automatability we find that this correlation is above average for the 3rd, the 8th, the 9th and the 10th decile of automatability (Figure 9). It appears that the tasks similarity and the KSA similarity of highly automatable occupations are more correlated than those of less automatable occupations, with exception of the 3rd decile. This observation suggests that the current wave of automation may be particularly disruptive because the tasks which it automates correspond more closely with particular combinations of KSA.

Figure 9. Correlations between tasks and KSA similarity along the degree of automatability



7. Conclusions

We know more than what we do. The knowledge, skills and abilities (KSA) that we have acquired through nurture and nature are broader than the set of tasks that we perform at any given job. As such, when technology threatens to eliminate a wide range of job tasks, we should be asking how these tasks relate to our KSA. Higher overlap between the degree of tasks automation and our broader skill domains at the level of occupations means that workers in affected occupations will have to make occupational moves characterized by more difficult KSA transitions. This creates challenges for requalification policy and may increase the possibility of structural unemployment of groups experiencing significant skill mismatch between the current and prospective jobs.

In this paper we attempt to answer a number of research questions. First, we argue that KSA capture the generality of our human capital while job tasks capture its specificity. In support of this, we find that occupations that are similar in terms of their job tasks are also similar in terms of their KSA. However, the opposite relationship does not hold: occupations that are similar in terms of KSA are not necessarily performing a similar set of job tasks. The same set of knowledge, skills and abilities can give rise to a wide range of job tasks; but a particular set of job tasks typically corresponds to a given set of KSA.

We then test if KSA similarity is more predictive of how we change occupations and how earnings progress when changing occupations, than are tasks similarity and tools similarity. In the case of occupational switching, we do not find support for this hypothesis – tasks similarity and tools similarity are equally or better predictive of occupational switching. In the case of earnings growth among individuals who switched occupations, we find that KSA similarity and tasks similarity are both predictive, while tools are not. These tests however are purely correlational and could benefit from a proper identification strategy. As such, the findings should be seen as preliminary.

Third, we study how the risk of job automation is distributed across occupations that are similar in terms of KSA, tasks and tools. We find that the correlation between tasks similarity and skills similarity is the highest among occupations that are at high risk of being automated. This suggests that this time around, technology may not be only affecting clusters of similar tasks, but also domains of similar KSA, making it difficult for affected workers to find jobs in skill-related occupations. We actually find that workers leaving more automatable jobs are making significantly larger skill transitions, again suggesting that automation is affecting full domains of related KSA.

The findings are relevant for policy. In spite of the generality of our KSA, the recent wave of automation seems to be affecting whole domains of KSA: our manual skills and administrative skills for example are becoming more and more embedded in technology. The occupations affected by these developments tend to be peripherally located in the KSA-based occupational space, meaning that the workers in these occupations need to make longer skill transitions in order to stay employed. These workers will either need to invest in re-qualification towards occupations requiring significantly different KSA than the ones they already acquired or risk prolonged periods of unemployment given the structural nature of the problem. Research focusing on the socio-demographic, educational and geographic characteristics of these workers could help policy-makers understand the group-specific needs for adjustment. The policies will need to vary depending on the group's age, level of education and geography among other characteristics.

References

Acemoglu, D. and Autor, D., 2011. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043-1171). Elsevier.

Alabdulkareem, A., Frank, M.R., Sun, L., AlShebli, B., Hidalgo, C. and Rahwan, I., 2018. Unpacking the polarization of workplace skills. *Science Advances*, *4*(7), p.eaao6030.

Anderson, J.E., 2011. The gravity model. *Annu. Rev. Econ.*, *3*(1), pp.133-160.

Anderson, K.A., 2017. Skill networks and measures of complex human capital. *Proceedings of the National Academy of Sciences*, p.201706597.

Angrist, J. and Pischke, J.S., 2009. Mostly harmless econometrics: an empiricists guide. Princeton University Press.

