Using Network Analysis of Job Transitions to Inform Career Advice

by

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Abstract

The importance of good career advice has become especially salient as the COVID-19 pandemic forces millions of displaced workers to look for stable employment. This research hopes to add to the career advice literature by using network analysis of U.S. job transitions data to model the universe of career paths available from a first job. By linking together the occupations that are connected by significant flows of workers and focusing on the paths that lead from precarious occupations, we can identify areas of the labor market that offer dependable channels to upward mobility and areas that do not, where workers could benefit from additional guidance. Overall, we find that, although there exist opportunities for workers of various educational attainment, upward mobility prospect are generally curtailed for workers without a Bachelor's degree. What's more, low-wage or shrinking occupations appear to offer limited access to stable, high-wage employment. Still, there are a number of bright spots occupations that can provide low-wage workers with dependable access to sustainable employment down the line. We hope to use this knowledge to inform the nature of advice given to workers by suggesting careers that are associated with living wages and stability in the long term.

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All errors are my own.

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Chapter 1

Introduction

As the COVID-19 pandemic continues to upend the livelihood of millions, a combination of policy-makers, academics, and private companies are exploring how they can help workers in jeopardized professions navigate to stable employment elsewhere[51]. In addition to these displaced workers, an unprecedented number of people are re-evaluating their work conditions and resigning from their jobs; they, too may seek guidance as they look for more competitive opportunities [9]. The relevance of good career advice is not restricted to the present moment however. For as long as there have been workers in dead-end or precarious jobs, this service has been essential.

One policy approach to helping workers identify new employment opportunities has come in the form of career pathways programs. These government initiatives supply workers with roadmaps that link "stackable" educational credentials to a sequence of jobs that together form a career (US ED, 2015)[47]. In essence, career pathways spell out the correspondence between educational programs and promotions. Underlying this model is the idea that career progression is driven by growth in the worker's skill, and that this *skills growth* often requires human capital investments that can be quite onerous, ranging from industry certificates to four year college degrees.

Another branch of career advice has focused on how workers can use the skills they already have to transition into similar but more rewarding jobs. Though not necessarily at odds with the career pathways model, this career progression strategy asks whether the worker's existing expertise could have higher returns in a different occupation, one with greater promise of security and better wages but similar requirements. Rather than focusing on skills growth, the suggested mechanism is one of *skills transfer*.

This thesis hopes to add to the career advice literature by using network analysis to extract patterns in U.S. job transitions data that describe workers' most likely career paths. By linking together the occupations that are connected by significant flows of workers and focusing on the paths that lead from precarious occupations, we can identify areas of the labor market that offer dependable channels to upward mobility and areas that do not, where workers could benefit from additional guidance. Furthermore, we can study successful career paths to identify which skills appear to be particularly useful in a pivotal transition, and whether these transitions are better explained by the *skills growth* or the *skills transfer model*. Finally, we can use this knowledge to inform the nature of advice given to workers, and to suggest careers that are associated with high-wages and security in the long term.

Chapter 2

Background

2.1 Recent literature on career advice

2.1.1 The skills growth approach: career pathways programs

Career pathways programs are on the rise (Peck et al, 2018)[40]. Their popularity has been fuelled by the 2013 Workforce Innovation and Opportunity Act (WIOA), which supports these programs as an instrument for aligning the US educational system with the needs of employers and the long-term career growth of workers (NSC, 2014)[27]. Still, these programs are not new. Before WIOA, they had already been endorsed by the U.S. Departments of Education, Labor, and Health and Human Services as a way to promote workforce learning (U.S.ED, 2015)[47]. A 2012 letter from the three departments defines them as

> "[a] series of connected education and training strategies and support services that enable individuals to secure industry-relevant certification and obtain employment within an occupational area and to advance to higher levels of future education and employment in that area."[1 2]

Their emphasis on sustained human capital investments is largely informed by two strands of research: one tracking the growing share of jobs that require education beyond high school, and the other identifying a "skills gap" between employer needs and employee qualifications (U.S. ED, 2015)[47]. Research on the effectiveness of these programs itself is fairly scarce

[1] see Figure A-1 in the Appendix for an illustration of this schema.

[2] As cited in (U.S. ED, 2015)[47]

however, and made difficult by the fact that they have very diverse implementations, often targeting different populations and portions of the educational system (Kazis, 2016)[21]. Still, a consensus conclusion emphasizes the importance of aligning career pathways with the "interests and needs of employers or the climate of particular industry sectors and labor markets", something that was not always prioritized (Kazis, 2016)[21]. In order to help improve these programs, one review of the literature suggests identifying "workers' career trajectories in the economy [...] in the absence of career pathways programs" (Strawn and Schwartz, 2018)[45]. The authors suggest leveraging the job transition data in the Current Population Survey (CPS) to this effect, providing support for the analysis proposed here.

2.1.2 The skills transfer approach

2.1.2.1 Governmental applications

At the same time that career pathway programs continue to grow, a number of governments and think tanks are basing their career guidance programs on the skills transfer approach instead. At the heart of this strategy is a call to recognize the learning that happens on-the-job, as in Blair et al.'s (2020) paper on why employers should give deeper consideration to workers without a college degree who are "STARs", or "Skilled Through Alternative Routes" such as work experience[7]. Ultimately, the skills transfer strategy is not necessarily at odds with skills growth, but it asks employers to consider that past employment provides a "signal" for worker qualifications that can be just as meaningful as more traditional forms of education[7].

On the ground, this approach has taken the form of tools that assess the similarity of job requirements and then suggest new employment opportunities based on these measures. In 2018, the World Economic Forum proposed such a framework for identifying "job transition opportunities" that essentially relied on computing the "similarity" between jobs as a function of the "overlap between the activities or tasks that need to be performed in a role as well as between primary indicators of job-fit such as knowledge, skills and abilities, and between secondary indicators of job-fit such as years of education and years of work experience" (WEF and BCG, 2018)[50]. Of the jobs that were most similar to the worker's latest occupation, the report then recommended transitions that offered equal or better wages and "stable" employment, as defined by the projected growth of the destination occupation (WEF and BCG, 2018)[50]. The WEF's framework has already been adapted by the Australian Department of

Education, Skills and Employment (Australia DESE, 2019)[3].

2.1.2.2 Academic and industry applications

The skills transfer approach is also widespread in academic literature. In fact, job similarity metrics are developed in many recent papers that propose job recommender systems. Dawson et al. (2020) compute job similarity scores based on pairwise skills similarities that are themselves determined by the extent that skills are required together in job postings[11]. Their indicator is then incorporated into a machine learning classifier to suggest job transitions. Research by Emsi (2020) investigates how new skills can be strategically "layered" on top of workers' existing skillset to facilitate transitions into nearby jobs[51]. Similarly, Dworkin (2019) uses network analysis to quantify the similarity of jobs in terms of their shared "skills, knowledge and abilities" and suggests transitions that take into consideration both this similarity and the "automatability" of the destination job[15]. Indeed, many papers complement their job similarity measure with other such features. For example, Shalaby et al.'s (2017) algorithm, which is used by the job-finding website CareerBuilder, displays suggested jobs based in part on user preferences captured by a network analysis of "behavioral and contextual signals" (such as co-clicks)[44]. Whether alone or as part of a larger algorithm, job similarity calculations are central to many of the services offered by job-finding websites, such as Linkedin's Career Explorer tool, which uses the portion of skills demanded by two jobs to suggest job transitions[23].

2.2 Recent literature on evaluating career trajectories

Unlike the career pathways model, tools that rely on the skills transfer approach rarely look beyond the single job transition. That is, while some frameworks consider worker's prior paths and many have built-in checks to assess the destination occupation's stability and wages, they do not consider whether their suggestion opens or closes doors to certain careers, or whether it typically offers a path towards upwards mobility in the long run. Of the papers we reviewed, only Dworkin (2019) creates network-based indicators to capture a job's upward-mobility potential and incorporates them into their job recommendation system[15]. Their indicators do not consider wage growth but they do include the "extent to which a job's position in the network serves to connect highly automatable jobs to highly safe jobs", and the "extent to which a job has relatively strong skill-based connections to jobs in sectors other than its own".

Nevertheless, there are a range of analytical techniques available for analyzing career trajectories beyond the single job move. Sequence analysis is one method used by Joseph et al. (2012) and Vinkenburg et al (2020) to characterize the careers of IT workers and scientific researchers, respectively[20, 49]. Others such as Biemann et al. (2012) and Kovalenko and Mortelmans (2014) use optimal matching analysis[3] to develop career "typologies", while Schellenberg et al (2016) and Huang and Sverke (2007) rely on Occupational Career Pattern concepts to characterize careers, such "orderliness", "stability", and the "direction" of development ("vertical vs. horizontal")[6, 22, 43, 19]. While these last concepts in particular are useful to think about, all of these methods require individual, sequential career histories such as those obtained from resumes or online professional networks.

2.3 Applications of network analysis in recent labor research

Network analysis provides tools that are particularly well-suited to studying career trajectories even when data is not longitudinal. And in fact, its use in the field of labor research is fast growing. A number of recent papers with diverse objectives provide methodological support for our analysis. Garg et al. (2019), Paparrizos et al. (2011), and Safavi et al (2018) all use network analysis of individuals' past career histories to predict their next job transition, as well as the likelihood of their retention[18, 38, 42]. Oentaryo et al. (2018) take a slightly different approach and use networks to characterize the factors that predict a future job transition[28]. Meanwhile, Xu et al. (2014) use network analysis of career histories to "model professional similarity between two people", a feature which has been incorporated in LinkedIn's Similar Profiles tool[53].

It is also possible to use network analysis to describe the evolution of a field and its top employers, an approach applied by Safavi et al. (2018) to the labor market for computing

[3]Garg et al. (2019): "The underlying logic of OMA is to measure the difference between two or more sequences in terms of counting the number of substitutions, insertions, and deletions that are required to transform one sequence into another. Next, these measures of difference are fed into clustering algorithms that yield information on "typical" patterns of sequences (Abbott and Hrycak 1990). In short, the sequences that require the fewest changes (substitutions, insertions, and deletions) before becoming identical sequences are grouped together as a distinct pattern."

research[42]. Similarly, Zhang et al. (2020) build a job transition network and use it to develop a measure of company "competitiveness" in terms attracting and retaining talent, while Xu et al. (2016) use a similar network setup to identify organizational "talent circles"[55, 52].

The studies that are most relevant to our research are those that use network analysis to evaluate how career trajectories can help us characterize occupational mobility and its interaction with job content. The first strand of this research relies primarily on networks that describe the shared skill requirements of jobs. In this group, Alabdulkareem et al (2018) create a network of shared job requirements and compare it to job transition data to argue that the intense skill "polarization" of the labor market "constrains the career mobility of individual workers, with low-skill workers 'stuck' relying on the low-wage skill set."[2] They develop a number of metrics and hypotheses that will influence our own investigation of mobility. Dworkin (2019) also uses a skills-based network to generate job recommendations and to investigate "which skills might be associated with higher or lower job automatability", a question which we will extend to the context of upward mobility[15].

The second strand of this research starts from the ground up, leveraging job-transition networks rather than skills-based networks. In this vein, Rio-Chanona et al. (2020) use a network of U.S. job transition data to develop a model of the labor market that can be used to study how automation affects worker flows and "labour reallocation"[12]. Others studies seek to characterize potential barriers to worker flows across occupations. For example, Yeyati and Montane (2020) use Argentinian job transition data to investigate how often workers transition within a similar field and address the question of how "'portable' [...] human capital is", while Cheng and Park (2021) use U.S. job transition data to identify communities of occupations within which mobility is concentrated[54, 10]. In another category, Villarreal (2020) uses U.S. job transition data to evaluate how patterns in mobility and labor market segmentation have changed over time[48]. While this study does not focus on identifying the areas of the labor market that offer better opportunities nor does it identify specific career paths and their associated skills characteristics, its focus on differential mobility patterns across demographics groups are crucial elements to keep in mind for our own analysis. Most relevant to this thesis is recent work by Ecscobari et al. (2021), which also leverages network analysis of job transitions to identify economic opportunities for workers[17]. While their definition of occupational mobility primarily relies on one-step transitions, they strategically leverage network analysis to identify occupations that act as gateways between "clusters" of occupations across which movement would otherwise be difficult, or as "conduits" between low-wage and high-wage work[17]. The questions asked in this paper are conceptually similar to those guiding this research, and their results could provide a good check to our own.

This research will draw from both strands, by starting from an empirical job-transition network and then enriching this network with the skills characteristics of connected jobs in order to investigate the relationship between skills and mobility. Methodologies and motivations are described in the following section.

Chapter 3

Questions and Methodology

3.1 Research Questions

Surely most people who wish to progress in their careers do so in their own unique way, relying on what they see happening around them, the informal advice of others, and perhaps the guidance provided by the various institutions they interact with throughout their lives. The result of these efforts is reflected in their resumes, which not only provide a history of their professional experiences but an overview of the educational investments they made and the career changes that followed. In particular, this thesis leverages a large dataset of digital resumes generously shared by Burning Glass Technologies[1] to create networks of job transitions that can be used to evaluate the career prospects offered by any occupation.

Although network analysis eliminates the longitudinal structure of resumes, it allows us to extract patterns in job transitions that can be used to model the universe of career paths available from a first job. In fact, the twin forces of personal preference and structural constraints would have made it difficult to extrapolate any kind of general trend from individual career trajectories, of which there are probably as many as there are people. Instead, the network configuration allows us to estimate the realm of what is possible when one enters the labor market through a certain occupation by chaining together the most likely transitions from that point on.

In our network analysis, jobs from a list of standardized professions are represented as nodes and the number of people transitioning between these jobs are represented by weighted,

[1] Now Emsi Burning Glass

directed edges. For every occupation in the data, a unique network will be created which comprises the most relevant career paths available from that occupation. These networks can then be used to evaluate the mobility potential of an occupation and tackle the following research questions:

1. What are the dimensions of occupational mobility and which occupations are upwardly-mobile?
    (a) Should mobility be defined in terms of wages, flexibility, or stability? How can we measure these concepts?
    (b) Is occupational mobility equally available to workers with different educational backgrounds?
    (c) Which jobs seem to offer a reliable path to career growth and where might more interventions be needed ?
2. What is the relationship between occupational requirements and mobility?
    (a) What are the characteristics of jobs with high-mobility potential?
    (b) How do skill requirements evolve over the course of upwardly-mobile career paths?
3. Do job transitions usually involve *skill growth* (i.e. growing one's competencies) or *skill transfer* (i.e. leveraging existing expertise)?
    (a) How often do educational investments facilitate job changes?
    (b) When might the skills growth mechanism prevail over skills transfer in a job transition?

We then use a case study of the Manufacturing industry to test the methods and indicators we developed to answer these broad questions. In particular, we'll investigate which jobs offer manufacturing workers the best long-term prospects, which skills could increase access to stable, high-wage employment, and whether there are retention and recruitment opportunities that could be leveraged by industry leaders.

3.2 Data

3.2.1 Employment Profiles from Burning Glass Technologies

This analysis is made possible by a proprietary data set of "employment profiles" created by Cognism and accessed through Burning Glass Technologies[2] (BGT). An employment profile is analogous to a digital resume pieced together from various online sources[3] that links educational, certification, and professional experience over time to over 16.5 million unique individuals in the US alone (BGT, 2022; Escobari et al., 2021)[16, 17]. Beyond aggregating this information, Cognism also converts each profile into a standardized form usable for large-scale data analysis (Babina et al., 2021)[5]. In this step, the individual experiences that make up each profile are coded into a set number of variables that include start and end date, position or degree, location, and the relevant institution. Educational, certification, and professional experiences are stored and coded separately to reflect their unique attributes. Finally, a subset of these variables is submitted through a "normalization" process that "leverages techniques from machine learning and natural language processing", allowing for greater generalization (Babina et al., 2021)[5]. For example, records of "bachelor of arts" and "bachelor of sciences" would both be stored as a "bachelor's degree". Perhaps most crucially for this analysis, the universe of raw professional positions in the employment profiles is connected to the 1110 occupations in O*NET's 2010 Standard Occupational Classification. This crosswalk not only greatly reduces the complexity of any analysis that takes jobs as its unit of focus, but it allows us to enrich the data with other measures supplied by O*NET and the Bureau of Labor Statistics. These supplementary data will be discussed in greater detail in section 3.2.4.

It should be noted that although this data is not directly available to the public, a similar analysis could be achieved using the US government's Current Population Survey (CPS). While the CPS samples a different population every year, it records the current occupation of individuals in each panel as well as their occupation one year prior[29]. These occupations can be compared and taken in aggregate to study job transition patterns and extract approximate career trajectories using network analysis, as is done in this paper. In fact, the CPS's main

[2] Now Emsi Burning Glass

[3] According to Babina et al., 2021, "Cognism obtains the resumes from a variety of sources, including publicly available online profiles, collaborations with recruiting agencies, third party resume aggregators, human resources databases of partner organizations, and direct user contributed data." Furthermore, "The processing of all profiles is compliant with the applicable GDPR and CCPA regulations".[5]

advantage is that it is designed to be representative of the US population, even though it has substantially fewer observations than the BGT data.

3.2.2 Data Processing

3.2.2.1 Imputation Rules

Because this analysis set out to evaluate the mobility potential of various occupations, it was important that the records in each employment profile be ordered sequentially so as not to muddle the chain of events. However, many records in the employment profiles did not list the specific months or years in which an experience took place. This could occur for purely mechanistic reasons: for example, the ultimate records in an employment profile (as defined by latest start date) often describe ongoing experience and as a result have no end date. For these data, the date on which the analysis was run was imputed as the end date of the experience in order to facilitate career length calculation. Conversely, if an ultimate record was missing an end date but was not flagged as being ongoing by Cognism, then the start date of that record was imputed as its end date so as not to overestimate career length.

In the case that the start or end years or educational records were missing, they were assumed to have come before the earliest work experience, unless they were flagged as being ongoing by Cognism, in which case they were set to be the ultimate record. Although this approach might lead to some educational shifts being improperly ordered, the segmentation of this analysis by the highest educational attainment of individuals overall prevents us from overestimating what opportunities might be available to someone with a particular degree.

A number of records had complete year information but were missing end or start months, perhaps reflecting the less granular way in which older experience might be listed on a resume. Education records in particular had no assigned end or start months. To preserve these records, the first month of the year was imputed for both start and end dates.

3.2.2.2 Inclusion Rules

Profiles had to meet a number of restrictions to be included in the data. Due to the focus on occupational mobility in the US, profiles with work experience outside of the country were removed from the analysis. Profiles with professional records that were missing start or end years were also removed. In the case of overlapping records (where the start dates of two consecutive professional records are the same) due to missing months, imputation rules or otherwise, profiles were also dropped. In addition, for the analysis on the rate of occupational change in section A.1, profiles with professional records that were missing O*NET occupation information were dropped because it could not be determined whether a transition was between two different occupations or not. However, these profiles were kept for the remainder of the analysis because certain foundational work experiences such as internships and apprenticeships are not represented in O*NET's occupational taxonomy, such that removing these resumes entirely might have led to omitting an important and specific subset of the population.

Finally, any profile that was linked to an educational record with a missing standardized degree field was also dropped because the accuracy of the highest educational attainment could not be guaranteed.

3.2.3 Study Population

In recent years, employers have begun to require college degrees for occupations that did not traditionally need one, a phenomenon known as "credential inflation" (BGT, 2014)[46]. To quantify the extent to which different opportunities may be afforded to those with more education, the entirety of the analysis described in this paper was run separately for individuals whose highest educational attainment does not include a Bachelor's (including no listed degree, a Certificate, a High School degree or equivalent, a Post-Secondary award, an Associate degree) and for individuals with a Bachelor's degree. The breakdown of these two populations in our subsetted data is shown below, along with other summary statistics. In particular, Table 3.2 shows the breakdown of employment profiles by the decade in which an individual first entered the labor market (defined as the decade of the start date of the first professional record). Table 3.2.3 shows the total number of professional records across profiles broken down by the industry of the relevant occupation.

It should be noted that because our data set consists of information from online networks, it is not entirely representative of the US population and in particular may be biased towards individuals in certain white-collar professions that are more reliant on digital resumes. This is an important limitation of this analysis that could be explored in further work by comparing the mobility results in this paper with findings that rely on sparser but more representative data sets, such as the US government's Current Population Survey (CPS). .

Table 3.1: Summary Statistics: Highest Educational Attainment

Highest Educational Attainment	**Less than a Bachelor's**	**Bachelor's**
Total	**1,476,904**	**2,203,272**
None listed (%)	43.2	0
Certificate (%)	36.8	0
High School (%)	0.3	0
Post-secondary Award (%)	2.7	0
Associate Degree (%)	17.0	0
Bachelor's Degree (%)	0.0	100

Counts represent the number of unique individuals in the Employment Profiles data.

Table 3.2: Summary Statistics: Decade of Entry by Highest Educational Attainment

Decade of Entry	**Less than a Bachelor's**	**Bachelor's**
Total	**1,476,904**	**2,203,272**
(1960, 1970] (%)	0.1	0.0
(1970, 1980] (%)	2.3	1.2
(1980, 1990] (%)	7.9	5.5
(1990, 2000] (%)	19.6	14.0
(2000, 2010] (%)	38.5	33.7
(2010, 2020] (%)	31.7	45.5

Counts represent the number of unique individuals in the Employment Profiles data.

3.2.4 Occupational Data

3.2.4.1 Data from O*NET

O*NET is a database of standardized occupational data supported by the U.S. Department of Labor/Employment and Training Administration[32]. It both defines the universe of occupations that make up the labor market and creates metrics that help uniformly characterize the requirements of these occupations (O*NET, 2022a)[32]. In the version of the employment profile data used in this analysis, Cognism's occupation matching algorithm converts raw job titles to occupations from the O*NET-SOC-2010 taxonomy, although a more up to date classification was created in 2019 that is linked to employment statistics from other institutions. However, O*NET supplies a crosswalk between the two systems that was used to incorporate external data sources[34]. In the case that more than one O*NET-SOC-2019 occupation was linked to an O*NET-SOC-2010 occupation, data was averaged across the O*NET-SOC-2019 occupations to create the O*NET-SOC-2010 measurement.

Beyond anchoring the analysis to the O*NET-SOC-2010 taxonomy, a number of other

Table 3.3: Summary Statistics: Industry

Industry	**Less than a Bachelor's**	**Bachelor's**
Professional, Scientific, and Technical Services (%)	21.1	26.1
Retail Trade (%)	14.1	11.8
Wholesale Trade (%)	7.6	10.3
Finance and Insurance (%)	8.5	9.8
Health Care and Social Assistance (%)	10.5	7.7
Educational Services (%)	6.2	6.8
Manufacturing (%)	7.5	6.5
Government (%)	4.6	5.3
Accommodation and Food Services (%)	5.8	4.5
Administrative and Support Services (%)	2.7	2.5
Other Services (%)	2.0	2.3
Information (%)	1.0	1.7
Transportation and Warehousing (%)	3.2	1.5
Real Estate and Rental and Leasing (%)	2.4	1.4
Construction (%)	2.3	0.9
Arts, Entertainment, and Recreation (%)	0.4	0.6
Agriculture, Forestry, Fishing, and Hunting (%)	0.1	0.1
Mining, Quarrying, and Oil and Gas Extraction (%)	0.0	0.0
Utilities (%)	0.1	0.0

Note: Percentages reflect the number of times an occupation within an industry appears in the Employment Profiles data and are not de-duplicated by individual IDs.

O*NET data points were incorporated in this work. In particular, this paper seeks to uncover the aspects of a job and career that may make it more suitable to occupational mobility. To this end, we use the skills data from O*NET's content model to characterize the unique requirements of each occupation.

Specifically, O*NET identifies 35 unique skills, or "developed capacities that facilitate learning or the more rapid acquisition of knowledge," and relies on its occupational analysts to rate the "importance" of each of these skills to an occupation and the "level" at which it needs to be performed (O*NET, 2022b; Burgoyne et al., 2021)[37, 8]. Both of these measures were standardized according to O*NET's official guidelines, and then combined to create a single skill centrality score that can take values between 0 and 100, adapting a methodology described in Muro et al., 2017 for creating a digital score (O*NET, 2022c)[24, 36]:

$$\text{Centrality}_{s,j} = \sqrt{\text{Importance}_{s,j} \times \text{Level}_{s,j}}$$

where s indicates a particular skill and j indicates a particular occupation.

For convenience, O*NET organizes these 35 skills into 6 larger categories: Basic Skills, Complex Problem Solving Skills, Resource Management Skills, Social Skills, Systems Skills, and Technical Skills (O*NET, 2022b)[37]. This classification can be found in Table A of the Appendix.

In addition to skills requirements, this analysis also relies on O*NET's classification of occupations into industries, defined as "broad groups of businesses or organizations with similar activities, products, or services" (O*NET, 2022d)[33]. O*NET determines this categorization by using the industries in which occupations are projected to have openings over 2020-2030 according to the BLS (O*NET, 2022d)[33]. This analysis assigns each occupation to the industry with the largest share of such openings. Industry partition follows the 2-digit North American Industry Classification System (NAICS).

3.2.4.2 Data from the Bureau of Labor Statistics

A number of measures from the Bureau of Labor Statistics' Occupational Employment and Wage Statistics were used to characterize the occupations in the BGT employment profiles. The Bureau of Labor Statistics (BLS) estimates national wage and employment numbers for the "nearly 800" occupations in its taxonomy "based on six panels of survey data collected over a 3-year cycle", as described in Dey et al. (2019)[14]. In this analysis, May 2020 estimates of the national, median annual wage were used to determine occupation salary, and May 2020 estimates of the national, projected employment change in 2030 relative to 2020 were used to determine occupation growth, regardless of when an experience took place. Methodology for the calculation of the latter is described at the following link (BLS, 2022)[31]. Since BLS data uses the SOC occupational taxonomy, wage and employment information were linked to the O*NET-SOC-2010 using O*NET crosswalks[35]. In the case that more than one BLS-SOC occupation was linked to an O*NET-SOC-2010 occupation, wage and employment data was averaged across the BLS-SOCs.

3.2.4.3 Defining Sustainable and Unsustainable Occupations

The wage and employment information from the BLS was used to break up occupations into *sustainable* and *unsustainable* occupations. Adapting methodology from a report by the World Economic Forum and the Boston Consulting Group, a job is defined to be *sustainable* if it has both "stable long-term prospects" in terms of projected employment and a wage that allows for a certain "standard of living." (WEF and BCG, 2018)[50] This paper retains the WEF's definition of stable employment as non-negative projected growth, and it defines a sustainable wage as equal to or greater than MIT's 2019 Living Wage of "16.54 per hour, or 68,808 per year" (Nadeau, 2020)[25]. Conversely, occupations with a negative projected employment change over 2030-2020 or a median annual wage of less than MIT's living wage were considered to be *unsustainable*.

Table 3.4: Industry Statistics by Highest Educational Attainment

Group	Industry	# of Unique Occupations: All	# of Unique Occupations: Sustainable	Mean Statistics: Wage	Mean Statistics: Employment Change (%), 2020-30
Less than a Bachelor's	Accommodation and Food Services	20	0	33,497	22
	Administrative and Support Services	20	0	47,209	7
	Agriculture, Forestry, Fishing, and Hunting	8	0	39,702	6
	Arts, Entertainment, and Recreation	6	0	38,672	31
	Construction	36	1	65,244	8
	Educational Services	29	5	50,580	-2
	Finance and Insurance	30	11	66,386	5
	Government	77	37	86,526	6
	Health Care and Social Assistance	94	29	62,364	13
	Information	20	4	60,317	12
	Manufacturing	74	22	66,346	6
	Mining, Quarrying, and Oil and Gas Extraction	4	1	64,973	16
	Other Services	22	3	60,122	14
	Professional, Scientific, and Technical Services	98	60	98,584	7
	Real Estate and Rental and Leasing	5	0	47,878	5
	Retail Trade	26	1	61,524	2
	Transportation and Warehousing	26	8	50,125	9
	Utilities	7	1	77,123	-1
	Wholesale Trade	10	5	83,311	5
Bachelor's	Accommodation and Food Services	20	0	31,227	20
	Administrative and Support Services	20	0	54,813	8
	Agriculture, Forestry, Fishing, and Hunting	8	0	40,297	5
	Arts, Entertainment, and Recreation	6	0	37,555	32
	Construction	36	1	71,093	8
	Educational Services	29	5	50,989	2
	Finance and Insurance	30	11	78,458	8
	Government	77	37	87,571	7
	Health Care and Social Assistance	94	29	61,672	12
	Information	20	4	59,718	12
	Manufacturing	74	22	79,090	7
	Mining, Quarrying, and Oil and Gas Extraction	4	1	108,501	12
	Other Services	22	3	73,530	13
	Professional, Scientific, and Technical Services	98	60	97,530	10
	Real Estate and Rental and Leasing	5	0	49,726	5
	Retail Trade	26	1	63,262	2
	Transportation and Warehousing	26	8	55,212	9
	Utilities	7	1	84,685	-4
	Wholesale Trade	9	5	82,208	5

Note: *The number of unique occupations reflects the number of unique O*NET-SOC-2010 present in the Employment Profiles data. The mean wage and expected growth calculations use data from the BLS OEWS that is weighted by occupation prevalence in the Employment Profiles data.*

3.3 Network Construction

3.3.1 Creating the Full Network

At their core, networks are simply a "collection of points" (or *nodes*) "joined together in pairs by lines" (or *edges*) (Newman, 2018)[26]. This simple structure is useful because it allows us to model the relationships between "the parts of a system" (Newman, 2018)[26]. In our particular model, the 617 O*NET occupations in our data are represented as nodes and the number of people transitioning between these occupations is represented by weighted, directed edges. This configuration is achieved first by transforming the sequential professional records in the employment profile data into a chain of transitions between occupations, and then aggregating these transitions at the level of pairs of occupations. In this grouped data, each transition between a pair of occupations has an associated weight reflecting the number of times this transition was observed in the universe of employment profiles. These weights are then converted into a probabilities by summing all of the transitions that start from a given origin occupation and computing the share that end at each possible destination. Although this network representation does away with the longitudinal aspect of the original employment profiles data, it allows us to model the career paths available from a given career by surfacing patterns in job transitions that would not have otherwise been visible.

Although we create this network of job transitions separately for people with and without a Bachelor's degree, it is still possible that an individual acquires additional education or certification between two consecutive positions. To capture this additional investment, if an educational or certification record separates two professional records in an employment profile, this transition is flagged as being characterized by an education or certification increase. When creating the grouped data, this flag is aggregated to reflect the share of transitions between two occupations that include an education or certification increase.

3.3.2 Creating the Occupation-Specific Networks

Next, for each of the eligible occupations in our data, we create sub-networks that model the most likely career paths available to an individual starting their career from that specific occupation. We call these sub-networks *Occupation-Specific Networks.* To simulate the sequential nature of individual careers, the Occupation-Specific Network (OSN) for an occupation j includes all the directed simple paths[4] from the full network described in section 3.3.1 that start at j, as well as any loop at j to represent within-occupation transitions at this occupation. While a number of improbable transitions will be observed, we can pare down this graph by considering only the most popular destinations from each occupation node, removing edges with weights below a certain *transition probability cutoff* ϕ, which was set at 5% in this paper.[5] If removing these edges leads to multiple connected components, we keep only the connected component that contains the occupation of interest j. Furthermore, paths are terminated when the path length exceeds the *path length cutoff* θ, a parameter that is meant to reflect the number of occupational transitions that can reasonably be achieved in a single career. The methodology for arriving at θ is described in section A.1 of the appendix. Finally, this analysis only builds OSNs for occupations that are the origin occupation in a minimum of 30 transitions in the un-grouped employment profiles data, such that of the 617 occupations, 541 had OSNs using the data for people without a Bachelor's, and 515 had OSNs using the data for people with a Bachelor's.

Table 3.5: Occupation-Specific Network Parameters

Parameter name	**Parameter value**	**Method for setting parameter value**
n-size cutoff (α)	30	User-defined
Transition probability cutoff (ϕ)	0.05	User-defined
Path length cutoff (θ)	7	Using the Rate of Occupational Change of Recent Social Profiles

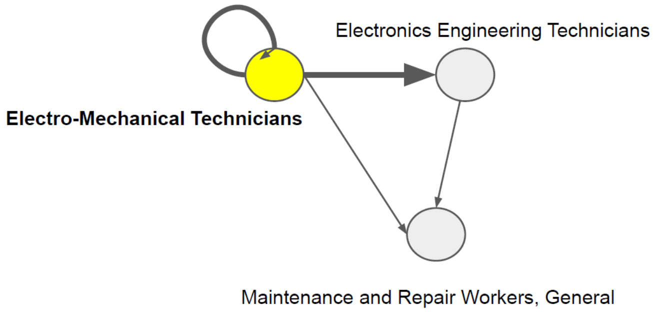
Note: The method for arriving at the Path length cutoff is described in detail in the section A.1 of the appendix.

Examples of the resulting OSNs for two occupations, 1) Electro-Mechanical Technicians and 2) Computer-Controlled Machine Tool Operators, Metal and Plastic are shown below, computed separately using the transitions of workers with and without a Bachelor's. Together, these graphs illustrate that workers may have fewer feasible career path options depending on their educational attainment, although the direction of that difference varies.

[4] Simple paths are paths that do not pass through the same node twice[13].

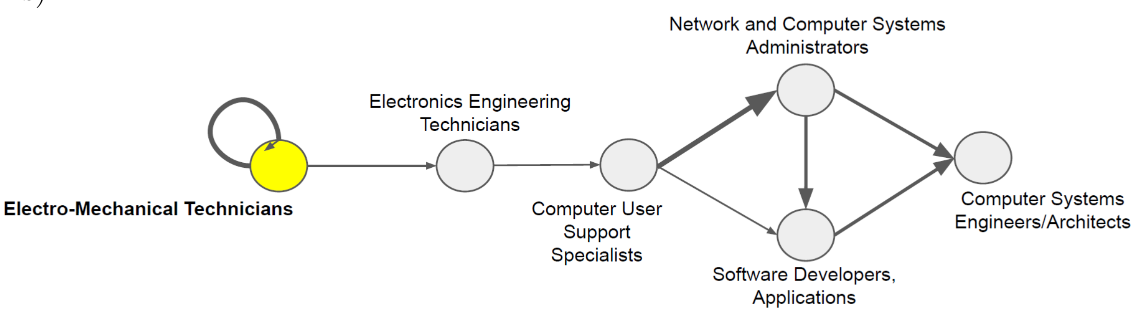
[5] The mean or median of all edge probabilities was considered as a method for calculating this parameter,but both were pulled down due by a high number of low probability edges that would have led to very dense OSNs themselves characterized by low-probability transitions.

Figure 3-1: Occupation-Specific Network for Electro-Mechanical Technicians (Less than a Bachelor's)



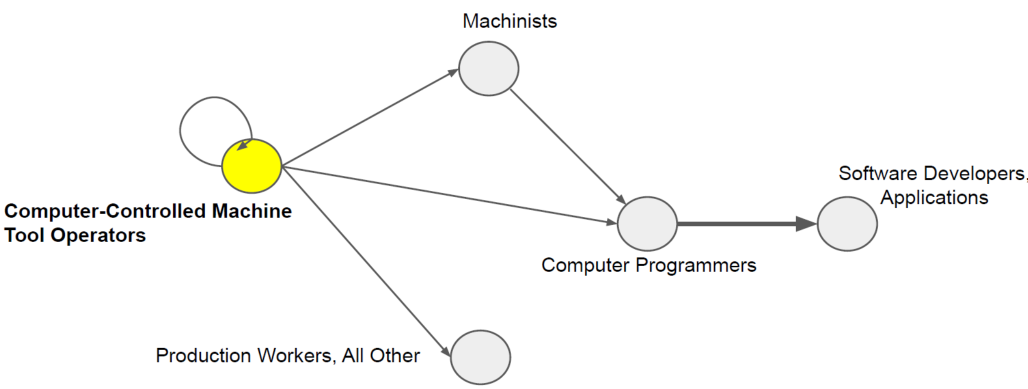
Note: Edge width is proportional to edge weight. Edge distance has no relationship to any edge attributes.

Figure 3-2: Occupation-Specific Network for Electro-Mechanical Technicians (Bachelor's)



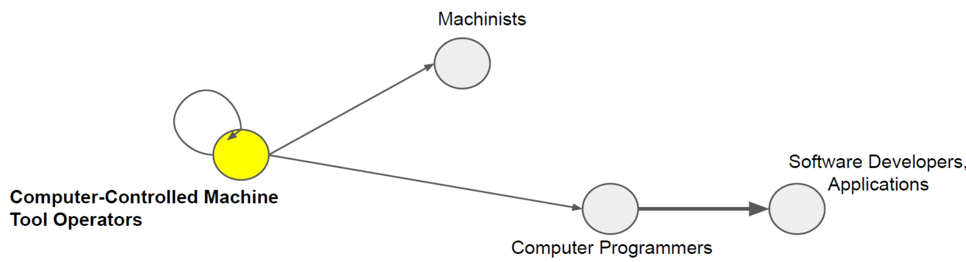
Note: Edge width is proportional to edge weight. Edge distance has no relationship to any edge attributes.

Figure 3-3: Occupation-Specific Network for Computer-Controlled Machine Tool Operators, Metal and Plastic (Less than a Bachelor's)



Note: Edge width is proportional to edge weight. Edge distance has no relationship to any edge attributes.

Figure 3-4: Occupation-Specific Network for Computer-Controlled Machine Tool Operators, Metal and Plastic (Bachelor's)



Note: Edge width is proportional to edge weight. Edge distance has no relationship to any edge attributes.

3.4 Occupational Mobility Indicators

Having built the Occupation-Specific Networks (OSNs), we can now leverage them to develop indicators that capture the mobility potential that different occupations have to offer. Because mobility can hold different meanings, from increased wages to greater flexibility of options, this paper proposes a range of indicators that focus on the various ways that a professional situation can be improved. Furthermore, indicators that rely on the longitudinal employment profile data rather than the network data are included to validate and add on to the network approach. To quote Villareal (2020), "an underlying assumption" of this analysis "is that there is something durable about occupations that affect individuals' life chances beyond the characteristics of the individuals who work in them."[48]

3.4.0.1 Network-based measures

Neighbor-based measures: In a network configuration, the nodes immediately adjacent (separated only by a single edge) to a node of interest are called its neighbors. In the OSN of an occupation G_j, the neighbor nodes N_j of the occupation of interest j represent the occupations that a worker is most likely to transition into next. Although these neighbors do not capture the whole career path, they describe the options that are most immediately available from an occupation.

As such, one straightforward measure of occupational mobility is to use the OSNs to determine the share of an occupation's neighbors that are *sustainable* versus *unsustainable* occupations, as defined in section 3.2.4.3. Similarly, the OSNs can tell us the share of an occupation's neighbors that are *better* occupations, as defined by having higher median annual wages than the origin occupation. The equations for these two indicators are below:

$$SN_j = \frac{\text{\# of sustainable occupations in } N_j}{\text{\# of occupations in } N_j}$$

$$BN_j = \frac{\text{\# of occupations better than } j \text{ in } N_j}{\text{\# of occupations in } N_j}$$

where N_j are the the neighbor nodes of the occupation of interest j in G_j, the OSN of occupation j.

We can created a weighted version of these measures by summing the weights of the edges connecting the occupation j to its neighbors in each set:

$$SN_{j,\text{ weighted}} = \frac{\sum_{s \in S \subseteq N_j} w_{(j,s)}}{\sum_{n \in N_j} w_{(j,n)}}$$

$$BN_{j,\text{ weighted}} = \frac{\sum_{b \in B \subseteq N_j} w_{(j,b)}}{\sum_{n \in N_j} w_{(j,n)}}$$

where $w_{(p,q)}$ indicates the weight of the edge between any two nodes p and q, S is the subset of the neighbors N_j that are sustainable occupations, and B is the subset of its neighbors that are better occupations. As a reminder, in our model, the weights which typically represent the number of people going from an occupation p to an occupation q have been re-scaled so that they represent the share of people in occupation p who end up in occupation q. As such, if N_p represents all the neighbors of a node p:

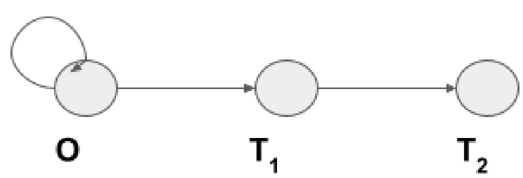
$$\sum_{q \in N_p} w_{(p,q)} = 1$$

<u>*Path-based measures:*</u> The purpose of the OSN is to model the career paths that are available to someone entering the labor market from a given occupation. Therefore, mobility measures that take full advantage of this representation should consider the whole structure. For one, the OSN should theoretically allow us to calculate the probability of reaching a sustainable occupation over the universe of career paths that start from the occupation of interest.

The probability of reaching a better occupation could be similarly estimated, as would the average expected wage growth over all paths.

However, creating these measures requires a methodology for computing the probability of each of the paths in the OSN and a definition for what constitutes a path. For our purposes, a path is any sequence of nodes joined together by directed edges that begins with the occupation of interest and whose terminus can include any of the other nodes in the network. Because we built the OSNs from simple paths, paths do not visit the same node twice, except in the case of loops at the origin (a connection from the origin node to itself) to reflect the probability that an individual will transition from one job to another within the same occupation in the O*NET-SOC-2010 taxonomy. However paths are terminated after this loop occurs. To illustrate this concept, a mock OSN is shown below along with the complete list of associated paths:

Figure 3-5: Sample OSN #1 for Occupation O



List of Paths Associated with the Sample OSN:

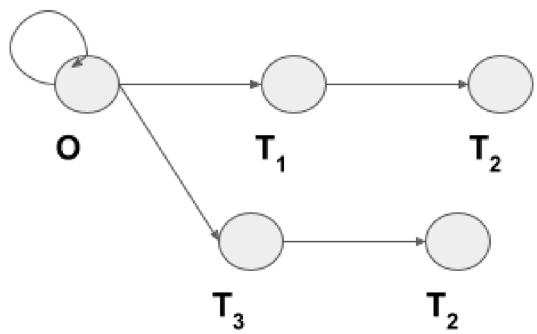
1. $O \rightarrow O$

2. $O \rightarrow T_1$

3. $O \rightarrow T_1 \rightarrow T_2$

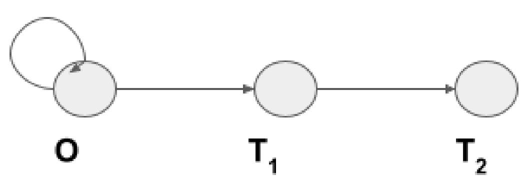
An attribute of these networks that might not be immediately clear from the graph above is that, even though a single path will not visit the same node twice (except in the case of loops at the origin node), there can be multiple paths that end at the same terminal node. An example of this is shown in the sample OSN below, where there are now two paths to node T_2: $O \rightarrow T_1 \rightarrow T_2$ and $O \rightarrow T_3 \rightarrow T_2$.