Autor, D., 2013. The “task approach” to labor markets: an overview. *Journal for Labour Market Research*, *46*(3), pp.185-199.

Autor, D.H. and Handel, M.J., 2013. Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, *31*(S1), pp.S59-S96.

Brynjolfsson, E. and McAfee, A., 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Brynjolfsson, E. and Mitchell, T., 2017. What can machine learning do? Workforce Implications. *Science*, *358*(6370), pp.1530-1534.

Coscia, M. and Neffke, F.M., 2017, April. Network backboning with noisy data. In *Data Engineering (ICDE), 2017 IEEE 33rd International Conference on* (pp. 425-436). IEEE.

Felten, E.W., Raj, M. and Seamans, R., 2018. A Method to Link Advances in Artificial Intelligence to Occupational Abilities. In *AEA Papers and Proceedings* (Vol. 108, pp. 54-57).

Flood, S., King, M., Ruggles, S. and Warren, J.R., 2017. Integrated Public Use Microdata Series, Current Population Survey: Version 5.0.[dataset]. Minneapolis: University of Minnesota, 2017.

Frank, M.R., Sun, L., Cebrian, M., Youn, H. and Rahwan, I., 2018. Small cities face greater impact from automation. *Journal of The Royal Society Interface*, *15*(139), p.20170946.

Frey, C.B. and Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation?. *Technological forecasting and social change*, *114*, pp.254-280.

Gathmann, C. and Schönberg, U., 2010. How general is human capital? A task-based approach. *Journal of Labor Economics*, *28*(1), pp.1-49.

Grace, K., Salvatier, J., Dafoe, A., Zhang, B. and Evans, O., 2017. When will AI exceed human performance? Evidence from AI experts. *arXiv preprint arXiv:1705.08807*.

Hahn, J.K., Hyatt, H.R., Janicki, H.P. and Tibbets, S.R., 2017. Job-to-Job Flows and Earnings Growth. *American Economic Review*, *107*(5), pp.358-63.

Hidalgo, C.A., Klinger, B., Barabási, A.L. and Hausmann, R., 2007. The product space conditions the development of nations. *Science*, *317*(5837), pp.482-487.

Jerome, H., 1934. *Mechanization in industry, no. 27*. National Bureau of Economic Research, New York.

Kambourov, G. and Manovskii, I., 2008. Rising occupational and industry mobility in the United States: 1968–97. *International Economic Review*, *49*(1), pp.41-79.

Kambourov, G. and Manovskii, I., 2013. A cautionary note on using (march) current population survey and panel study of income dynamics data to study worker mobility. *Macroeconomic Dynamics*, *17*(1), pp.172-194.

Lebergott, S., 1966. Labor force and employment, 1800–1960. In *Output, employment, and productivity in the United States after 1800* (pp. 117-204). NBER.

Mátyás, L., 1997. Proper econometric specification of the gravity model. *World Economy*, *20*(3), pp.363-368.

Mealy, P., del Rio-Chanona, R.M. and Farmer, J.D., 2018. What You Do at Work Matters: New Lenses on Labour.

Minnesota Population Center., 2018. ELIGORG Comparability. *CPS IPUMS*. Retrieved July 12, 2018, from https://cps.ipums.org/cps-action/variables/ELIGORG#comparability_section

National Center for O*NET Development., 2018a. Overview. *O*NET Resource Center*. Retrieved July 12, 2018, from https://www.onetcenter.org/overview.html

National Center for O*NET Development., 2018b. Office of Management and Budget Clearance. *O*NET Resource Center*. Retrieved July 12, 2018, from https://www.onetcenter.org/ombclearance.html

National Center for O*NET Development., 2018c. Knowledge. *O*NET Resource Center*. Retrieved June 21, 2018, from https://www.onetonline.org/find/descriptor/browse/Knowledge/

National Center for O*NET Development., 2018d. Skills. *O*NET Resource Center*. Retrieved June 21, 2018, from https://www.onetonline.org/find/descriptor/browse/Skills/

National Center for O*NET Development., 2018e. Abilities. *O*NET Resource Center*. Retrieved June 21, 2018, from https://www.onetonline.org/find/descriptor/browse/Abilities/

Nedelkoska, L., Neffke, F. and Wiederhold, S., 2015, January. Skill mismatch and the costs of job displacement. In *Annual Meeting of the American Economic Association*.