Figure 3-6: Sample OSN #2 for Occupation O



Having defined what constitutes a path, we can now tackle the matter of calculating the relative probability of each path in the network. This analysis makes the simplifying assumption that the probability of transitioning from one node to the next is independent of any prior transitions. As such, each of our paths can be modelled as Markov Chains where the total probability of the path consists of the product of the probabilities of each of the transitions that make up the path. For example, returning to our first mock graph and assuming that $P_{O \to O} = 0.75$, $P_{O \to T_1} = 0.25$, $P_{T1 \to T_2} = 0.5$ and $P_{T1 \to T_T 1} = 0.5$:

Figure 3-7: Sample OSN #3 for Occupation O



List of Probabilities Associated with the Paths in the Sample OSN:

1. $P_{O \ \to \ O} = 0.75$

2. $P_{O \ \to \ T_1} = 0.25$

3. $P_{O \ \to \ T_1 \ \to \ T_2} = P_{O \to T_1} \times P_{T1 \to T_2} = 0.25 \times 0.5 = 0.125$

A problem with this approach quickly becomes clear: the probabilities of all the paths in the system do not sum to 1. This is because multiple paths pass through the same node T_1 but their relative probability is not taken into consideration. Evaluating the relative probability of the path that ends at T_1 and the path that ends to T_2 requires us to assume that this first path is akin to staying at T_1 rather than transitioning to T_2. As such, we need to artificially extend this path and create a loop at T_1 to reflect the status quo and compute relative probabilities:

Updated List of Probabilities Associated with the Paths in the Sample OSN:

1. $P_{O \rightarrow O} = 0.75$
2. $P_{O \rightarrow T_1} = P_{O \rightarrow T_1} \times P_{T_1 \rightarrow T_1} = 0.25 \times 0.5 = 0.125$
3. $P_{O \rightarrow T_1 \rightarrow T_2} = P_{O \rightarrow T_1} \times P_{T1 \rightarrow T_2} = 0.25 \times 0.5 = 0.125$

The path probabilities now sum to 1, as desired. Note that because creating the OSN entails removing a large number of low probability edges, there is no guarantee that $P_{O \rightarrow O} + P_{O \rightarrow T_1} = 1$ or that $P_{T_1 \rightarrow T_1} + P_{T_1 \rightarrow T_2} = 1$. The probabilities need to be re-scaled at each step of the network so that the weights associated with each edge coming from the same node sum to 1.

Now that we have defined an approach for computing path probabilities, we can leverage this method to compute the probability of reaching a sustainable occupation from the occupation of interest. For each occupation, this probability is simply the sum of the probabilities of the paths that end in a sustainable occupation. Similarly, the probability of reaching a better occupation is simply the sum of the probabilities of the paths that end in a better occupations than the origin occupation. Finally, the expected wage change is simply the difference in wages between the origin occupation and the last occupation of each path, weighted by the probability of that path.

$$P\big(\text{Sustainable}\big)_j = \sum_{s \in S} \sum_{(j,s)_i \subseteq (j,s)} P\big((j,s)_i\big)$$

$$P\big(\text{Better}\big)_j = \sum_{b \in B} \sum_{(j,b)_i \subseteq (j,b)} P\big((j,b)_i\big)$$

$$\text{Wage Change}_{j,\ \text{OSN}} = \sum_{v \in V(G_j)} \sum_{(j,v)_i \subseteq (j,v)} P\big((j,v)_i\big) \cdot \frac{\text{wage}_v - \text{wage}_j}{\text{wage}_v}$$

where (p, q) indicates the set of i directed paths in G_j from a node p to a node q, S is the set of sustainable occupations in G_j, B is the set of occupations in G_j that are better than occupation j, and $V(G_j)$ is the full set of occupations in G_j.

Structural measures: Structural features of the OSNs can also help us get at different aspects of occupational mobility. In particular, the number of occupations in the OSN other than the origin occupation $v \in V(G_j),\ v \neq j$ can be interpreted as a measure of the career flexibility available to someone entering the labor market through that occupation.

3.4.0.2 Career history-based measures

We can also take advantage of the longitudinal, individual career histories to create a few indicators that do not require the network structure. These measures can be thought of as validation instruments for the network measures, but they also provide unique information such that we should not expect a total overlap between the two sets of indicators.

First, we can simply look at all the transitions from a given occupation and compute the average wage change over these transitions:

$$\text{Wage Change}_{j,\ \text{Single-transition}} = \frac{1}{|T_j|} \sum_{d \in D} |T_{(j,d)}| \cdot \frac{\text{wage}_d - \text{wage}_j}{\text{wage}_d}$$

where $|T_j|$ is the number of transitions starting from occupation j in the full employment profiles data, D is the set of destination occupations and $|T(j, d)|$ is the number of job transitions between j and d.

To evaluate wage growth on a longer horizon, we can subset the employment profiles to all of those whose first professional experience is in a given occupation, and compute the average wage change between that occupation and the last occupation in each profile. However, this is an imperfect measure of the expected full-career wage change for someone entering the labor market through that occupation because it looks at career histories of different lengths.

$$\text{Wage Change}_{j,\ \text{EP, Full Career}} = \frac{1}{|R_{j_f}|} \sum_{d_l \in D_L} |R_{(j_f,d_l)}| \cdot \frac{\text{wage}_{d_l} - \text{wage}_{j_f}}{\text{wage}_{d_l}}$$

where R_{j_f} is the set of employment profiles that begin with occupation j, and D_L is the set of last occupations within these resumes.

An analysis restricted to full-career employment profiles would be preferable, but unfortunately there are not enough of these data points to properly evaluate the wage growth potential of all occupations. To get at this problem, we can slightly shorten our horizon and compute the average mid-career wage change of someone entering the labor market through that occupation. Defining the mid-career point as 15 years, we can subset the employment profiles to those covering at least 15 years of professional experience between the first and last occupation. Then, we can truncate the career histories so that they end at the first record where the career length has reached or surpasses 15 years, and compute the average wage change between the origin occupation and the last occupation of those profiles.

$$\text{Wage Change}_{j,\ \text{EP, Mid-Career}} = \frac{1}{|R_{j_f}|} \sum_{d_{15} \in D_{15}} |R_{(j_f, d_{15})}| \cdot \frac{\text{wage}_{d_{15}} - \text{wage}_{j_f}}{\text{wage}_{d_{15}}}$$

where we use R_{j_f} is the set of employment profiles that begin with occupation j, and D_{15} is the set of occupations at the 15 year mark within these employment profiles.

Chapter 4

Results

In this chapter, we'll use our occupational mobility indicators to investigate which occupations offer the best chances at upward mobility. Then, we'll explore how the skills requirements of a job interact with its mobility potential, and how these requirements evolve differently over favorable and less favorable and career paths. We'll also try to understand when the *skills growth* mechanism might prevail over *skills transfer* in an occupation transition, in order to identify the factors that may facilitate different types of job changes. Finally, we'll zoom in on the manufacturing industry and use the tools developed in this analysis to identify opportunities for retention and development in the field. A high-level overview of the findings is shown below:

Research question	**Findings**
What are the dimensions of occupational mobility?	In this thesis, occupational mobility is the extent to which a job provides access to 1) *sustainable jobs* (jobs that are secure and high-wage), 2) higher wages, or 3) flexible career paths. We find that access to sustainable jobs is a more relevant measure overall, especially when it comes to evaluating unsustainable occupations.
Which occupations are upwardly-mobile?	Although *unsustainable jobs* (jobs that are low-wage or shrinking) provide limited access to sustainable occupations, a number of industries such as Professional Services offer reliable access to sustainable employment.
What is the relationship between occupational requirements and mobility?	A number of skills are more heavily required by unsustainable occupations with high-mobility potential than they are by unsustainable occupations with low-mobility potential, in particular Systems skills and Basic skills. However, other attributes, such as baseline wages, appear to play a larger role in determining occupational mobility than any specific skill.
Do job transitions usually involve *skill growth* or *skill transfer*?	Educational investments are more often involved in transitions from unsustainable occupations and transitions that cross different industries. However, longer work experience and investing in certifications may facilitate transitions between jobs with a higher skills distance.

4.1 Which occupations are upwardly-mobile?

In section 3.4, we described how the models of career paths available from an occupation (Occupation-Specific Networks, or OSNs) and the longitudinal career histories could be used to build a range of indicators that capture the mobility potential of a starter job. With these indicators, we set out to measure some of the different aspects of occupational mobility, from the capacity of a job to unlock access to higher-paying jobs, to its ability to lead to secure, high-wage employment, to the flexibility of career paths that it offers. This section explores the extent to which these indicators agree with each other, and then selects a subset to guide the remainder of our analysis. Using this subset, we then review the occupations and sectors that offer the most and least potential. Overall, we find that 1) the different definitions of mobility lead to disagreement in the ratings, 2) agreement between indicators measuring the same concepts over different time horizons suggest that mobility may be strongly determined early on in the career, 3) unsustainable occupations offer little access to sustainable employment, and that 4) upward mobility prospect are generally better for workers with a Bachelor's degree.

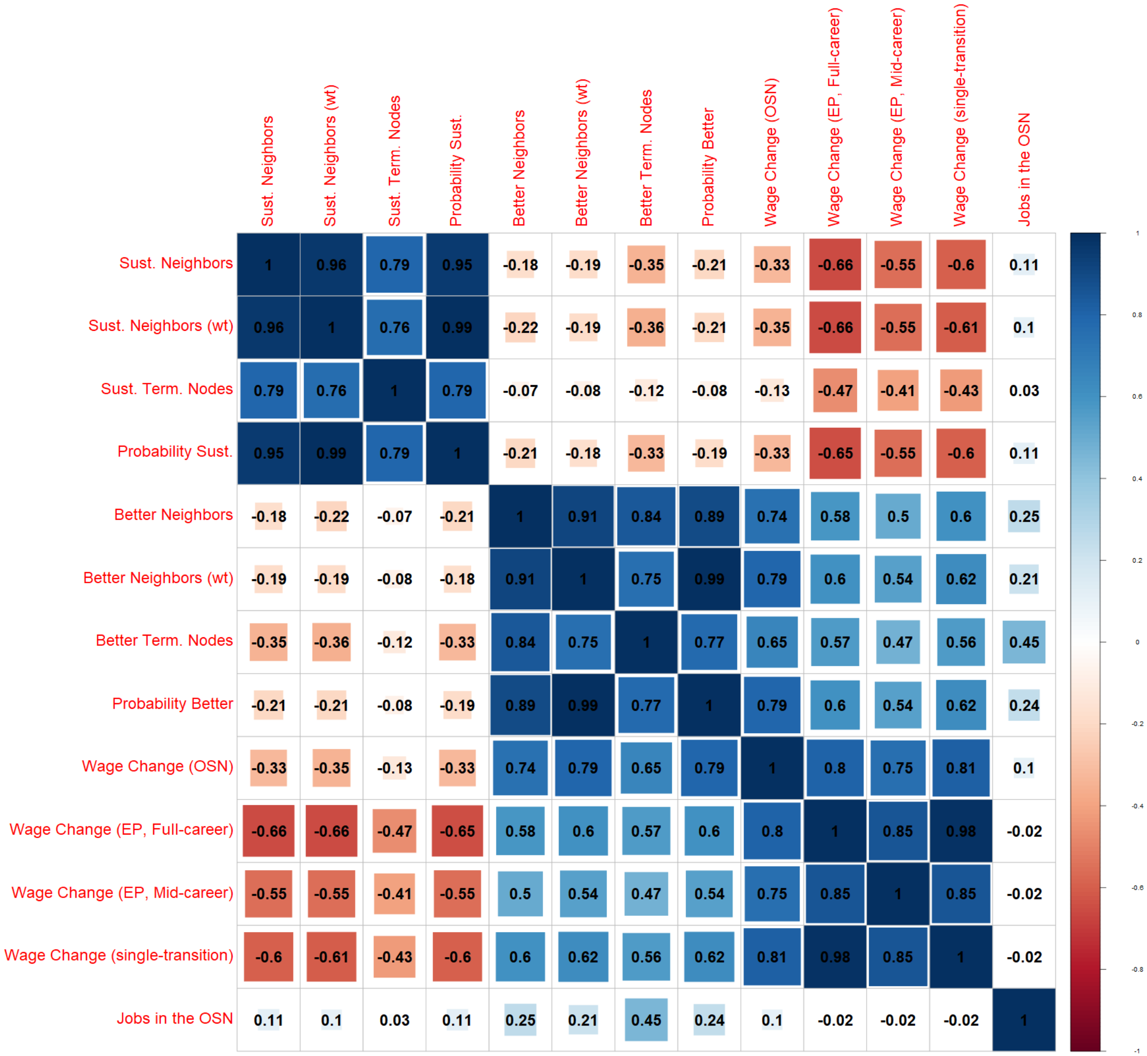
4.1.1 Do the different aspects of mobility agree with each other?

Eligible occupations[1] in the O*NET-SOC-2010 taxonomy were evaluated for their mobility potential according to the 13 indicators described in section 3.4. The correlation plot in figure 4-1 below displays the strength of the association between those scores for each indicator pairing. Because the results were nearly identical for the two educational groups, only one plot is shown, but its counterpart can be found in the Figure B-1 of the Appendix.

In general, we find that indicators that use different methods to capture the same dimension of upward mobility are highly correlated, but that indicators capturing different dimensions are only weakly or even negatively correlated, suggesting that there is disagreement between the various aspects of upward mobility. What's more, the indicators measuring the same concepts over different time horizons are highly correlated, suggesting that mobility may be strongly determined in the first few transitions of the career.

[1]To ensure that findings were generalizable, only occupations with at least 30 out-transitions in the employment profiles data were scored according to the network-based indicators. This threshold resulted in 541 of the 617 occupations being rated for people without a Bachelor's, and 515 of the 617 for people with a Bachelor's degree.

Figure 4-1: Correlation of Occupational Mobility Measures (Bachelor's)



Note: Network-based indicators that evaluate a job's proximity to sustainable occupations: 1) The share of neighbor nodes that are sustainable SN_j (*Sust. Neighbors*), 2) The weighted share of neighbor nodes that are sustainable $SN_{j,weighted}$ (*Sust. Neighbors (wt)*), 3) The share of terminal nodes that are sustainable (*Sust. Term. Nodes*), 4) The probability of reaching a sustainable occupation $P(\text{Sustainable}_j)$ (*Probability Sust.*).

Network-based indicators that evaluate a job's proximity to better (higher-wage) occupations: 1) The share of neighbor nodes that are better occupations BN_j (*Better Neighbors*), 2) The weighted share of neighbor nodes that are better occupations $BN_{j,weighted}$ (*Better Neighbors (wt)*), 3) The share of terminal nodes that are better occupations (*Better Term. Nodes*), 4) The probability of reaching a better occupation $P(\text{Better}_j)$ (*Probability Better*).

Indicators that evaluate a job's wage growth potential: 1) The average, probability weighted wage growth over the OSN (*Wage Change, OSN*), 2) The average wage growth over employment profiles that start with the occupation of interest (*Wage Change (EP, Full-career)*), 3) The average wage growth at the mid-career point over employment profiles that start with the occupation of interest (*Wage Change (EP, Mid-career)*), 4) The average wage growth over transitions that start with the occupation of interest (*Wage Change (single-transition)*).

Network-based indicators that evaluate a job's career flexibility: 1) The number of occupations in the network other than the occupation of interest (*Jobs in the OSN*).

As expected, Figure 4-1 shows us that the measures derived from similar concepts are all highly correlated: the indicators that use networks to evaluate a job's proximity to *sustain-*

able occupations (high-wage occupations that are not projected to decline) have correlation coefficients ranging from 0.76 to 0.99, those that use networks to evaluate a job's proximity to *better occupation* (occupations that are higher wage) have coefficients ranging from 0.75 to 0.99, and those that use longitudinal career histories to evaluate a job's wage growth potential have coefficients ranging from 0.75 to 0.98. These associations persist even when the measures are derived from different data structures. Indeed, the network-based wage growth measure is strongly related with the career history-based wage growth measures, with correlation coefficients ranging from 0.75 to 0.81, providing some endorsement of the network approach. Similarly, the career history-based wage change measures are also highly correlated with the network-based measures that look at access to a better job.

However, there are areas of the plot that suggest differences, if not outright discordance. The indicator that measures career flexibility using the number of occupations in an occupation's OSN is only weakly correlated with all of the other indicators. This suggests that the notion of career flexibility represented by this indicator does not necessarily lead to higher wages or greater access to sustainable occupations.

What's more, the indicators that evaluate a job's proximity to sustainable occupations are weakly to strongly negatively correlated with the *better job* indicators and the *wage change* measures. This hints at a potential shortcoming of relying exclusively on measures that look at relative wage growth: the lower a starting wage, the more likely it is that any transition will result in a wage gain, resulting in an indicator that is biased towards low-wage occupations. On the other hand, the *sustainable* indicators that rely on an absolute definition of high-wages do not tell us anything about growth, focusing instead on the reliability of prospects. Given their complementarity, these two sets of indicators may best be used in tandem.

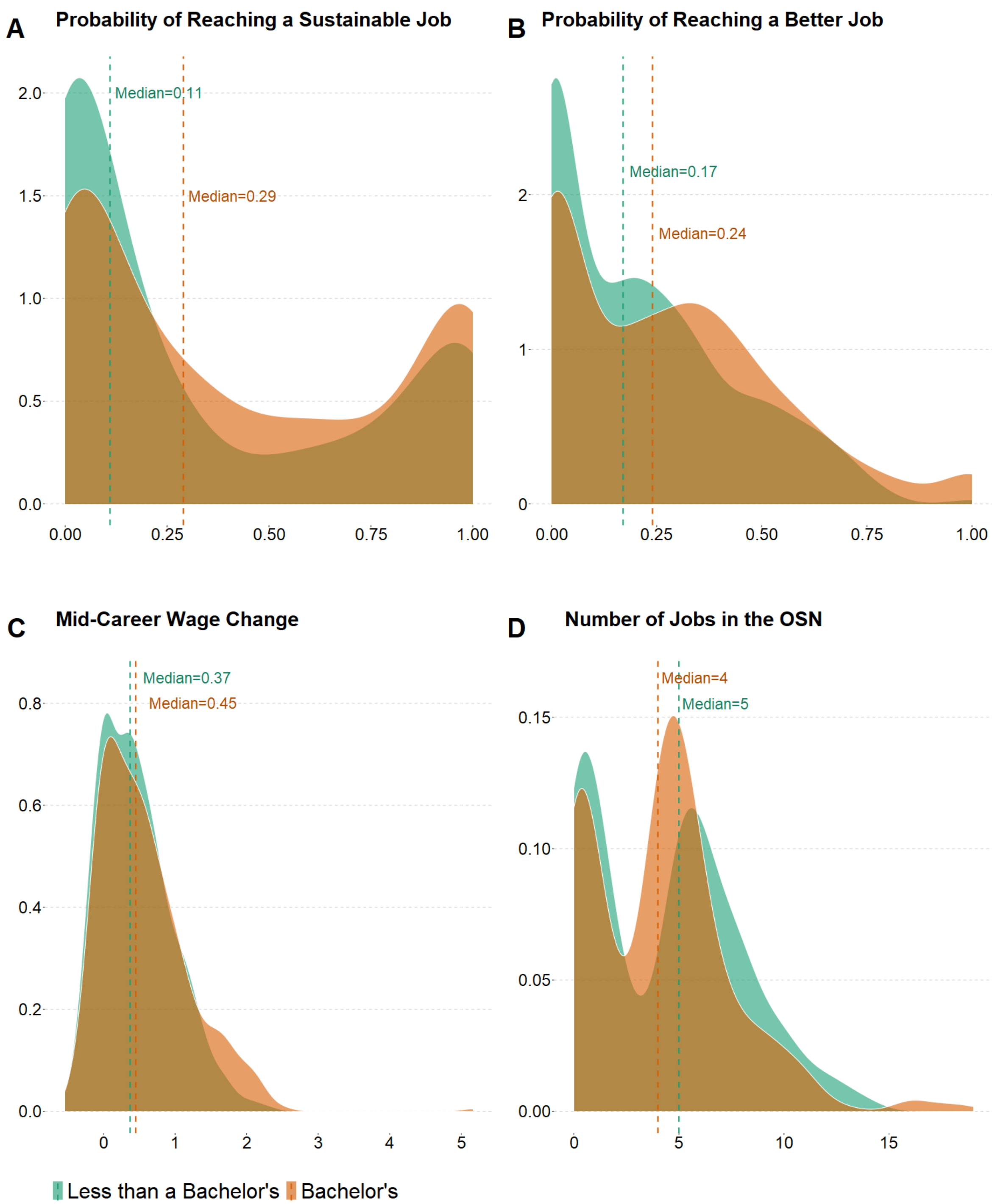
A final point to address is the very high correlation between the indicators measuring an occupation's probability of reaching a sustainable/better occupation, and the indicators measuring the weighted share of that occupation's neighbor's nodes that are sustainable/better (at R=0.99 and R=0.98, respectively). There are mechanical reasons for this correspondence: a number of occupation's OSNs have short path lengths, in which case the two measures are basically equivalent. Furthermore, the probability of a path decreases as a function of its length, biasing the probability measures towards shorter paths such as paths that end at neighbors nodes. But looking at the career history-based wage measures suggests that this correspondence between short- and long-term measures is not strictly a function of the network structure. Indeed, the indicator that looks at wage growth over a single transition is also highly correlated with the indicators that look further down the line to the full or mid career point. This agreement between short- and long-perspective measures across the board suggests that mobility may be strongly determined in the first few transitions of the career, making occupational mobility a potential misnomer.

Ultimately, given that the indicators that are conceptually related are also strongly numerically related, we only need to consider one indicator per concept as we continue to paint a portrait of occupational mobility. Going forward, this analysis will only consider four measures: 1) the probability of reaching a sustainable occupation $P(\text{Sustainable}_j)$, 2) the probability of reaching a better occupation $P(\text{Better}_j)$, 3) the mid-career wage change $\text{Wage Change}_{j,\text{ EP, Full Career}}$, and 4) the number of jobs in the network. These indicators not only have conceptual range, but they also cover a number of computational methods. The first two use the OSNs to look at both improvement and reliability of prospects, the third provides balance to the network-based measures by using the longitudinal career histories to assess wage growth, and the fourth is a structural measure evaluating the flexibility of career options rather than the nature of these options.

4.1.2 How is mobility distributed across occupations?

Because this analysis is interested in quantifying the extent to which different opportunities may be afforded to those with more education, each of the occupations were evaluated on their mobility potential using job transition data from people with a Bachelor's degree, and then again using job transition data from people without a Bachelor's. Figure 4-2 below shows the distribution of scores for the two education groups across the 515 to 541 occupations. Although these density plots are not weighted by the prevalence of the occupations in the data, a weighted version is available in Figure B-2 of the appendix, but the results are similar.

Figure 4-2: Distribution of the Mobility Indicators by Highest Educational Attainment



Note: The distribution of occupational mobility scores are not weighted by the prevalence of the occupations in the employment profiles data. The Probability of Reaching a Sustainable Job, The Probability of Reaching a Better Job, and the Number of Jobs in the OSN (or Network) are all derived from the Occupation-Specific Networks. The Mid-Career Wage Change is derived from the longitudinal employment profiles data.

A general takeaway from these density plots is that people with a Bachelor's degree appear to have better occupational mobility prospects than their peers (particularly in terms of the probability of reaching sustainable or better jobs). Indeed, an analysis of the 482 occupations that were rated for both groups reveals that, on average, the same job offers a probability of reaching a sustainable occupation that is about 5 ± 12 percentage points higher for workers with Bachelor's degrees, and a probability of reaching a better occupation that is about 6.7 ± 16 percentage points higher. Still, these differences are small enough that the occupations scored in this analysis should offer comparable opportunities for both groups.

With respect to the probability of reaching a sustainable occupation, the distributions for both groups are bi-modal, suggesting that while there exist many occupations with low odds, there are also many occupations (albeit fewer) with very good odds. With respect to the probability of reaching a better occupation, both of the distributions have a positive skew, centering at the lower end but exhibiting long right tails, suggesting again that there are many occupations with opportunity for growth. In terms of mid-career wage change, the two distributions are very similar and are approximately normal about 0.5%, although there are some outliers at the top end of the distribution that are derived from the Bachelor's population. Finally, the number of jobs in the network also exhibits a bi-modal distribution that is not substantially different between the two groups.

Figure 4-3 now splits the mobility scores by whether occupations are sustainable or not. Because the results are similar for the two education groups, only the plot for people without a Bachelor's is shown, although its counterpart can be found in Figure B-3 of the appendix.

Figure 4-3: Distribution of the Mobility Indicators by Occupation Type (Less than a Bachelor's)

Note: The distribution of occupational mobility scores are not weighted by the prevalence of the occupations in the employment profiles data. The Probability of Reaching a Sustainable Job, The Probability of Reaching a Better Job, and the Number of Jobs in the OSN (or Network) are all derived from the Occupation-Specific Networks. The Mid-Career Wage Change is derived from the longitudinal employment profiles data.

It is immediately clear that sustainable and unsustainable occupations have dramatically different odds of providing access to sustainable employment: sustainable occupations have a median 93% change of leading to other sustainable jobs, while unsustainable occupations only offer a median 4% chance. In fact, the two distributions barely overlap around the 50% mark. This trend may be explained by the prevalence of within-occupation transitions in the data (i.e. the likelihood that people transition from one job to another in the same occupational category), as well as the likely scenario that it is much easier to transition from one high-wage, stable occupation to another.

On the other hand, this trend is flipped for the two indicators that look at wage change: unsustainable occupations generally have better odds or reaching better jobs and a greater expected mid-career wage growth. As previously discussed, this is likely because lower starting wages make it mechanically more likely that any transition will result in a wage gain. Finally, the distribution of the number of jobs in the network does not offer such differentiation, suggesting that sustainable and unsustainable occupations offer similarly flexible career paths.

In conclusion, this analysis sheds some light on how best to use our four indicators. In particular, it might be more informative to evaluate unsustainable occupations in terms of their probability of reaching a sustainable job, since access to these jobs seems all but guaranteed for sustainable occupations. On the other hand, sustainable occupations might best be evaluated in terms of their wage growth potential and their access to better jobs, since these jobs already have high-wages to begin with. Finally, the number of jobs in the network remains relevant for both groups.

4.1.3 Ranking Industries by Mobility

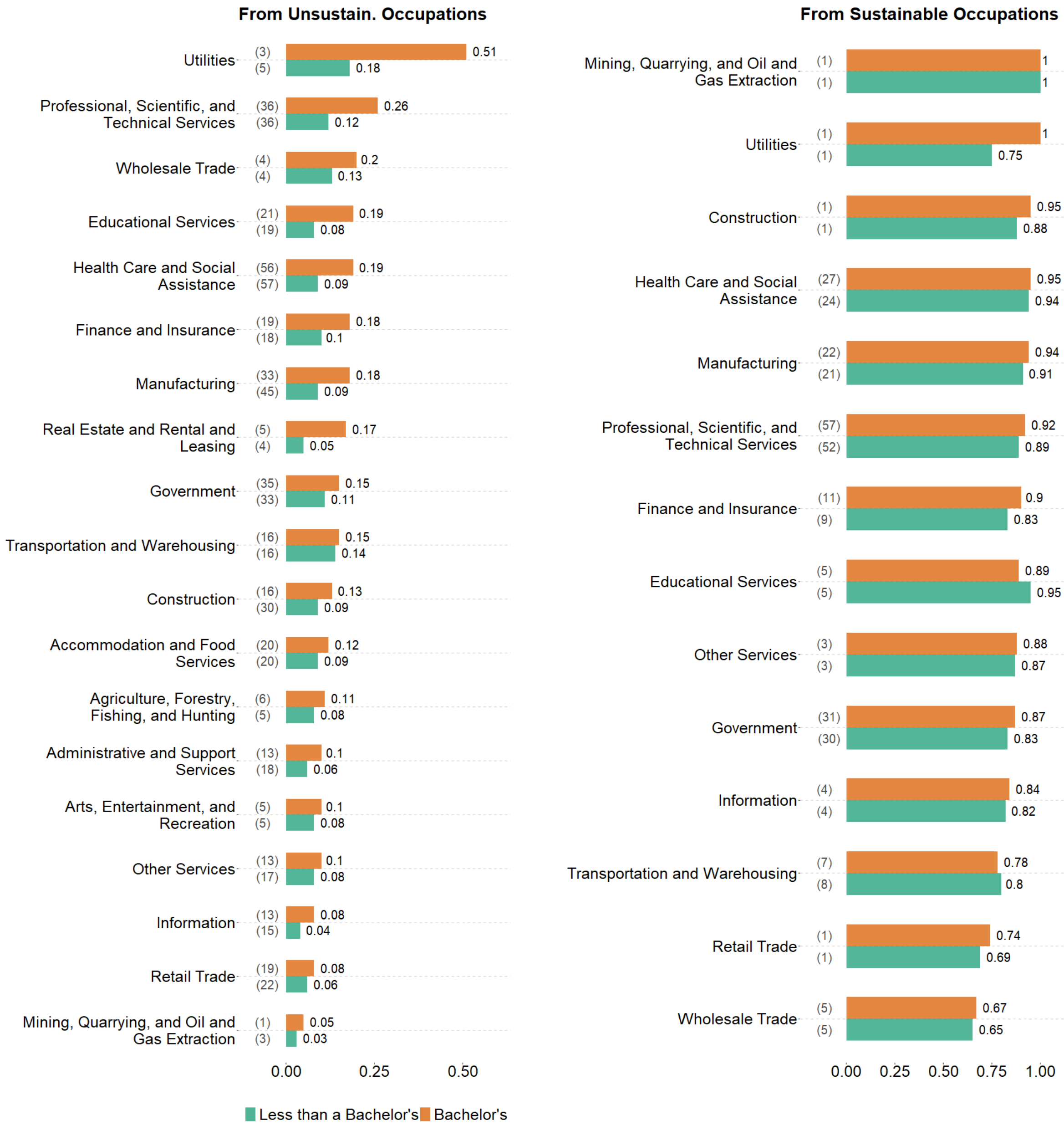
Figures 4-4 through 4-7 below rank industries on each of the four mobility indicators. Scores are separated by worker educational attainment and whether the occupations of interest are themselves sustainable or not. In general, the findings reflect the general takeaways from section 4.1.2: 1) sustainable occupations, regardless of industry, offer better access to sustainable jobs, and 2) mobility scores by industry are generally higher for workers with a Bachelor's degree. While the rankings vary widely across indicators, some industries rate consistently low across the network-based indicators. However, it is possible that this is an artifact of the OSNs: when there are no or few consistently likely career paths associated with an occupation, then the number of jobs in its sub-network and its probability of reaching a better or sustainable occupation[2] will all trend towards zero.

In figure 4-4, we first rank industries by the access that they offer to sustainable employment. As before, odds are greatly improved by being employed in a sustainable occupation in the first place, and this is true for both education groups. In fact, the industry with the worst odds across sustainable occupations (Whole Sale Trade for both educational groups) still has markedly better odds than the industry with the worst odds across unsustainable occupations (Utilities for both educational groups). Similarly, access is greater for people with a Bachelor's degree. Starting from unsustainable occupations, workers with a Bachelor's degree have anywhere between 1.07 and 3.4 times[3] the odds of reaching a sustainable occupation of their counterparts in the same industry.

The industries that offer the best access to sustainable employment to workers without a Bachelor's degree starting in an unsustainable occupation are: utilities, transportation and warehousing, wholesale trade, professional services, and government. Meanwhile, the industries that offer the best access to sustainable employment to workers with a Bachelor's degree starting in an unsustainable occupation are: utilities, professional services, wholesale trade, educational services, and health care and social assistance. The rankings across unsustainable and sustainable occupations are markedly different. For example, Wholesale Trade offers some of the best prospects to workers starting out in unsustainable employment, but some of the worst odds for workers starting in sustainable employment.

[2] Unless the occupation is sustainable to begin with, because of within-occupation transitions.
[3] in Transportation and Real Estate, respectively

Figure 4-4: Industries by Probability of Reaching a Sustainable Occupation



Note: The number in parentheses indicates the number of unique occupations in that industry that were rated for each group. The average of occupational mobility scores across industries does not take into account the prevalence of the occupations in the employment profiles data.

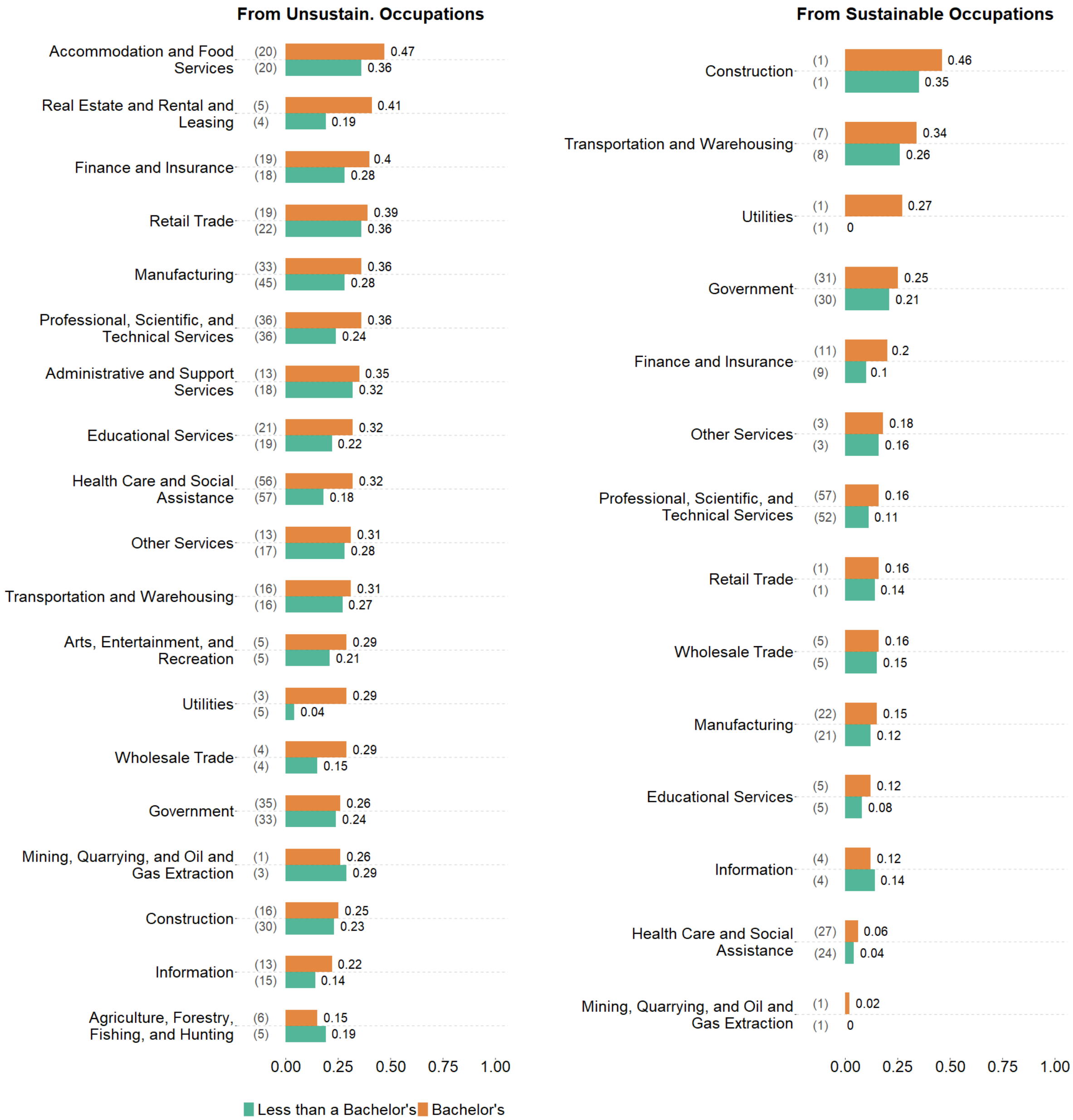
Looking at industries in terms of their access to better occupations in figure 4-5 offers up a whole different picture. The odds of accessing higher-wage jobs are now substantially greater across the unsustainable occupations, in all likelihood because those occupations have lower wages to begin with, making wage growth mechanically more likely. Indeed, one of the top two industries for workers without a Bachelor's, Accommodation and Food Services- is also the one with the lowest median wage according to Table 3.4.

In this respect, it is more informative to look at the industry rankings for sustainable occupations, which already guarantee a living wage. Starting from these sustainable occupations, those with a Bachelor's degree have anywhere between 0.857 and 2.0 times[4] the odds of reaching a better occupation than their peers in the same industry. Across both education groups, sustainable occupations in Construction, Transportation and Warehousing, and Government rank highly in terms of access to higher wages, while Mining, Health Care and Social Assistance, and Educational Services are near the bottom of rankings. Utilities has a very different ranking for both groups; however, this volatility can be explained by the fact that only a few occupations in this sector were rated.

Moving on to the mid-career wage change in figure 4-6 offers a bit more color on the previous findings. For the same reason as before, we focus on the rankings of sustainable occupations. Among these occupations, Utilities, Information, and Educational Services industries offer the best prospects for those without a Bachelor's. Similarly, the Utilities, Educational Services, and Finance and Insurance industries best serve those with a Bachelor's degree. In general, the mid-career wage change is surprisingly low for sustainable occupations across industries, peaking at only at 17% for those with a Bachelor's degree in the utilities sector. However, this might be a shortcoming of comparing occupations based on their national median wages, which lump together entry-level wages with wage increases that come from accumulated experience.

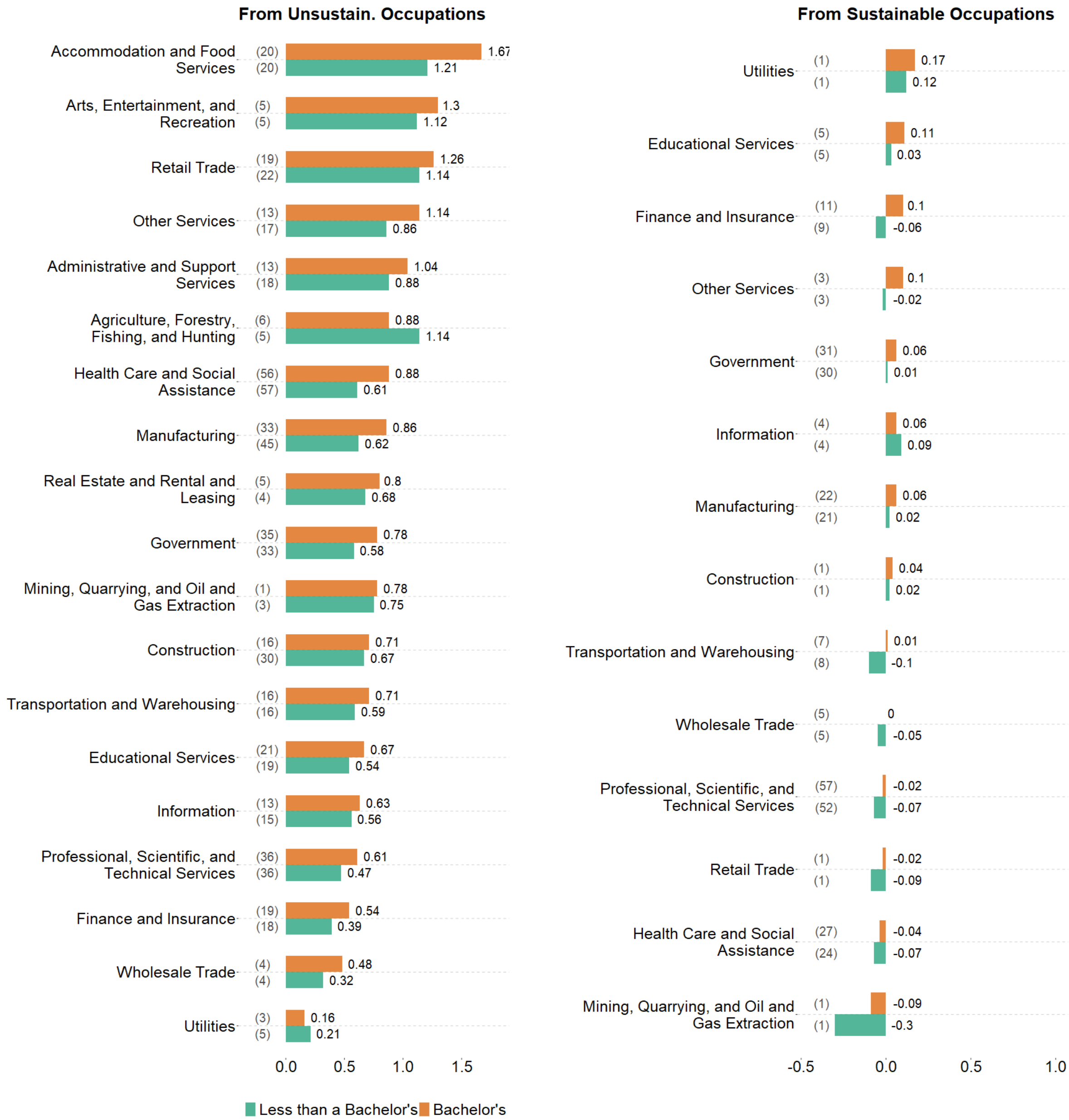
[4]in Information and Finance, respectively. Not including the Mining and Utilities industries, were odds are null for workers without a Bachelor's.

Figure 4-5: Industries by Probability of Reaching a Better Occupation



Note: The number in parentheses indicates the number of unique occupations in that industry that were rated for each group. The average of occupational mobility scores across industries does not take into account the prevalence of the occupations in the employment profiles data.

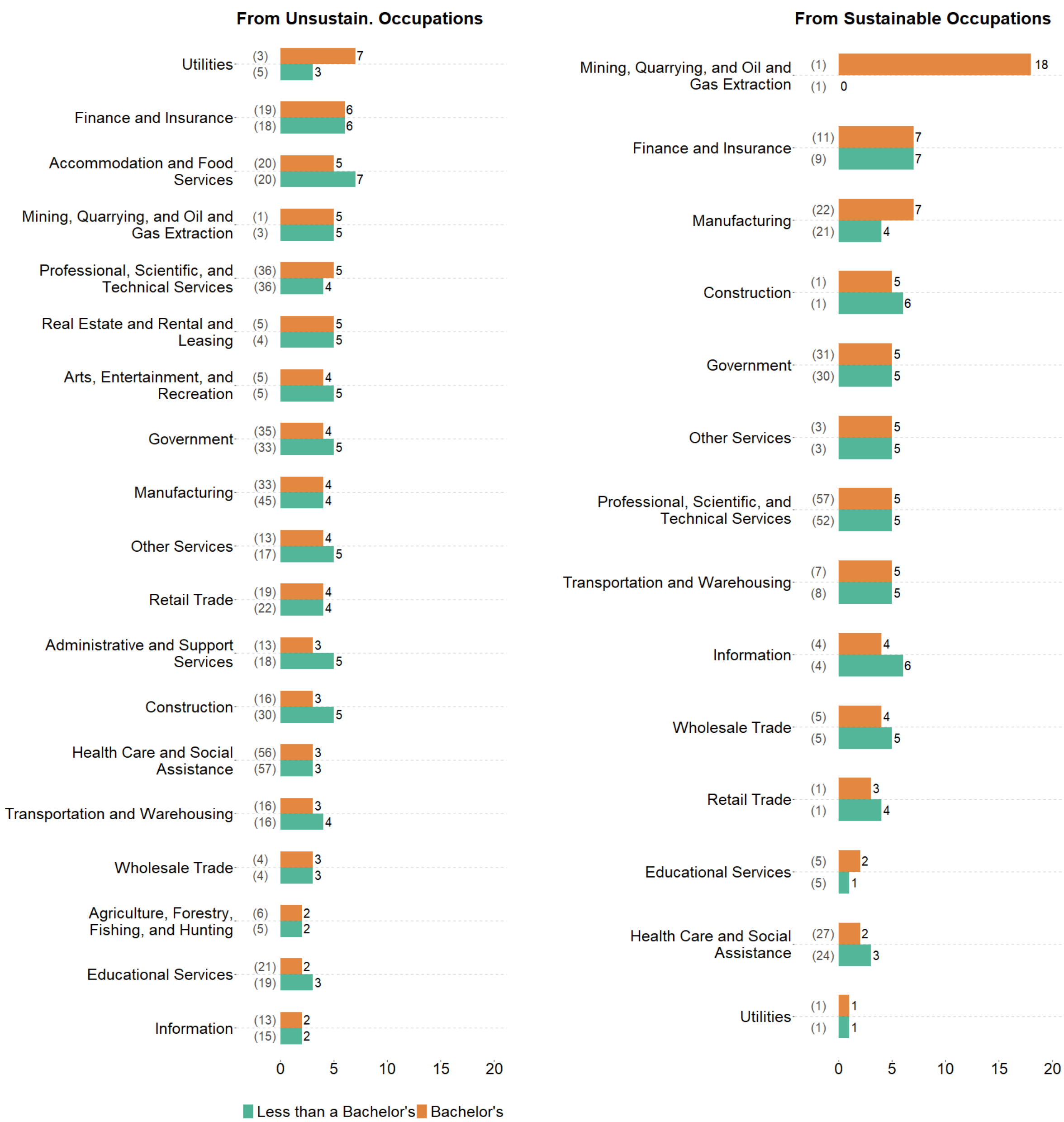
Figure 4-6: Industries by the Expected Wage Change at Mid-Career



Note: The number in parentheses indicates the number of unique occupations in that industry that were rated for each group. The average of occupational mobility scores across industries does not take into account the prevalence of that occupation in the employment profiles data.