Neffke, F. and Henning, M., 2013. Skill relatedness and firm diversification. *Strategic Management Journal*, *34*(3), pp.297-316.

Neffke, F.M., Otto, A. and Weyh, A., 2017. Inter-industry labor flows. *Journal of Economic Behavior & Organization*, *142*, pp.275-292.

Poletaev, M. and Robinson, C., 2008. Human capital specificity: evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000. *Journal of Labor Economics*, *26*(3), pp.387-420.

Shaw, K.L., 1987. Occupational change, employer change, and the transferability of skills. *Southern Economic Journal*, pp.702-719.

U.S. Census Bureau., 2006. Current Population Survey Design and Methodology. Technical Paper 66. October 2006.

Yamaguchi, S., 2012. Tasks and heterogeneous human capital. *Journal of Labor Economics*, *30*(1), pp.1-53.

Yildirim, M.A. and Coscia, M., 2014. Using random walks to generate associations between objects. *PloS one*, *9*(8), p.e104813.

Appendix A

Table A1: Summary statistics of the mobility sample

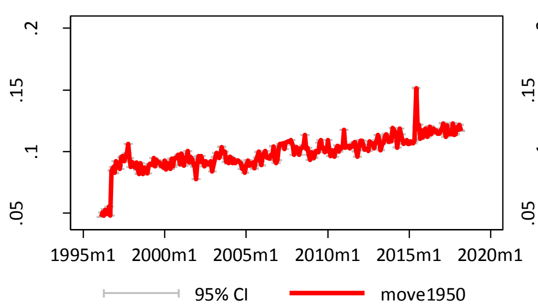
	Obs.	Mean	S.D.	Min.	Max.
Tasks similarity	2,843,904	0.059	0.085	0.000	1.000
Tools similarity	2,843,904	0.099	0.094	0.000	1.000
KSA similarity	2,843,904	0.551	0.127	0.125	1.000
ln(occupational flows)	2,843,904	0.397	1.757	0.000	12.773
Year	2,843,904	2007.7	6.415	1997	2018

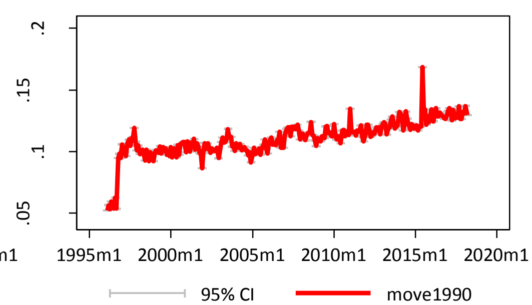
Table A2: Summary statistics of the earnings sample

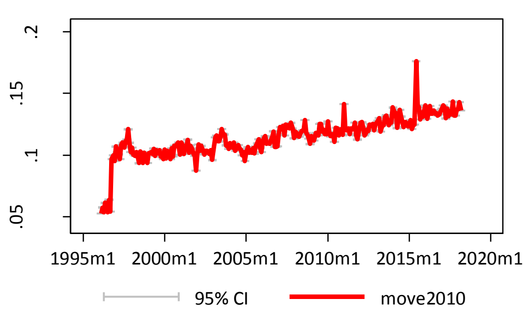
	Obs.	Mean	S.D.	Min.	Max
ln(current earnings)	124,979	6.428	0.606	0.393	8.004
ln(past earnings)	124,979	6.406	0.614	1.099	8.004
Automatability	124,979	0.571	0.334	0.003	0.990
Potential experience	124,979	21.891	10.495	0	54
Years of education	124,979	13.0	2.436	0	21
Year	124,979	2007.5	6.069	1997	2018