The rankings in terms of the number of jobs in the network in figure 4-7 present yet another perspective. Overall, we do not observe the same differentiation between sustainable and unsustainable occupations or across education groups. Comparing numbers across specific industries however (e.g. Information, Wholesale Trade, Manufacturing, Finance and Insurance), suggests that on the whole, sustainable occupations offer up more a more diverse array of career paths, with some industries bucking the trend (for those without a Bachelor's: Mining, Utilities, Educational Services; for those with a Bachelor's degree: Retail trade, Utilities).

Figure 4-7: Industries by the Number of Jobs in the OSN



Note: The number in parentheses indicates the number of unique occupations in that industry that were rated for each group. The average of occupational mobility scores across industries does not take into account the prevalence of the occupations in the employment profiles data.

For more granularity, tables B through B in the Appendix provide rankings of specific occupations for each of the indicators.

4.2 The Relationship between Job Requirements and Mobility

In this section, we'll investigate how the skills requirements of a job interact with its mobility potential, focusing on unsustainable occupations. We'll first look at how requirements between unsustainable jobs with high and low mobility potential differ at baseline, and then at how those requirements evolve differently over career paths that end in sustainable and unsustainable occupations. Overall, we find that the skills that are more typical of high-mobility potential occupations are not necessarily the ones that tend to grow the most over career paths that end in sustainable occupations. This suggests that while workers may best be served by one set of skills upon labor market entry, training over the course of the career should target a different skill set to set them up for sustained success. For example, we find that basic skills are more typical of high-mobility potential occupations at baseline, but requirements for resource management skills grow the most over sustainable paths, while systems skills appear to be important at both time points. Models estimating the determinants of upward mobility provide a caveat to these findings however, suggesting that baseline job attributes such as wages may play a more important role than any specific skill.

4.2.1 Baseline Job Requirements and Mobility

4.2.1.1 Descriptive Analysis

The skills requirements of a job allow us to compare how occupations might differ in terms of the types of competencies they ask workers to apply on a regular basis. This section asks whether the intensity and the nature of these competencies are related to an occupation's potential to offer greater mobility down the line. Figure 4-8 below shows us the differences in skill requirements for the five major skill groups between occupations who have the highest mobility potential and occupations who have the lowest mobility potential. The trends are similar regardless of which education group was used to derive the ratings, so only the plot for workers without a Bachelor's is shown here, but its counterpart can be found in figure

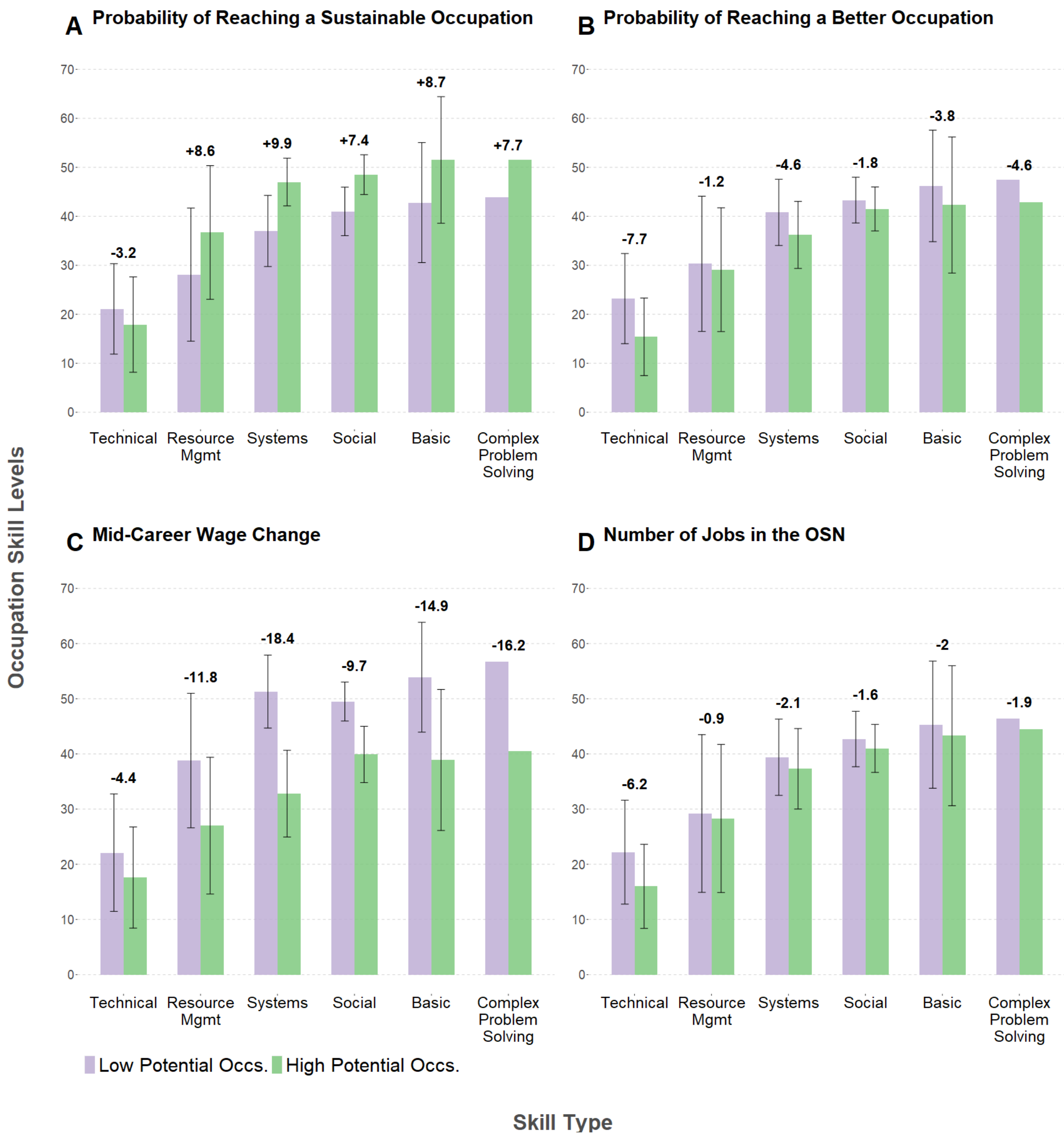
B-4 of the Appendix. Because we are more interested in how the development prospects of unsustainable occupations can be increased, this analysis focuses exclusively on unsustainable occupations. Results broken up by skill rather than skill groups are available in Tables B through B of the Appendix.

Each indicator is associated with a unique pattern in skill differences. In terms of the *probability of reaching a sustainable job* in panel A, it appears that occupations with greater mobility potential tend to have higher skill requirements overall, except when it comes to technical skills. Systems skills (i.e. Judgment and Decision Making, Systems Analysis, and Systems Evaluation) appear to be particularly important, followed by Basic skills, Resource Management skills, and Social skills. Although the trends are similar across the two education groups, the differences between the low and high-mobility potential occupations are substantially larger for those without a Bachelor's. Overall, the graph suggests that more skill-intensive occupations yield better prospects down the line, perhaps because they are perceived to facilitate learning experiences for workers, or simply because workers in those fields are perceived to be more qualified.

With respect to the two indicators that evaluate wage growth prospects (i.e. *probability of reaching a better job* and the *mid-career wage change*), we run up against a familiar problem: lower starting wages make it mechanically more likely that any job change will result in a wage improvement. This mechanism might explain why jobs with fewer requirements appear to offer better wage growth prospects. Controlling for these starting conditions would be useful in teasing apart the dynamics at work here, something we will do in the following section.

Finally, in terms of the *number of jobs in the OSN*, we notice that there is much less differentiation between high- and low- mobility potential occupations. In fact, table B in the Appendix shows that there are few significant difference in skill levels between the two groups. Technical skills present a notable exception: the results in panel D suggest that occupations that score higher on this indicator of career flexibility have lower technical skill requirements overall. This finding highlights the fact that professional specialization often entails investing in technical skills, and that a higher degree of this investment might result in fewer career paths (whether because workers are committed to a certain trajectory or because employers perceive them to be).

Figure 4-8: Differences in the skill requirements of unsustainable occupations that are either high or low-mobility potential (Less than a Bachelor's)



Note: The bolded number above each set of bars indicates the difference in skill centrality levels between the occupations with high mobility potential and occupations with low mobility potential. The averages across occupation types are not weighted by the prevalence of the occupations in the employment profiles data. Occupations were binned differently for each indicator: for the *mid-career wage change* and the *number of jobs in the OSN*, the high-mobility potential occupations are in the upper quartile of the distribution of scores across the unsustainable occupations, and the low-mobility potential occupations are in the lower quartile. With respect to the *probability of reaching a sustainable job*, the high-mobility potential occupations have a score of 0.3 or more, and low-mobility potential occupations have a score of 0.05 or less. Finally, with respect to the *probability of reaching a better job*, the high-mobility potential occupations have a score of 0.5 or more, and the low-mobility potential occupations have a score of 0.10 or less. The last two indicators were partitioned manually because they did not have enough spread across the unsustainable occupations to properly create quartiles.

4.2.1.2 Predictors of Occupational Mobility

As has become apparent in our previous discussions, there are a number of baseline characteristics that may influence the mobility potential of an occupation. In an attempt to tease apart the impact of these factors, this section presents the results of OLS regression models where the independent variables are the occupational mobility indicators, and the dependent variables are various attributes of these occupations and the individuals who work in them. In particular, we'll first model (1) the relationship between mobility and a vector of occupational characteristics that includes the occupation's predicted employment growth over the next ten years, its median national wages, whether it requires a college degree [5], and industry fixed effects. In the second model (2), we'll add a vector of job transition characteristics to the predictor set that consists of the frequency at which an occupation appears as a first or last job in the individual career histories, the occupation's share of within-occupation transitions, and the number of jobs in its OSN. In the third model (3), we'll add a vector of skills requirement that includes the occupation's centrality level for each skill. Finally, the fourth, full model (4) will add a vector of workforce controls that includes the share of workers in these occupations with a certain educational attainment[6], the share of workers who entered the labor market in a given decade, and the share of workers in a certain US region. To summarize, the full model will be of the form:

$$y_{o,i} = \beta_j OC_{j,n} + \gamma_k JT_{j,k} + \delta_l SK_{j,l} + \lambda_m WF_{j,m} + e_{j,i}$$

where $y_{j,i}$ is the mobility score for occupation j using indicator i, $OC_{j,n}$ is the vector of n baseline occupation attributes, $JT_{j,k}$ is the vector of k job transition characteristics, $SK_{j,l}$ is the vector of skill centrality values, and $WF_{j,m}$ is the vector of workforce controls.

As usual, the analysis was conducted separately for the two education groups. However, because the estimates are generally similar across the two analyses, only results for individuals without a Bachelor's are shown in this section, but full results are available in Tables B through B of the Appendix. Furthermore, we will not model the determinants of the number of jobs

[5] According to the BLS

[6] While the analysis is run separately for the two education groups, a number of transitions occur before an individual has reached their highest educational attainment. This means for example, that an individual who ultimately obtains a Bachelor's degree might at some point be coded as having a High School education.

in the network, but rather include this indicator in the predictor set for the other models to study the interaction of career flexibility with more traditional measures of mobility.

Table 4.2.1.2 shows the results of models estimating the determinants of the probability of reaching a sustainable occupation. Overall, we find that the baseline occupational characteristics (i.e. wage (+), employment growth (+), and whether an occupation typically requires a BA (+)) have the strongest relationship with the probability of reaching a sustainable job, followed by a number of specific skills.

The first model (1) includes only the occupational characteristics in the predictor set, and this alone explains over half of the variance. All of the occupational variables are found to have a significant and positive association with the mobility indicator, with the predicted employment growth of an occupation having the strongest relationship. The addition of the transition variables in the model (2) has little effect on these estimates. Of these variables, only the measure that captures how often an occupation is a first job has a strong negative association with the mobility indicator. The inclusion of the skills variables in the model (3) causes the estimates for the effects of the occupational characteristics to decrease slightly (although they remain significant) and the association with the first job measure disappear to disappear entirely. What's more, a number of skills are found to have a significant association with the probability of reaching a good job that persist through the full model: Complex Problem Solving, Coordination, and Systems Analysis have a positive relationship, while Critical Thinking, Instructing, Repairing, and Social Perceptiveness have a negative relationship (with significant estimates ranging from -0.114 to 0.067 in the full model). Controlling for workforce characteristics in the full model (4) does not add much information, although the estimates for the effects of the occupational characteristics again decrease slightly (but remain significant).

There are a few differences to note for the estimates arrived at using the Bachelor's sample: firstly, the inclusion of the skills vector in Model (3) causes the positive estimate for the effect of the number of jobs in the OSN to become significant, and this persists through the full model. Secondly, a slightly different set of skills are related with the probability of reaching a good job with effects that persist through model (4): Coordination (as before) and Programming have a positive association, while Social Perceptiveness (as before) has a negative association (with significant estimates ranging from -0.075 to 0.052 in the full model). Finally, controlling for workforce characteristics in Model (4) causes the effect of whether an occupation requires a college degree to disappear.

Table 4.1: Regression Results: Determinants of the Probability of Reaching a Sustainable Occupation (Less than a Bachelor's)

	Occupational Characteristics	Job Transition Characteristics	Skills Characteristics	Workforce Characteristics
	(1)	(2)	(3)	(4)
const	0.270***	0.629***	0.469**	8.050
	(0.031)	(0.186)	(0.203)	(7.135)
Occ. Predicted Growth	0.420***	0.409***	0.404***	0.383***
	(0.110)	(0.110)	(0.121)	(0.128)
Occ. Wage	0.180***	0.178***	0.164***	0.166***
	(0.028)	(0.027)	(0.029)	(0.031)
Occ. Requires College	0.240***	0.225***	0.148***	0.144***
	(0.041)	(0.041)	(0.044)	(0.044)
Occ. is a first job		-0.758**	-0.310	-0.292
		(0.309)	(0.343)	(0.385)
Occ. is a last job		-0.477	-0.515	-0.599
		(0.405)	(0.421)	(0.465)
Within-Occ Transition Share		0.032	0.041	0.061
		(0.116)	(0.120)	(0.138)
Number of Jobs in OSN		0.004	0.011	0.011
		(0.013)	(0.014)	(0.013)
% of workers with education				-0.012
beyond HS				(0.257)
Industry dummies	Yes	Yes	Yes	Yes
Skill Centrality Variables			Yes	Yes
Decade of Entry dummies				Yes
Region dummies				Yes
Observations	521	521	494	494
R^2	0.574	0.582	0.676	0.678
Adjusted R^2	0.556	0.561	0.631	0.625
Residual Std. Error	0.254	0.253	0.232	0.234
F Statistic	35.222***	33.768***	25.895***	22.114***

Standard errors are heteroskedasticity robust. Numerical variables were re-scaled using Z-score normalization.

*p<0.1; **p<0.05; ***p<0.01

Table 4.2.1.2 shows the results of models estimating the determinants of the probability of reaching a better occupation. Controlling for occupation wages, we find that a number of the job transition characteristics (i.e. the share of within-occupation transitions (-) and the number of jobs in the OSN ((+)) as well as projected employment growth (-) have the strongest relationships with this indicator. Skills appear to have little relationship with mobility here, at least for workers without a Bachelor's.

This time, the coefficients for an occupation's wages and projected growth introduced in model (1) are significant and negative throughout. These wage results were expected, but the growth findings are more difficult to interpret. It is possible that workers in occupations projected to decline know that their job is at risk, and that this causes them to seek out other occupations, or that this decline is ongoing and has already displaced a number of workers into other occupations. Of the variables introduced in Model (2), the share of within-occupation transitions returns a large, negative estimate that persists through the full model, which can be explained by the fact that this measure captures a sort of status quo in the data that is incompatible with reaching better occupations. The number of jobs in the OSN has more moderate positive effect that also persists through the full model. The inclusion of the skills variables in the third model (3) has no substantial effect on the estimates for the effects of the occupational or transitional characteristics. What's more, only a few skills have significant relationships with the probability of reaching a better job that persist through the full model: Programming has a positive effect, while Technology Design has a negative effect (with significant estimates ranging from -0.030 to 0.036 in the full model). Finally, none of the estimates for the workforce controls in the full model (4) are significant.

As before, there are a differences to note for the estimates arrived at using the Bachelor's sample. In the full model, the effect of an occupation's predicted growth has disappeared after the inclusion of the skills vector. However, the frequency at which an occupation is a first job, the share of workers with a Bachelor's degree, and the number of jobs in the network now all have positive and significant estimates. What's more, a larger set of skills are related with the probability of reaching a better job: Programming (as before), Quality Control Analysis, and Reading Comprehension have a positive association, while Coordination, Technology Design (as before), and Writing have a negative association (with significant estimates ranging from -0.103 to 0.053 in the full model).

Table 4.2: Regression Results: Determinants of the Probability of Reaching a Better Occupation (Less than a Bachelor's)

	Occupational Characteristics (1)	Job Transition Characteristics (2)	Skills Characteristics (3)	Workforce Characteristics (4)
const	0.223***	0.424***	0.368***	-1.451
	(0.028)	(0.096)	(0.112)	(5.639)
Occ. Predicted Growth	-0.439***	-0.216***	-0.141*	-0.145*
	(0.091)	(0.068)	(0.075)	(0.081)
Occ. Wage	-0.080***	-0.066***	-0.063***	-0.054***
	(0.011)	(0.009)	(0.014)	(0.014)
Occ. Requires College	0.045*	0.019	0.013	-0.001
	(0.024)	(0.020)	(0.026)	(0.028)
Occ. is a first job		-0.262*	-0.060	-0.114
		(0.153)	(0.175)	(0.181)
Occ. is a last job		-0.115	-0.113	-0.188
		(0.221)	(0.244)	(0.247)
Within-Occ Transition Share		-0.432***	-0.404***	-0.391***
		(0.059)	(0.063)	(0.067)
Number of Jobs in OSN		0.087***	0.091***	0.087***
		(0.008)	(0.009)	(0.010)
% of workers with education				0.047
beyond HS				(0.120)
Industry dummies	Yes	Yes	Yes	Yes
Skill Centrality Variables			Yes	Yes
Decade of Entry dummies				Yes
Region dummies				Yes
Observations	521	521	494	494
R^2	0.209	0.470	0.517	0.533
Adjusted R^2	0.175	0.444	0.450	0.456
Residual Std. Error	0.198	0.163	0.162	0.161
F Statistic	7.821***	17.425***	8.926***	8.359***

Standard errors are heteroskedasticity robust. Numerical variables were re-scaled using Z-score normalization.

*p<0.1; **p<0.05; ***p<0.01

Finally, Table 4.2.1.2 shows the results of models estimating the determinants of the change in mid-career wages. Controlling for occupation wages, we find that workforce educational attainment (-) and a number of skills have the strongest effect on this indicator, although not necessarily in the expected direction.

Again, the coefficients on an occupation's wages introduced in Model (1) are significant and negative throughout, as expected, but no other occupational variable has a similarly lasting effect. Of the transition variables introduced in Model (2), the share of within-occupation transitions returns a large, negative estimate. Again, this can be explained by the fact that this indicator measures a sort of status quo that is incompatible with unlocking higher wages in a way that would be captured by our data. Meanwhile, the number of jobs in the OSN has more moderate positive effect. The inclusion of the skills variables in the third model (3) leads the estimated effects of the share of within-occupation transitions and the number of jobs in the OSN to become insignificant. The skills that have a significant and positive association with the change in wages that persists through the full model are: Complex Problem Solving, Equipment Maintenance, and Installation. The skills that have a negative association that similarly persists are: Programming, Reading Comprehension, Repairing, Systems Evaluation, and Writing (with significant estimates ranging from -0.195 to 0.138 in the full model). Finally, the inclusion of workforce controls in the full model (4) results in the estimated effect of an occupation requiring a college degree to become insignificant. Instead, the share of individuals with education beyond High School is now strongly negatively related to the change in wages.

Comparing these estimates to those arrived at using the Bachelor's sample, a few differences emerge once again. This time, whether an occupation requires a college degree has a significant and negative association with wage changes that persists through the full model. In terms of the transition variables introduced in Model (2), the number of jobs in the OSN has a significant and positive effect that persists through the full model. Finally, a different set of skills are related with the change in wages: Management of Personnel Resources, Programming (as before), Reading Comprehension (as before), and Time Management all have a significant, negative associations (with significant estimates ranging from -0.121 to -0.048 in the full model).

Table 4.3: Regression Results: Determinants of the Change in Mid-Career Wages (Less than a Bachelor's)

	Occupational Characteristics	Job Transition Characteristics	Skills Characteristics	Workforce Characteristics
	(1)	(2)	(3)	(4)
const	0.422***	0.056	0.376*	-1.230
	(0.029)	(0.179)	(0.193)	(8.440)
Occ. Predicted Growth	0.124	0.256	0.006	-0.043
	(0.163)	(0.162)	(0.164)	(0.162)
Occ. Wage	-0.329***	-0.316***	-0.284***	-0.273***
	(0.028)	(0.026)	(0.028)	(0.027)
Occ. Requires College	-0.112***	-0.109***	0.007	-0.055
	(0.035)	(0.034)	(0.040)	(0.040)
Occ. is a first job		0.827**	0.103	-0.022
		(0.348)	(0.357)	(0.384)
Occ. is alast job		0.692*	0.314	-0.097
		(0.366)	(0.375)	(0.365)
Within-Occ Transition Share		-0.394***	-0.366***	-0.144
		(0.102)	(0.105)	(0.102)
Number of Jobs in OSN		0.037***	0.022	0.018
		(0.014)	(0.014)	(0.014)
% of workers with education				-0.709***
beyond HS				(0.175)
Industry dummies	Yes	Yes	Yes	Yes
Skill Centrality Variables			Yes	Yes
Decade of Entry dummies				Yes
Region dummies				Yes
Observations	521	521	494	494
R^2	0.717	0.736	0.796	0.812
Adjusted R^2	0.705	0.723	0.768	0.781
Residual Std. Error	0.277	0.269	0.245	0.238
F Statistic	49.169***	47.234***	27.868***	26.537***

Standard errors are heteroskedasticity robust. Numerical variables were re-scaled using Z-score normalization.

*p<0.1; **p<0.05; ***p<0.01

4.2.2 Exploring How Skills Requirements Evolve over Sustainable and Unsustainable Paths

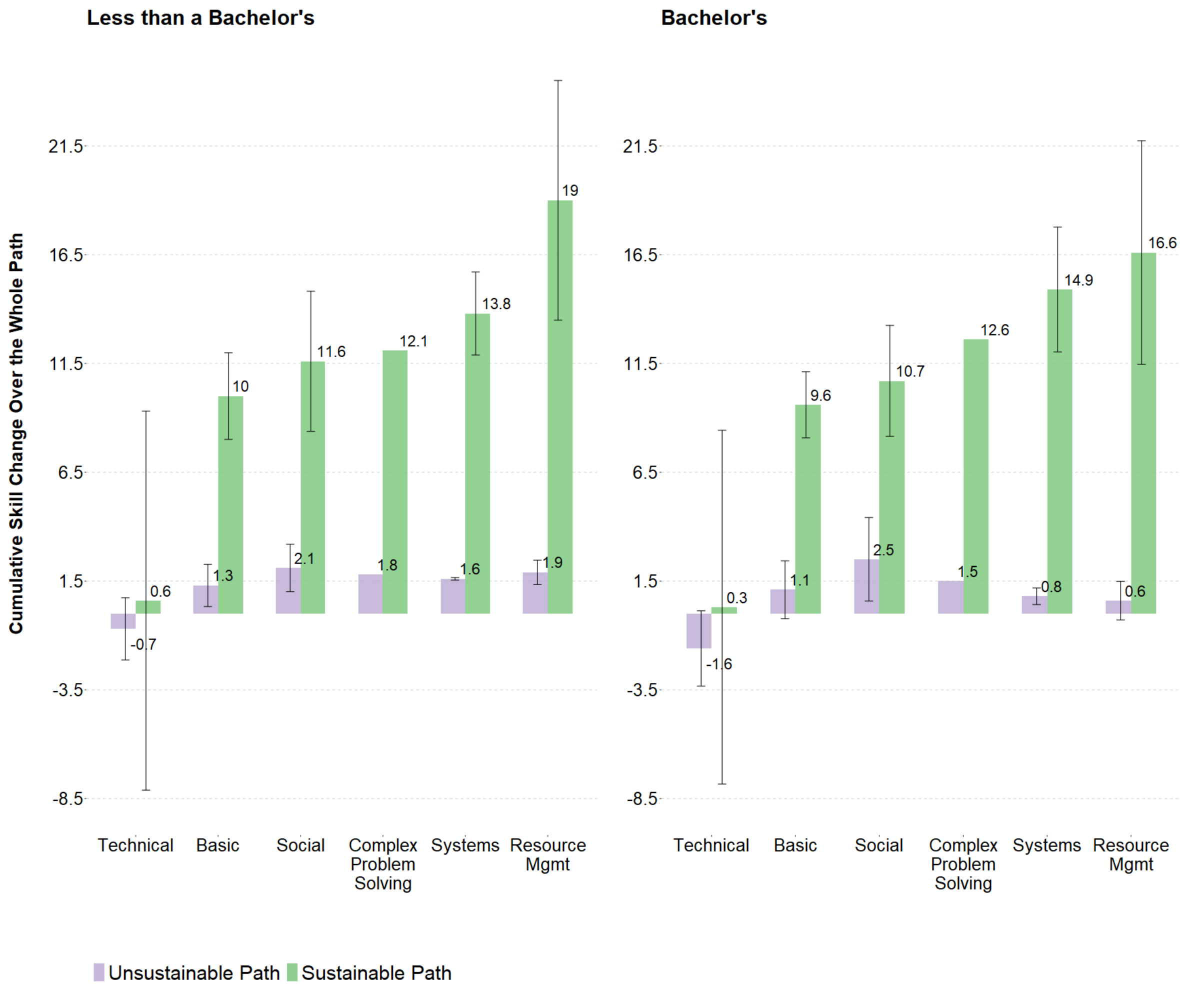
Now that we have investigated how skills requirements vary at baseline, we'll look briefly at how they might evolve differently over career paths that end in sustainable occupations and career paths that end in unsustainable occupations. To do this, we compute cumulative changes in centrality for each skill over each career path in an occupation's OSN. We then aggregate those changes by whether paths end in a sustainable or unsustainable occupation, weighing the averages by the path probability calculated as in section 3.4.0.1. As before, this analysis focuses exclusively on paths originating in unsustainable occupations, because we are more interested in how their development prospects can be increased. Figure 4-9 below displays a summary of the results, the full set of which can be found in table B of the Appendix. For convenience, we'll define a *sustainable path* as any path that starts in an unsustainable occupation but ends in a sustainable occupation, and an *unsustainable path* as any path that starts and ends in an unsustainable occupation.

A general takeaway is that skill requirements grow more over sustainable paths than they do over unsustainable paths. The extent to which this is true varies by skill type. Resource Management skills and Systems skills appear to show the greatest level of differentiation, followed by Complex Problem Solving. These sets of skills all seem typical of managerial occupations that require high-level decision making, so this is in some ways unsurprising. Perhaps more surprisingly is the lack of difference in growth of technical skills between both types of paths. However, technical skills cover a wide range of faculties[7], and the large standard deviation bars suggest that our graph may not be painting a full picture. In fact, looking at the specific skills differences in table B of the Appendix reveals that most technical skills actually grow more over unsustainable paths, with the exception of Operations Analysis, which is near the top of ranking of skills growing the most in sustainable paths relative to unsustainable paths (3 out of 35 for people without a Bachelor's, 2 out of 35 for people with a Bachelor's degree). Ultimately, it appears that sustainable paths steer workers towards more managerial responsibilities rather than increased technical responsibilities. However, it should be noted

[7]Equipment Maintenance, Equipment Selection, Installation, Operation and Control, Operations Analysis, Operations Monitoring, Programming, Quality Control Analysis, Repairing, Technology Design, Troubleshooting

that these findings may reflect a potential white-collar bias in our resume data.

Figure 4-9: Difference in Skill Changes Over Sustainable and Unsustainable Paths, by Highest Educational Attainment



Note: The averages are not weighted by the prevalence of the occupations in the employment profiles data.

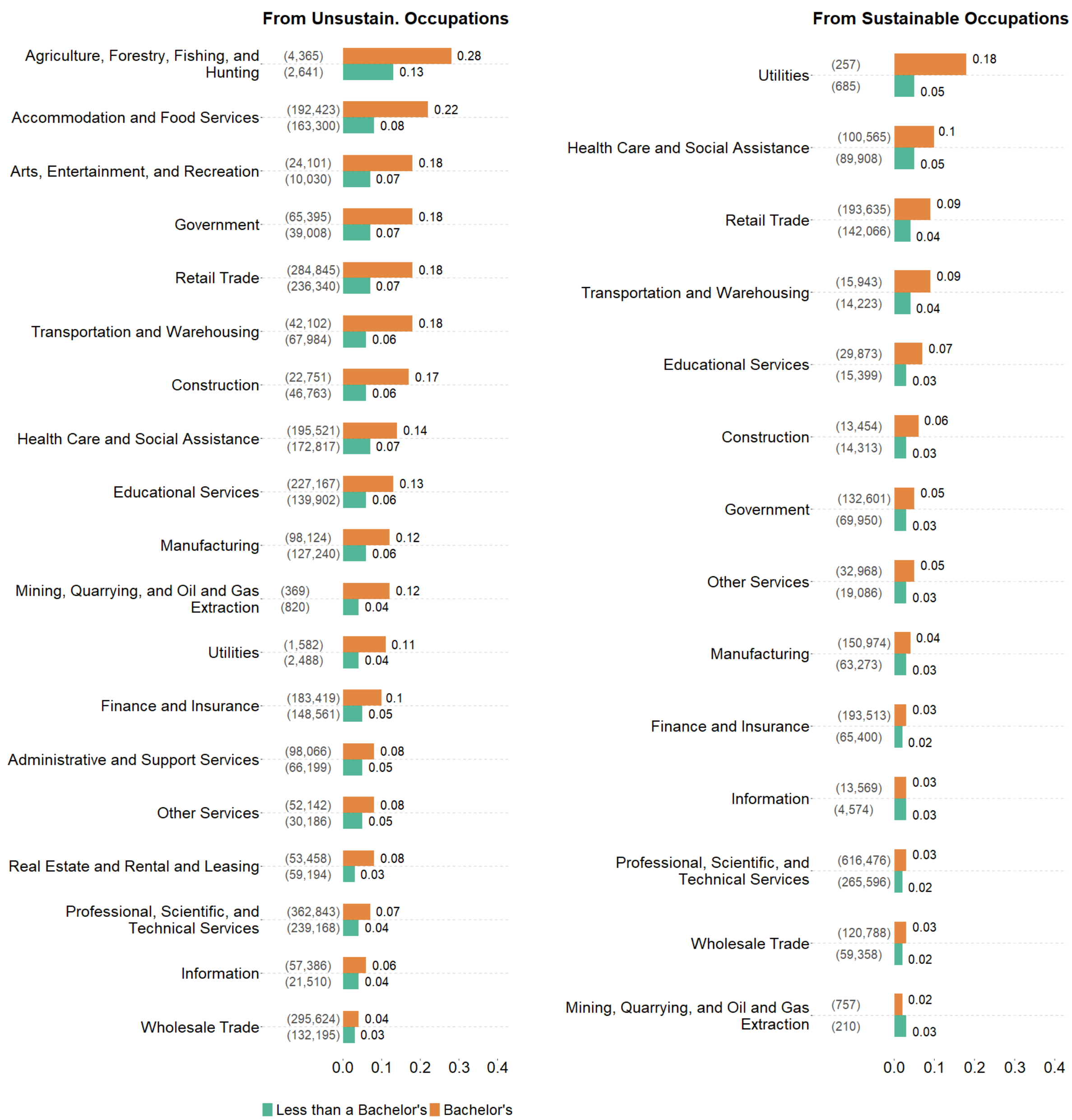
4.3 Characterizing the Dynamic at Work: Skills Growth versus Skills Transfer

As discussed in the introduction to this paper, two branches of career advice have characterized the response to the challenge of helping displaced workers find suitable employment. The *skills growth* variety suggests that human capital investments- through training, schooling, or apprenticeships- are key to progressing professionally. More recently, a number of voices have suggested a *skills transfer* approach, asking whether the worker's existing expertise could have higher returns in a different occupation. In this section, we'll attempt to tease out whether a *skills growth* or *skills transfer* dynamic is most characteristic of what is currently happening on the ground, and what kind of factors may drive which of the two mechanism prevails. Given that skills requirements tend to grow more over sustainable career paths (as seen in section 4.2.2), we'll be particularly interested in the determinants of skill growth over a single transition. Overall, we find that educational investments are more often involved in transitions from unsustainable occupations than from sustainable occupations, which may reflect workers' perception that they need to invest in more education in order to leave these types of precarious employment. Educational investments are also more prevalent in job transitions that occur between industries, possibly because they facilitate more radical career changes that would otherwise be difficult. Finally, models of the determinants of skill change over a job transition reveal that longer work experience does facilitate transitions between jobs with higher skills distance, as does baseline education level for workers with a Bachelor's. The impact of additional educational investment in between jobs is less clear; for workers without a Bachelor's, it is negatively related to skills growth, possibly because these investments are more characteristic of cross-industry transitions that may require workers to rely on entirely new skill sets.

4.3.1 The prevalence of post-labor market entry educational investments

We'll begin by investigating how often educational investments support a job transition, by calculating the share of job transitions that include a new degree. Specifically, this phenomenon occurs any time two consecutive professional records are separated by an educational record in the employment profile data. Figure 4-10 below shows the results of this analysis for the two education groups, grouped by the industry and type of the origin occupation. Overall, we find that education is more often involved in transitions from unsustainable occupations, while certifications are roughly equally involved in transitions from unsustainable and sustainable occupations.

Figure 4-10: Share of Transitions that Include an Educational Investment, by Origin Occupation Industry and Highest Educational Attainment



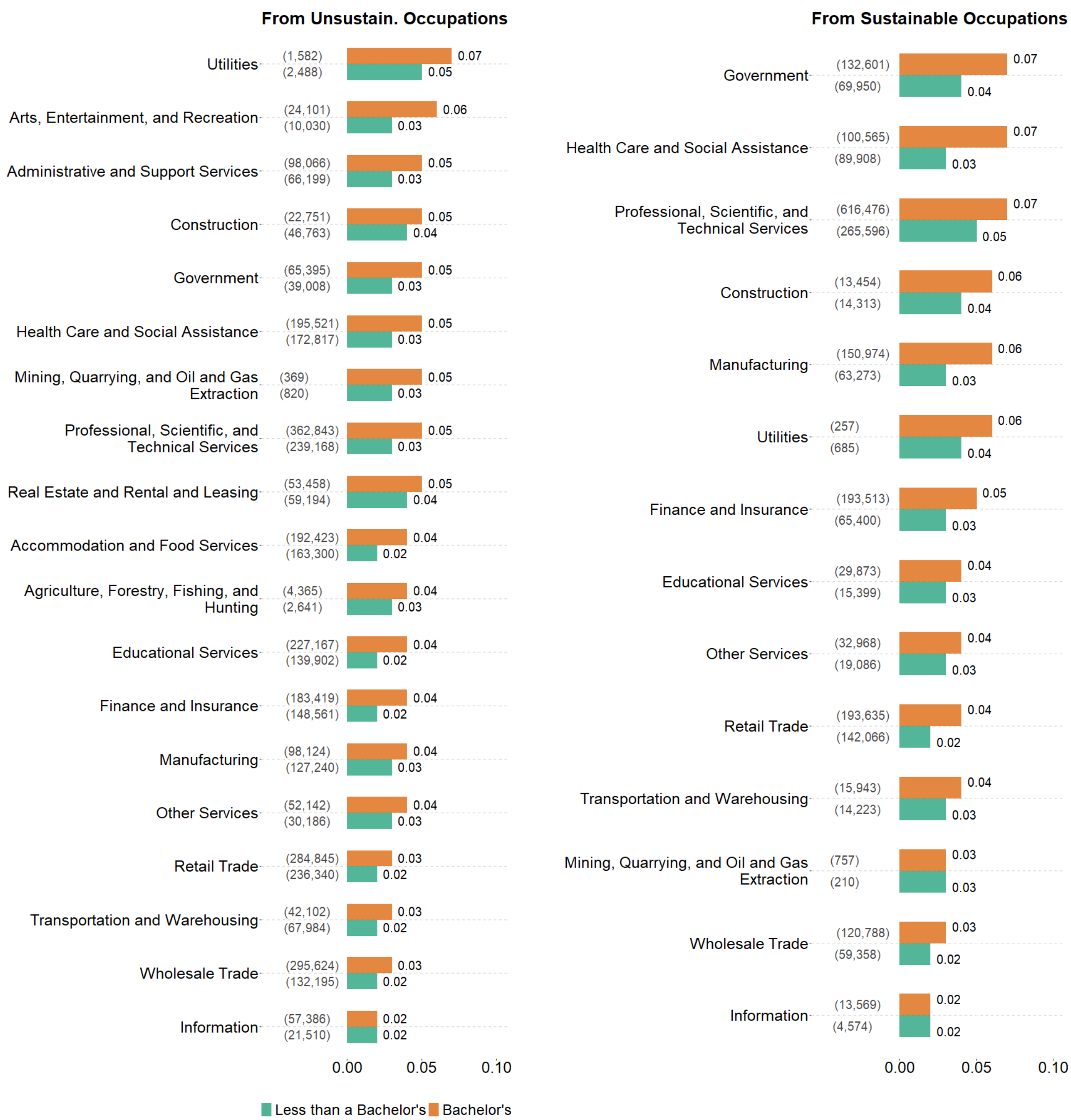
Note: The number in parentheses indicates the number of unique transitions that started from an occupation in that group. The averages of occupational mobility scores across industries are weighted by the prevalence of the origin occupation in the job transition data.

The graph above suggests that educational investments are more often involved in workers with a Bachelor's job transitions than they are for workers without a Bachelor's, although this may be a redundant observation given that one group has a higher educational ceiling than the other. Perhaps more interesting is the divide between occupation type: job transitions from unsustainable occupations have up to 2.5 times[8] the chance of involving an educational investment than transitions from sustainable occupations (for people without a Bachelor's, 6 times[9] for people with a Bachelor's). This trend may reflect workers' perception that they need to invest in more education in order to unlock access to stable prospects. On the flip side, it may also reflect the fact that workers in sustainable occupations feel more confident that they can remain within a similarly comfortable profession without paying an additional cost.

Figure 4-11 below shows the results of a similar analysis that computes the share of consecutive professional experiences that are separated by the reception of a new certification. The overall picture is markedly different from before. First, although the difference between the two education groups remains, it is substantially reduced. Second, the difference between transitions from unsustainable and sustainable occupations has largely disappeared. This suggests that certifications are perceived to be equally useful by people with and without a Bachelor's, and that they may not lose their appeal even for people in sustainable occupations. Still, it should be noted that the fractions of transitions that involve certifications remains generally small, never going beyond ten percent within a sub-group. In contrast, additional education underlies up to nearly a third of transitions for some groups and occupations. Still, most transitions are not contingent upon additional human capital investment beyond what the worker may already possess at baseline.

[8]in Finance and Insurance
[9]in Mining

Figure 4-11: Share of Occupational Transition that Include a Certification, by Origin Occupation Industry and Highest Educational Attainment



Note: The number in parentheses indicates the number of unique transitions that started from an occupation in that group. The averages of occupational mobility scores across industries are weighted by the prevalence of the origin occupation in the job transition data.

4.3.2 Predictors of Skills Growth in a Job Transitions

To understand when *skills growth* might prevail over *skills transfer* and vice versa, this section presents the results of OLS regression models where the independent variable is the sum of changes across all skills in a single transition, and the dependent variables are various individual characteristics and attributes of the origin occupation. Unlike the analysis in section 4.2.1.2, which was conducted at the occupational level, this analysis leverages the individual transition data, but standard errors are adjusted for clustering at the origin occupation level. Overall, we find that the time spent in the origin occupation, the length of the career up that point, and the receipt of a new certification all have a positive relationship with skills growth. Meanwhile, for workers without a Bachelor's, making an additional educational investment in between two jobs has a negative relationship with skills growth, a finding that is possibly explained by the fact that education is more characteristic of cross-industry transitions that could require workers to rely on entirely new skill sets. For workers with a Bachelor's on the other hand, baseline educational attainment is found to have a positive effect on skills growth in job transitions down the line.

We first model (1) the relationship between skills growth over a job transition and a vector of occupational characteristics that includes the sum of skill centrality values required by the origin occupation, as well as the origin occupation's wages and predicted employment growth over the next ten years. In the second model (2), we'll add a vector of individual characteristics to the predictor set that includes career length up to that point[10], dummies indicating the decade when the individual first entered the labor market, the amount of time the individual spent in the origin occupation prior to the transition, their highest educational attainment at the time that they began working at the origin occupation, and whether they made an additional investment in education or certifications before joining the destination occupation. Finally, the third and full model (3) will add a vector of workforce characteristics that includes origin industry dummies and region dummies. To summarize, the full model will be of the form:

$$\Delta S_{j,d} = \beta_j OC_{j,n} + \gamma_k I_{i,k} + \lambda_m WF_{j,m} + e_{i,j}$$

where $\Delta S_{j,d}$ is the total skill difference between two occupations in a transition starting from

[10] the amount of time the individual spent in the labor market up to that transition

occupation j made by an individual i, $OC_{j,n}$ is the vector of n origin occupation attributes, $I_{j,k}$ is the vector of k individual attributes, and $WF_{j,m}$ is the vector of workforce controls.