Figure A1: Occupational mobility over time

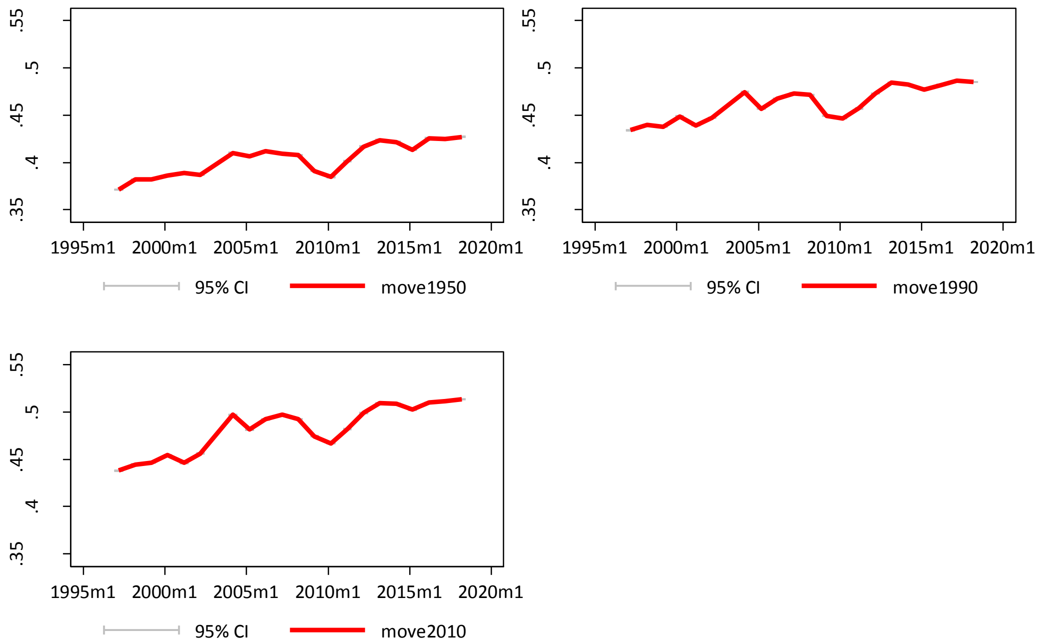
a. Monthly mobility







b. Annual (March-March) mobility



Note: The figures show the share of workers reporting a different occupation compared to the one reported in the previous month (in the case of monthly occupational mobility) and compared to the one reported in March in two consecutive years (in the case of annual occupational mobility). Move1950 uses the Census 1950 occupational classification, move1990 uses the Census 1990 occupational classification and move2010 uses the SOC 2010 occupational classification, which we use throughout this paper. The patterns show growing occupational mobility, independent of the employed occupational classification. The Figures exclude 2003 observations which were affected by the occupational reclassifications.