Table 4.3.2 below provides the results of the models estimating the determinants of skill growth over a single job transition for individuals without a Bachelor's. The first model (1), which includes only the occupational characteristics in the predictor set, captures about a quarter of the variance. Only the estimated coefficient for the origin occupation's total skill requirements suggests a strong, negative association with skills growth that persists through the full model (3). This is to be expected, similar to how transitions from low-wage occupations having a higher probability of unlocking higher wages. Neither origin occupation wage nor origin occupation growth are found to have any effect. The addition of individual characteristic in the second model (2) does not improve the model's explanatory power by much, but it provides some interesting new information. First, the length of the career up to that point is found to have a positive and significant association with skills growth. This might indicate that employers do substitute professional experience for education when making hiring decisions, since larger jumps in skill requirements seem to be correlated with more experience. On the flip side, making an educational investment is negatively associated with skills growth, while acquiring a new certification is positively associated with the response variable. One explanation for this finding could be that workers rely more heavily upon educational investments to make career changes that require them to practice a whole new set of skills at an overall lower level, since they are now new entrants to a field. On the other hand, certifications may be more typical of transitions requiring skills growth within the same field. In fact, further analysis reveals that educational investments are present in 6% of job transitions that involve different industries (for people without a Bachelor's, 11% for people with a Bachelor's), but only 3% of job transitions that are within the same industry (for people without a Bachelor's, 6% for people with a Bachelor's). Conversely, certifications are equally present in 3% of job transitions that involve the same or different industries (for people without a Bachelor's, 5% and 4% for people with a Bachelor's, respectively). Full results of this investigation broken down by industry can be found in Table B of the Appendix.

Finally, the introduction of workforce characteristics in model (3) similarly has little effect on the model's explanatory power, but it does result in the coefficient for the time spent in the origin occupation becoming significant, lending further support to the theory that more professional experience facilitates transitions with larger jumps in overall skill requirements.

Table 4.4: Regression Results: Determinants of Skill Growth in Occupational Transitions (Less than a Bachelor's)

	Occupational Characteristics	Individual Characteristics	Workforce Characteristics
	(1)	(2)	(3)
const	1.367**	2.699***	4.406***
	(0.549)	(0.552)	(1.129)
Occ. Sum of Skill Requirements	-11.014***	-11.242***	-11.434***
	(0.575)	(0.569)	(0.517)
Occ. Wage	-0.311	-0.697	-1.286
	(0.945)	(0.894)	(0.889)
Occ. Predicted Growth	2.221	4.285	7.660
	(4.615)	(4.627)	(5.126)
Career Length		1.544***	1.472***
		(0.192)	(0.188)
Time Spent in Occ.		0.204	0.280**
		(0.139)	(0.120)
Education beyond HS		-0.354	-0.215
		(0.261)	(0.260)
Educational Investment		-3.157***	-2.874***
		(0.480)	(0.457)
Certification Investment		2.899***	2.611***
		(0.246)	(0.198)
Entry decade dummies		Yes	Yes
Industry Dummies			Yes
Region Dummies			Yes
Observations	2,410,971	2,410,971	2,410,971
R^2	0.254	0.264	0.272
Adjusted R^2	0.254	0.264	0.272
Residual Std. Error	19.251	19.125	19.019
F Statistic	246.255***	154.075***	106.674***

Standard errors are cluster-robust.

Numerical variables were re-scaled using Z-score normalization.

*p<0.1; **p<0.05; ***p<0.01

Table 4.3.2 displays the results of the same analysis using the population of workers who ultimately obtain a Bachelor's degree. The patterns in estimates are the same as before, with few exceptions. Firstly, the positive estimate for the effect of the time spent in the origin occupation is significant from its inclusion in model (2), and not just with the addition of the workforce characteristics in model (3). Secondly, the coefficients for the effect of additional educational investments are no longer significant. However, greater baseline educational attainment (introduced in model (2)) now has a positive and significant association with skills growth that persists through the full model (3). As a reminder, these two measures are not the same, the latter capturing the highest level of educational investment at the time that a worker was employed into the origin occupation, and the former capturing whether additional investments were made before joining the destination occupation. As such, this finding can be interpreted to mean that having greater educational attainment at baseline facilitates higher skills distance transitions down the line, potentially for signalling reasons. As before, the inclusion of workforce characteristics in model (3) does not affect our results very much.

Table 4.5: Regression Results: Determinants of Skill Growth in Occupational Transitions (Bachelor's)

	Occupational Characteristics	Individual Characteristics	Workforce Characteristics
	(1)	(2)	(3)
const	2.026***	-2.736***	2.779**
	(0.565)	(0.737)	(1.377)
Occ. Sum of Skill Requirements	-11.232***	-11.545***	-12.296***
	(0.604)	(0.590)	(0.509)
Occ. Wage	0.392	-0.476	-0.643
	(0.891)	(0.809)	(0.761)
Occ. Predicted Growth	2.231	4.514	6.235
	(4.526)	(4.125)	(4.873)
Career Length		1.695***	1.673***
		(0.187)	(0.186)
Time Spent in Occ.		0.344***	0.416***
		(0.129)	(0.116)
Educational Investment		-0.079	0.023
		(0.190)	(0.191)
Certification Investment		2.393***	2.183***
		(0.198)	(0.191)
College Degree		5.888***	5.815***
		(0.396)	(0.352)
Education beyond HS		2.186***	2.240***
		(0.360)	(0.372)
Entry decade dummies		Yes	Yes
Industry Dummies			Yes
Region Dummies			Yes
Observations	3,639,843	3,639,843	3,639,843
R^2	0.272	0.292	0.303
Adjusted R^2	0.272	0.292	0.303
Residual Std. Error	17.752	17.511	17.381
F Statistic	219.295***	114.712***	129.711***

Standard errors are cluster-robust.

Numerical variables were re-scaled using Z-score normalization.

*p<0.1; **p<0.05; ***p<0.01

4.4 Manufacturing Case Study

In this section, we'll delve deeper into some of our previous analyses by using the manufacturing industry as a case study. Whenever relevant, we'll try to 1) identify occupations with high mobility potential, 2) identify the skills that are most commonly required by high potential jobs to help inform up-skilling and re-skilling efforts, and 3) identify opportunities to retain and recruit workers who may otherwise leave manufacturing.

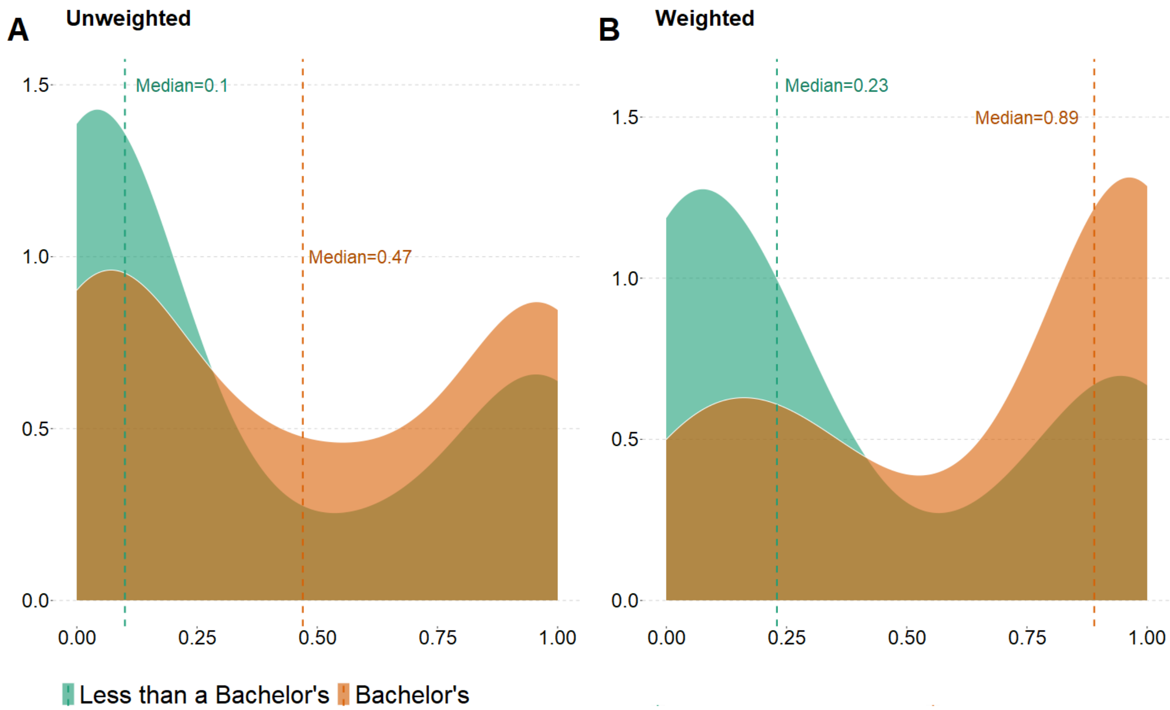
4.4.1 How is mobility distributed across occupations in manufacturing?

Figures 4-12 and 4-13 below show the distribution of mobility scores for occupations in manufacturing, first broken up by educational attainment of workers, and then by education and occupation type. We'll focus on the probability of reaching a sustainable job, because it has revealed itself to be the most useful indicator for this analysis. The distribution of the other indicators can be found in Figures B-5 through B-8 of the appendix.

Comparing with the distribution of this indicator across all industries (in Figures 4-2 and B-2), we see that manufacturing offers similar upward mobility prospects to workers without a Bachelor's degree than other industries. However, it offers substantially better access to sustainable occupations to workers with a Bachelor's. This difference is probably driven by the fact that the manufacturing industry comprises a larger number of sustainable occupations relative to other occupations [11], and that these occupations are generally more accessible to those with a Bachelor's degree. In fact, figure 4-13 confirms that, as in the general analysis, workers starting in sustainable occupations have a much higher chance of reaching a sustainable occupation than workers starting in unsustainable occupations, regardless of their educational attainment.

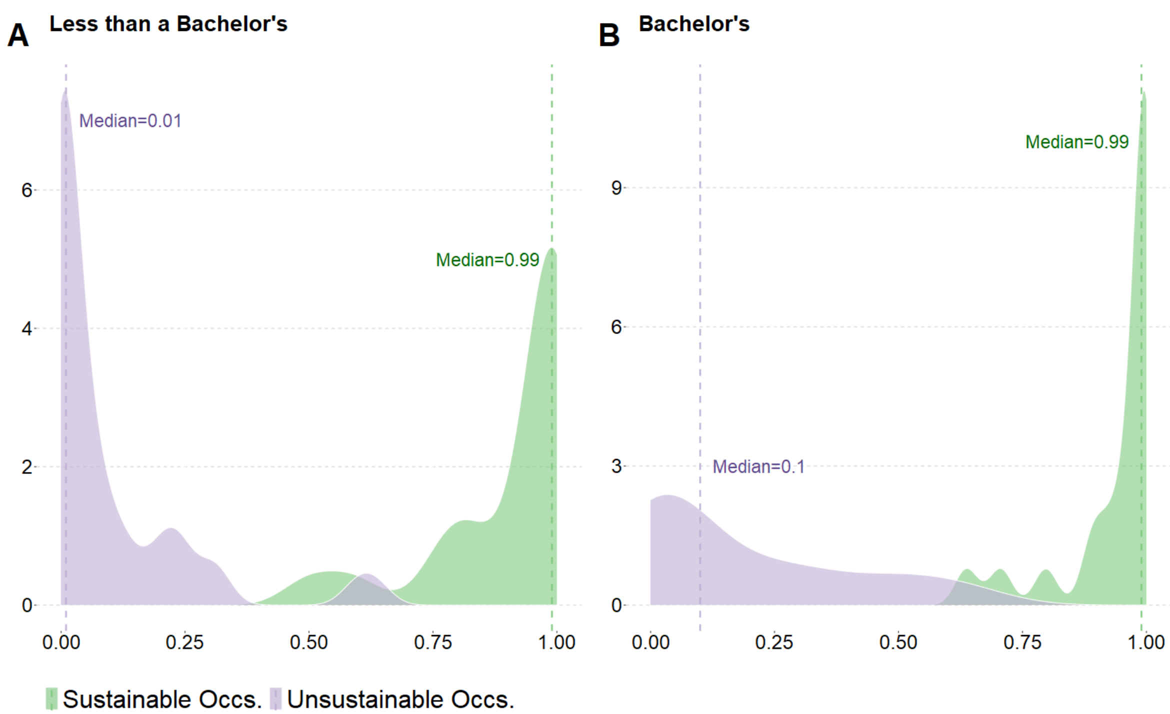
[11] It is the 7th industry out of 19 in terms of its share of sustainable occupations. See Table 3.4 for more details.

Figure 4-12: Distribution of the Probability of Reaching a Sustainable Occupation Across Manufacturing Occupations, by Highest Educational Attainment



Note: Graph A does not take into account the prevalence of the occupations in the employment profiles data. Graph B shows the distribution of scores weighted by the prevalence of the occupation in the employment profiles data.

Figure 4-13: Distribution of the Probability of Reaching a Sustainable Occupation Across Manufacturing Occupations, by Highest Educational Attainment and Occupation Type



Note: These graphs do not take into account the prevalence of the occupations in the employment profiles data.

4.4.2 What are the manufacturing occupations with high mobility potential?

As before, we'll focus primarily on unsustainable occupations because workers in those professions have the most to gain from interventions. Table 4.4.2 below leverages all of our occupational mobility measures to identify the unsustainable occupations in manufacturing that have the highest mobility potential. To achieve this, the manufacturing occupations are sorted in descending order 1) first, by their probability of reaching a sustainable job, 2) second, by their probability of reaching a better job, 3) third, by their mid-career wage change, and 4) finally by the number of jobs in their Occupation-Specific Network (OSN). The top ten occupations are then retained. This approach prioritizes the most relevant indicator for this sub-group of jobs (the probability of reaching a sustainable occupation) but allows the other indicators to break ties. Results are shown below, broken down by education group.

A number of occupations appear in the top of the rankings regardless of educational attainment: "Chemical Technicians", "Occupational Health and Safety Technicians", "First-Line Supervisors of Production and Operating Workers", "Inspectors, Testers, Sorters, Samplers, and Weighers", and "Mechanical Drafters". In general, technician roles abound across both rankings, while few managerial roles appear. It should be noted that even though these are the top-ranked professions, the probability of reaching a sustainable job remains low for many of these roles. What's more, the potential for salary growth appears to be generally smaller for people without a Bachelor's than for people with a Bachelor's degree.

Conversely, table 4.4.2 below lays out the unsustainable occupations in manufacturing that have the lowest mobility potential, and whose workers could benefit the most from targeted policy interventions. To identify these occupations, the manufacturing occupations are sorted 1) first, in ascending order by their probability of reaching a sustainable job, 2) second, in descending order by the number of jobs in their OSN, and 3) finally, in ascending order by their mid-career wage change.[12]

As before, a number of technician roles are also prevalent throughout the rankings, although this time there are no managerial roles. Occupations that appear in both rankings regardless of educational attainment are: "Avionics Technicians", "Industrial Machinery Mechanics", "Dental Laboratory Technicians", "Welders, Cutters, and Welder Fitters", and the very general "Production Workers, All Other". As such, the workers in these occupations who wish to progress in their career may benefit from additional career guidance.

4.4.3 Which skills should manufacturing workers leverage?

In this section, we'll identify the particular skills that characterize high-mobility potential occupations, as well as the skills that tend to be increasingly more required over careers that end in sustainable occupations. As we have seen in the past, the skills that best equip workers at baseline are not necessarily the ones that may help them grow over the course of their careers, suggesting that education interventions should target different skill sets depending on the stage of their career that their clients are in.

[12]The reason for this different ranking approach is to take into account the fact when there are no or few career paths associated with an occupation, then the number of jobs in its network and its probability of reaching a better or sustainable occupation will all trend towards zero. As such, we prioritize the indicator measuring the probability of reaching a sustainable job as before, but we try to balance the network approach by prioritizing jobs with low odds despite having a number of career paths in the network.

4.4.3.1 Are there differences in skill requirements between occupations with high and low mobility potential?

In this analysis, we'll try to identify the skills that might be most useful to manufacturing workers by investigating whether job requirements differ between unsustainable occupations with high and low mobility potential. In particular, we'll partition jobs by their probability of reaching a sustainable occupation, since that appears to be the most relevant indicator for unsustainable jobs. We'll define high-mobility jobs as any job with a probability of 25% or more of reaching a sustainable occupation, and low-mobility jobs as any job with a probability of 5% or less of reaching a sustainable occupation. Although the cutoff for high-mobility jobs may appear low, this reflects the unfortunate reality that unsustainable occupations have generally low odds of reaching sustainable occupations. Table 4.4.3.1 computes the average difference in skill centrality values between these high and low mobility occupations (unweighted by their prevalence in the data) and evaluates whether these differences are significant overall. The skills are ordered in descending order of difference, where a positive difference indicates that high-mobility occupations tend to require more of a skill than low-mobility occupations, and conversely a negative difference indicates that low-mobility occupations tend to require more of a skill than high-mobility occupations.

As we have seen in the general analysis in section 4.2.1.1, technical skills such as Repairing or Installation tend to be more characteristic of low-mobility occupations, regardless of educational attainment. A notable exception is that high-mobility occupations tend to require much higher levels of Operations Analysis than low-mobility occupations, at least for workers with a Bachelor's degree. In general, high-mobility occupations require higher levels of basic skills such as Writing or Active Listening, as well as a number of social skills (Negotiation, Persuasion). A number of management skills also rank high across both rankings (Management of Personnel Resources for people without a Bachelor's, Management of Financial Resources for people with a Bachelor's degree), while a systems-level skill (Systems Analysis) also appears high in the ranking for people without a Bachelor's.

4.4.3.2 Are there differences in how skill requirements evolve over sustainable and unsustainable career paths?

Now that we have investigated how skills requirements vary at baseline, we'll look briefly at how they might evolve differently over career paths that end in sustainable occupations and career paths that end in unsustainable occupations. As in section 4.2.2, we'll compute cumulative changes in centrality for each skill over each career path in an occupation's OSN. We'll then aggregate those changes by whether paths end in a sustainable or unsustainable occupation, weighing the averages by the path probability calculated as in section 3.4.0.1. As before, this analysis focuses exclusively on paths originating in unsustainable manufacturing occupations. The results are shown in table 4.4.3.2 below, where a positive difference indicates that the demand for a skills tends to increase more over paths that end in sustainable occupations, while a negative difference indicates that the demand for a skills tends to increase more over paths that end in unsustainable occupations.

Again, the results echo those of the general analysis in section 4.2.2. With regards to the rankings for people without a Bachelor's, it is clear that management skills are much more emphasized in career paths that end in sustainable occupations (Management of Financial Resources, Management of Personnel Resources Management of Material Resources), as are a number of social skills (Negotiation, Persuasion, Social Perceptiveness). With the exception of Operations Analysis, nearly all of the technical skills appear to be more emphasized in career paths that end in unsustainable occupations. In terms of the ranking for people with a Bachelor's degree, the emphasis seems to be on Operations Analysis as well as a number of Systems-level (Systems Analysis and Systems Evaluation) and management skills (as before: Management of Financial Resources, Management of Personnel Resources Management of Material Resources). Again, save for Operations Analysis, the technical skills appear to be more emphasized in paths that end in unsustainable occupations. However, as previously discussed, it is possible that these findings are influenced by a potential white-collar bias in our resume data.

Table 4.6: Unsustainable manufacturing occupations with the highest occupational mobility scores, by highest educational attainment

Group	Occupation	Probability Sustainable	Probability Better	Mid-Career Wage Change	Number of Jobs in OSN
Less than a Bachelor's	Chemical Technicians (74)	0.64	0.64	0.42	3
	Occupational Health and Safety Technicians (347)	0.60	0.60	0.60	1
	Mixing and Blending Machine Setters, Operators, and Tenders (54)	0.31	0.74	0.80	12
	First-Line Supervisors of Production and Operating Workers (4,264)	0.30	0.36	0.27	6
	Production, Planning, and Expediting Clerks (1,145)	0.25	0.31	0.50	5
	Inspectors, Testers, Sorters, Samplers, and Weighers (2,171)	0.23	0.24	0.84	6
	Maintenance Workers, Machinery (2,282)	0.23	0.24	0.45	7
	Mechanical Drafters (1,394)	0.20	0.20	0.34	10
	Industrial Engineering Technicians (694)	0.19	0.19	0.31	7
	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers (53)	0.13	0.73	0.90	9
Bachelor's	Chemical Technicians (248)	0.66	0.73	0.85	3
	Food Science Technicians (79)	0.62	0.64	1.26	10
	Occupational Health and Safety Technicians (486)	0.58	0.58	0.58	1
	Helpers–Production Workers (67)	0.52	1.00	1.56	9
	Printing Press Operators (179)	0.48	0.78	1.10	11
	Mechanical Drafters (638)	0.47	0.48	0.50	9
	First-Line Supervisors of Production and Operating Workers (3,358)	0.39	0.42	0.43	5
	Inspectors, Testers, Sorters, Samplers, and Weighers (1,584)	0.35	0.37	1.11	5
	Cabinetmakers and Bench Carpenters (49)	0.28	0.65	1.59	6
	Tool and Die Makers (51)	0.27	0.27	0.58	19

Notes: Unsustainable manufacturing occupations are sorted in descending order 1) first, by their probability of reaching a sustainable job, 2) second, by their probability of reaching a better job, 3) third, by their mid-career wage change, and 4) finally by the number of jobs in their Occupation-Specific Network (OSN). The number in parentheses represents the number of times that occupation appears in the employment profile data.