Figure A2: Monthly growth of weekly earnings among occupational switchers

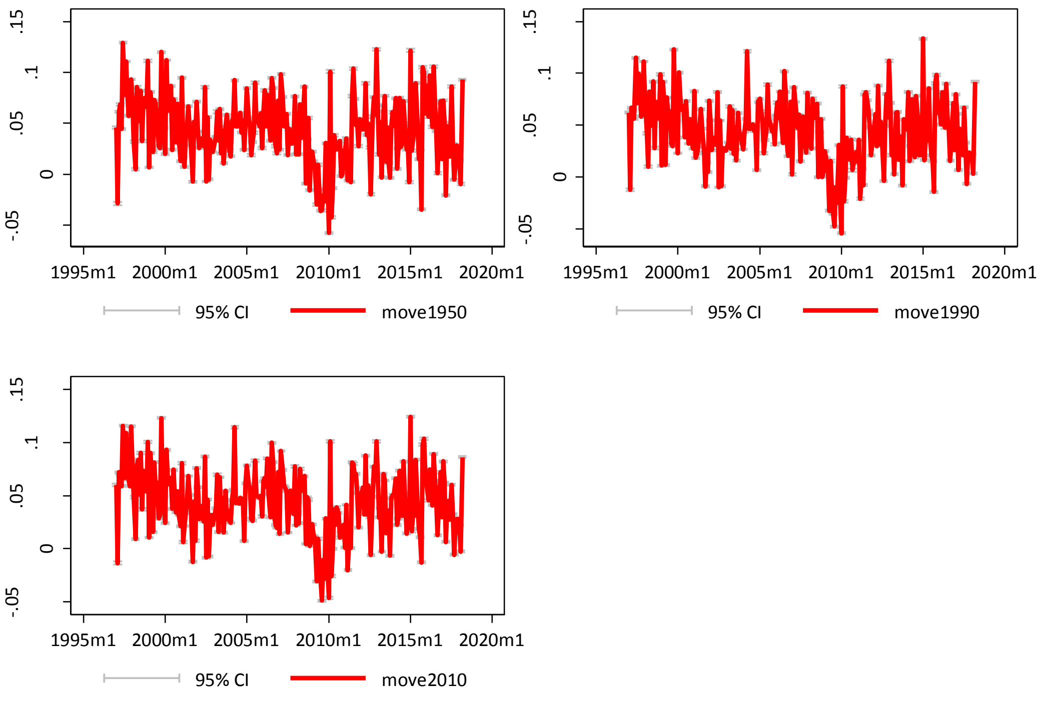
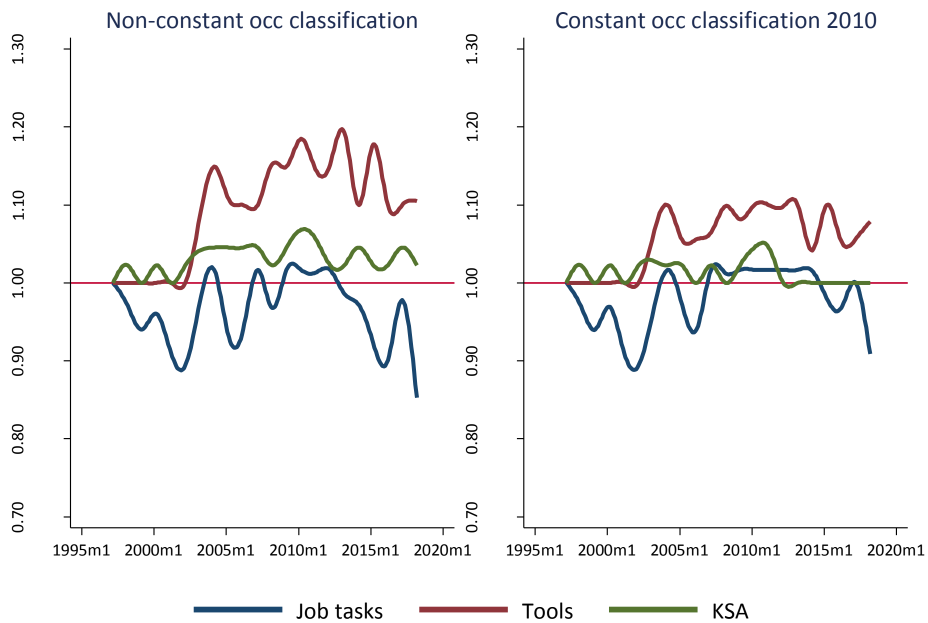


Figure A3: Tasks, Tools and KSA similarity over time



Note: The left sub-figure allows for the occupational classification to significantly change in 2003, as it is the case in the original CPS data. However, this is an artifact created by an occupational revision (U.S. Census Bureau 2006). The right sub-figure only considers occupations that are present in both periods, pre-2003 and post-2003. Inspection of the occupations which disappeared or occurred for the first time in 2003 shows that these occurrences and disappearances are unrelated to real-world developments.