Table 4.7: Unsustainable manufacturing occupations with the lowest occupational mobility scores, by highest educational attainment

Group	Occupation	Probability Sustainable	Probability Better	Mid-Career Wage Change	Number of Jobs in OSN
Less than a Bachelor's	Electro-Mechanical Technicians (1,236)	0	0.13	0.27	2
	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic (55)	0	0.27	0.35	2
	Industrial Machinery Mechanics (493)	0	0.20	0.35	2
	Packers and Packagers, Hand (381)	0	0.69	1.11	2
	Electronics Engineering Technicians (1,685)	0	0.00	0.13	1
	Chemical Equipment Operators and Tenders (119)	0	0.00	0.31	1
	Dental Laboratory Technicians (422)	0	0.00	0.47	1
	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic (194)	0	0.35	0.62	1
	Printing Press Operators (109)	0	0.39	0.69	1
	Electrical and Electronic Equipment Assemblers (538)	0	0.43	0.72	1
Bachelor's	Electrical and Electronic Equipment Assemblers (143)	0	0.43	1.07	1
	Packers and Packagers, Hand (34)	0	1.00	1.24	1
	Molding and Casting Workers (56)	0	0.43	1.47	1
	Avionics Technicians (188)	0	0.00	0.31	0
	Manufacturing Production Technicians (203)	0	0.00	0.37	0
	Industrial Engineering Technicians (97)	0	0.00	0.56	0
	Industrial Machinery Mechanics (55)	0	0.00	0.56	0
	Dental Laboratory Technicians (86)	0	0.00	0.76	0
	Production Workers, All Other (1,419)	0	0.00	0.76	0
	Machinists (371)	0	0.00	0.93	0

Notes: Unsustainable manufacturing occupations are sorted 1) first, in ascending order by their probability of reaching a sustainable job, 2) second, in descending order by the number of jobs in their OSN, and 3) finally, in ascending order by their mid-career wage change. The number in parentheses represents the number of times that occupation appears in the employment profile data.

Table 4.8: Skill differences between unsustainable manufacturing occupations in the top and bottom of the rankings of the probability of reaching a sustainable job

Less than a Bachelor's	**Δ(Top - Bottom)**		**Bachelor's**	**Δ(Top - Bottom)**	
	difference	p-value		difference	p-value
Writing	15.9	**	Speaking	4.4	
Science	14.7		Active Listening	4.3	
Negotiation	13.8	**	Negotiation	3.9	
Active Listening	13.6	*	Operations Analysis	3.8	
Reading Comprehension	12.9	*	Mgmt of Financial Resources	3.7	
Mgmt of Personnel Resources	11.7	.	Reading Comprehension	3.5	
Speaking	11.5	*	Writing	3.4	
Systems Analysis	11.5	***	Persuasion	3.1	
Persuasion	11.4	*	Coordination	2.2	
Mgmt of Financial Resources	11.0	*	Mgmt of Material Resources	2.2	
Learning Strategies	10.3	*	Social Perceptiveness	2.1	
Critical Thinking	10.3	*	Mgmt of Personnel Resources	2.1	
Service Orientation	10.2	*	Time Mgmt	2.0	
Mgmt of Material Resources	9.5	*	Mathematics	1.8	
Time Mgmt	9.1	*	Service Orientation	1.7	
Monitoring	8.9	*	Critical Thinking	1.1	
Social Perceptiveness	8.9	.	Judgment and Decision Making	0.8	
Systems Evaluation	8.8	.	Active Learning	0.7	
Operations Analysis	7.7		Learning Strategies	0.5	
Active Learning	7.3	*	Monitoring	0.3	
Instructing	7.1	.	Complex Problem Solving	0.3	
Coordination	6.3		Systems Evaluation	0.2	
Judgment and Decision Making	5.8	*	Systems Analysis	0.0	
Complex Problem Solving	5.3	*	Quality Control Analysis	-0.6	
Mathematics	4.0		Instructing	-0.8	
Programming	-0.1		Science	-1.2	
Technology Design	-0.5		Technology Design	-1.2	
Operations Monitoring	-4.2		Troubleshooting	-2.3	
Quality Control Analysis	-4.9		Programming	-2.7	
Operation and Control	-6.8		Operations Monitoring	-2.7	
Troubleshooting	-8.8		Operation and Control	-3.1	
Equipment Selection	-10.0		Equipment Selection	-5.1	
Equipment Maintenance	-11.8		Equipment Maintenance	-6.5	
Repairing	-12.6		Repairing	-10.0	
Installation	-12.7	***	Installation	-10.7	.

Notes: Unsustainable occupations only. Signif. codes: *** (p <= 0.001), ** (p <= 0.01), * (p <= 0.05), . (p <= 0.1). Occupations are bucketed by their probability of reaching a sustainable occupation. Occupations in the "Top" category, or high-mobility jobs, have a probability of 25% or more of reaching a sustainable occupation. Occupations in the "Bottom" category, or low-mobility jobs, have a probability of 5% or less of reaching a sustainable occupation. The difference column shows the average difference in skill centrality values between these high and low mobility occupations (unweighted by their prevalence in the data).

Table 4.9: Differences in skill change between career paths that start in unsustainable manufacturing occupations and end in either sustainable or unsustainable occupations, by highest educational attainment

Less than a Bachelor's	**(Δ Sustainable) - (Δ Unsustainable)**		**Bachelor's**	**(Δ Sustainable) - (Δ Unsustainable)**	
	difference	p-val		difference	p-val
Mgmt of Financial Resources	16.7	***	Operations Analysis	16.6	***
Mgmt of Personnel Resources	14.8	***	Systems Evaluation	15.3	***
Operations Analysis	13.9	***	Mgmt of Financial Resources	15.0	***
Negotiation	13.8	***	Systems Analysis	13.8	***
Mgmt of Material Resources	13.5	***	Mgmt of Personnel Resources	12.9	***
Persuasion	13.5	***	Mgmt of Material Resources	12.3	***
Social Perceptiveness	12.3	***	Persuasion	11.2	***
Systems Evaluation	12.3	***	Judgment and Decision Making	10.7	***
Speaking	12.0	***	Complex Problem Solving	10.6	***
Writing	11.9	***	Programming	10.5	***
Reading Comprehension	11.1	***	Negotiation	10.1	***
Systems Analysis	11.0	***	Active Learning	10.0	***
Coordination	10.5	***	Learning Strategies	10.0	***
Judgment and Decision Making	10.5	***	Science	9.8	***
Active Listening	10.3	***	Writing	9.6	***
Learning Strategies	10.3	***	Reading Comprehension	9.2	***
Monitoring	10.2	***	Social Perceptiveness	8.8	***
Service Orientation	10.1	***	Critical Thinking	8.7	***
Critical Thinking	9.8	***	Instructing	8.4	***
Active Learning	9.5	***	Service Orientation	8.4	***
Time Mgmt	9.2	***	Monitoring	8.3	***
Complex Problem Solving	8.5	***	Speaking	8.3	***
Instructing	8.5	***	Coordination	8.2	***
Science	7.7	*	Active Listening	7.9	***
Programming	6.4	.	Time Mgmt	7.0	***
Technology Design	2.9		Mathematics	6.8	**
Mathematics	0.3		Technology Design	5.9	***
Quality Control Analysis	-1.9		Quality Control Analysis	0.4	
Installation	-2.1		Installation	-0.9	
Troubleshooting	-4.5	*	Troubleshooting	-3.0	
Operations Monitoring	-4.7	*	Operations Monitoring	-3.6	
Operation and Control	-10.4	***	Equipment Selection	-7.4	**
Equipment Selection	-12.8	***	Operation and Control	-9.9	**
Repairing	-20.4	***	Repairing	-13.2	***
Equipment Maintenance	-21.2	***	Equipment Maintenance	-14.4	***

Signif. codes: *** (p <= 0.001), ** (p <= 0.01), * (p <= 0.05), . (p <= 0.1). The difference columns shows the difference in skill requirement changes between career paths that start in unsustainable occupations and end in sustainable occupation, and career paths that start and end in unsustainable occupations. To do this, cumulative changes in centrality are computed for each skill over each career path in an occupation's OSN. Those changes are then aggregated by whether paths end in a sustainable or unsustainable occupation, weighing the averages by the path probability, but not by the occupation prevalence in the employment profiles data.

4.4.4 Where are the retention and recruitment opportunities?

In order to identify potential retention and recruitment opportunities, this section will look more closely at where careers in the manufacturing industry begin and end. First, we'll estimate the retention rate of workers who join the labor force through a manufacturing occupation. Secondly, we'll identify potential gateways jobs into the manufacturing industry from within and outside the field.

4.4.4.1 Where do careers that start in manufacturing lead to?

We'll begin by painting a picture of where career paths that start in manufacturing end. For each occupation in the manufacturing industry, we'll use its Occupation-Specific Network (OSN) to look at the unique paths that are available from that occupation and compute the likelihood that a career starting from this occupation also ends in manufacturing. We'll use the path probabilities as computed in section 3.4.0.1 to estimate this likelihood, and then further multiply these by the count of the origin occupation in the data, to give paths that start from more prevalent occupations more weight. The results of this analysis are shown below in table 4.4.4.1.

Table 4.10: Share of paths starting in manufacturing occupations that end in manufacturing occupations, by occupation type and highest educational attainment

			Careers Ending in Manufacturing			**Careers Ending in Any Industry**	
Group	**Origin occupations**	**n**	All	Sustainable Jobs	Better Jobs	Sustainable Jobs	Better Jobs
Less than a Bachelor's	All	58,659	0.81	0.38	0.07	0.41	0.17
	Unsustainable	36,539	0.83	0.05	0.10	0.11	0.19
	Sustainable	22,120	0.77	0.94	0.03	0.89	0.13
Bachelor's	All	87,448	0.78	0.75	0.09	0.75	0.22
	Unsustainable	23,603	0.74	0.12	0.14	0.21	0.29
	Sustainable	63,845	0.80	0.97	0.07	0.94	0.19

Notes: Calculations are weighted by path probability and prevalence of the origin occupation in the employment profiles data. The sustainable jobs and better jobs columns under the 'Ending in Manufacturing' show the proportion of paths ending in manufacturing that end in sustainable or better occupations.

We find that across education groups, the overwhelming majority of careers that begin in the manufacturing industry also end in manufacturing (around 80%). However, of the workers who began their careers in unsustainable manufacturing occupations, only 5 - 12% are estimated to end up in sustainable manufacturing occupations, depending on their educational attainment. In fact, people who start their career in an unsustainable occupation but end their career in any industry appear to have about twice the odds of ending up in sustainable occupations than if they had stayed in manufacturing, suggesting that other industries offer better mobility prospects for these workers. On the other hand, the retention rate into sustainable careers is better for those who end their careers in manufacturing.

To further understand where there might be leaks in the manufacturing pipeline, we'll look at the specific manufacturing occupations with the lowest retention rates. Again, we'll use the OSN of each manufacturing occupation to estimate the likelihood that a career starting from a given occupation also ends in manufacturing. Results showing the ten occupations with the lowest retention rates are shown below in table 4.4.4.1.

Table 4.11: Manufacturing Occupations with the Lowest Industry Retention Rates

Group	Occupation	Sustainable	Careers Ending in Manufacturing: All	Careers Ending in Manufacturing: Sustainable Jobs	Careers Ending in Manufacturing: Better Jobs	Careers Ending in Any Industry: Sustainable Jobs	Careers Ending in Any Industry: Better Jobs	Destination: Top Destination
Less than a Bachelor's	Biomedical Engineers	Yes	0.50	1.00	0.00	0.50	0.00	Maintenance and Repair Workers, General
	Chemical Technicians	No	0.52	0.29	0.29	0.64	0.64	Chemists
	Electronics Engineers, Except Computer	Yes	0.35	1.00	0.00	0.96	0.54	Managers, All Other
	Industrial Engineering Technicians	No	0.54	0.00	0.00	0.19	0.19	First-Line Supervisors of Mechanics, Installers, and Repairers
	Industrial Production Managers	Yes	0.54	1.00	0.00	0.80	0.13	General and Operations Managers
	Industrial Safety and Health Engineers	Yes	0.55	0.89	0.00	0.94	0.00	Occupational Health and Safety Specialists
	Maintenance Workers, Machinery	No	0.54	0.00	0.00	0.23	0.24	First-Line Supervisors of Mechanics, Installers, and Repairers
	Mixing and Blending Machine Setters, Operators, and Tenders	No	0.50	0.00	0.48	0.31	0.74	Computer Operators
	Occupational Health and Safety Technicians	No	0.40	0.00	0.00	0.60	0.60	Occupational Health and Safety Specialists
	Slaughterers and Meat Packers	No	0.53	0.00	0.00	0.01	0.05	Waiters and Waitresses
Bachelor's	Cabinetmakers and Bench Carpenters	No	0.35	0.00	0.00	0.28	0.65	Managers, All Other
	Chemical Technicians	No	0.50	0.45	0.45	0.66	0.73	Operations Research Analysts
	Electronics Engineers, Except Computer	Yes	0.44	1.00	0.00	0.98	0.49	Managers, All Other
	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	No	0.42	0.00	0.00	0.02	0.11	Retail Salespersons
	Maintenance Workers, Machinery	No	0.48	0.00	0.00	0.27	0.29	First-Line Supervisors of Mechanics, Installers, and Repairers
	Occupational Health and Safety Technicians	No	0.42	0.00	0.00	0.58	0.58	Occupational Health and Safety Specialists
	Prepress Technicians and Workers	No	0.56	0.00	0.00	0.10	0.44	Graphic Designers
	Printing Press Operators	No	0.22	0.00	0.00	0.48	0.78	Public Relations and Fundraising Managers
	Production, Planning, and Expediting Clerks	No	0.43	0.00	0.00	0.26	0.57	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products
	Shipping, Receiving, and Traffic Clerks	No	0.48	0.00	0.00	0.10	0.52	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products

Notes: Career paths are determined using the Occupation-Specific Network. Calculations are weighted by path probability. The origin occupation is removed from the list of top destination results if necessary.

A first observation is that the ranking for people with a Bachelor's degree includes nearly only unsustainable occupations, while the ranking for people without a Bachelor's also includes a few sustainable occupations (e.g. Electronics Engineers and Industrial Production Managers). We can look closer at the career paths to understand where these workers might be going when they to forego a career in manufacturing. This investigation reveals that for a few occupations, such as Electronics Engineers, the drop-off can be explained by the fact that these workers tend to go into management roles that are not specific to the manufacturing industry. It is therefore possible that these workers are staying in the industry but are not being coded as such in our data. However, for other occupations, the low retention rate appears to be driven by workers ending up in technical positions in other fields. For example, for workers without a Bachelor's, "Mixing and Blending Machine Setters, Operators, and Tenders" are likely to end up as Computer Operators or Computer User Support Specialists, while "Maintenance Workers, Machinery" and "Industrial Engineering Technicians" are likely to end up as "Maintenance and Repair Workers, General" or "First-Line Supervisors of Mechanics, Installers, and Repairers". For workers with a Bachelor's degree, "Printing Press Operators" are are likely to end up as "Public Relations and Fundraising Managers" and "Graphic Designers", while "Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic" are likely top end up as "Secretaries and Administrative Assistants" or "Retail Salespersons". Ultimately, it should be noted that many of these occupations could still be within the manufacturing industry, even if that is not the main industry associated with those jobs. Whatever the case may be, workers in these occupations have the option to leave the field if they wanted to, so extra care should be put into retaining them.

4.4.4.2 What are the most common entry points into good manufacturing jobs?

We'll end our case study of the manufacturing industry by using our career path models to identify occupations that are good gateways into the manufacturing industry. To do this, we'll the OSNs to estimate which occupations have a high likelihood of leading to sustainable manufacturing occupations. As before, we'll use the path probabilities as computed in section 3.4.0.1 to estimate this likelihood, and then further multiply it by the count of the origin occupation in the data, to give paths that start from more prevalent occupations more weight. We'll focus on gateway jobs that are not in the manufacturing industry (see table 4.4.4.2 for top ten results), but the top ten gateway jobs from the manufacturing industry can be found in Table B of the Appendix. Each of these occupations could be targeted for potential recruitment efforts into manufacturing, as our data shows that many have already transitioned successfully into a number of manufacturing professions. Given the increasing evidence of a worker shortage in manufacturing, recruiting workers in these roles might be one strategy to improve hiring efforts.

Looking at the specific paths emanating from these occupations reveals a number of potential opportunities. In terms of workers without a Bachelor's, Quality Control Analysts could be recruited into "Inspectors, Testers, Sorters, Samplers, and Weighers" or "Quality Control Systems Managers" roles. Power Plant Operators could be recruited for "Industrial Production Managers" roles. Civil Drafters could be recruited into Mechanical Drafters roles. Robotics Engineers could be recruited into Electrical Engineering positions. Finally, Construction and Building Inspectors could be recruited into "Inspectors, Testers, Sorters, Samplers, and Weighers" and "Quality Control Systems Managers" roles.

In terms of workers with a Bachelor's degree, Medical and Clinical Laboratory Technicians could be recruited into Chemists roles. Civil Engineers could be recruited for "Electronics Engineers, Except Computer" and "Mechanical Engineers" roles. Quality Control Analysts could be recruited into "Inspectors, Testers, Sorters, Samplers, and Weighers" or "Quality Control Systems Managers" roles. Computer Hardware Engineers could be recruited into Electrical Engineering positions. Finally, Petroleum Engineers could be recruited into "Industrial Engineers" and "Manufacturing Engineers" roles.

Table 4.12: Gateway Non-Manufacturing Occupations into Sustainable Manufacturing Occupations:

Group	Origin				Destination
	Occupations	Sustainable	Industry	n size	Top Destination
Less than a Bachelor's	Drafters, All Other	No	Professional, Scientific, and Technical Services	8,968	Civil Drafters
	Railroad Conductors and Yardmasters	No	Transportation and Warehousing	737	Electrical Engineers
	Quality Control Analysts	No	Educational Services	5,233	Quality Control Systems Managers
	Nuclear Engineers	No	Utilities	310	Computer Systems Engineers/Architects
	Supply Chain Managers	Yes	Transportation and Warehousing	3,722	General and Operations Managers
	Civil Drafters	No	Professional, Scientific, and Technical Services	3,410	Drafters, All Other
	Power Plant Operators	No	Utilities	2,298	Industrial Production Managers
	Procurement Clerks	No	Government	2,097	Purchasing Agents, Except Wholesale, Retail, and Farm Products
	Robotics Engineers	Yes	Professional, Scientific, and Technical Services	138	Software Developers, Applications
	Construction and Building Inspectors	No	Government	1,587	Inspectors, Testers, Sorters, Samplers, and Weighers
Bachelor's	Drafters, All Other	No	Professional, Scientific, and Technical Services	9,172	Managers, All Other
	Supply Chain Managers	Yes	Transportation and Warehousing	7,394	General and Operations Managers
	Computer Hardware Engineers	Yes	Professional, Scientific, and Technical Services	6,744	Software Developers, Applications
	Quality Control Analysts	No	Educational Services	6,119	Quality Control Systems Managers
	Transportation Planners	Yes	Government	2,690	Logistics Analysts
	Procurement Clerks	No	Government	2,428	Purchasing Agents, Except Wholesale, Retail, and Farm Products
	Civil Engineers	Yes	Professional, Scientific, and Technical Services	17,443	Managers, All Other
	Medical and Clinical Laboratory Technicians	No	Health Care and Social Assistance	16,668	Operations Research Analysts
	Engineering Technicians, Except Drafters, All Other	No	Professional, Scientific, and Technical Services	13,509	Managers, All Other
	Petroleum Engineers	Yes	Mining, Quarrying, and Oil and Gas Extraction	1,380	Mining and Geological Engineers, Including Mining Safety Engineers

Notes: Calculations are weighted by path probability and origin occupation count. Within-occupation transitions are not included in the estimation of top gateway occupations.

Chapter 5

Discussion

5.1 Findings

This thesis set out to evaluate which occupations across the U.S. labor market offer the best prospects to their workers, and whether these opportunities are curtailed for individuals without a Bachelor's degrees. We found that:

(1) The definition of occupational mobility can draw from a range of concepts—from the flexibility of career paths, to access to higher-wage jobs, to access to stable and high-paying jobs—and these dimensions do not necessarily agree with each other, as evidenced by the low or negative correlations of scores derived from different concepts.

(2) Although the same jobs provide people with Bachelor's degrees with greater access to high-wage, stable jobs than they do people without a Bachelor's degree, there are a number of occupations that offer solid opportunities for both groups.

(3) However, employment in low-wage or shrinking occupations appears to be a powerful barrier to upward mobility. The career pathways models suggest that these "unsustainable" occupations provide little access to sustainable employment, with only an estimated 13%[1] chance of attaining high-wage, stable employment over the course of a career. In fact, an occupation's baseline wages is often one of the strongest predictors of whether it offers occupational mobility.

[1] This figure reflects an average across unsustainable occupations that is not weighted by the number of workers employed in these occupations.

Furthermore, this thesis delved into the relationship between the skills mechanisms that accompany occupational mobility, in the hopes of identifying competencies that could help unlock greater access to upward mobility in the long-run. We found that:

(4) *Unsustainable occupations* (i.e. low-wage or shrinking) that have a high mobility potential tend to have higher skill requirements than unsustainable occupations with low-mobility potential, except when it comes to technical skills. Similarly, requirements for skills tend to increase more steeply over career paths that lead from unsustainable occupations to sustainable occupations than they do over career paths that lead back to unsustainable occupations. The demand for resource management and systems skills increases most strongly over these favorable paths.

(5) Educational investments are more often involved in job transitions from unsustainable occupations than they are in job transitions from sustainable occupations. This trend may reflect workers' belief that they need to invest in further credentials in order to unlock access to stable prospects. Educational investments are also more commonly involved in job transitions that span two different industries, perhaps because career changes are otherwise more difficult.

(6) Longer tenure and career length may be substitutable for higher educational achievement for workers seeking to make a high-skills distance occupation transition. Certifications also provide a good alternative to more onerous degrees.

5.2 Contributions

This thesis made a significant departure from the literature by using network analysis to model the universe of career paths that are available from a first job, and using this representation to evaluate the potential for mobility over the course of a whole career. Existing studies and tools generally guide workers towards occupations that provide an immediate boost in circumstances. With few exceptions, these approaches do not consider the long-term prospects offered by the jobs towards which they are steering individuals. However, our network representations can be used to describe mobility prospects over the course of a whole career and when used in tandem with existing strategies, could broaden the horizon of career advice tools by balancing short-term and long-term gains.

Another advantages of the network approach that is not specific to this paper is that it eliminates the need for individual career histories. Rather, our method can be adapted to public data-sets that capture snapshots of job transitions across different samples over time, such as the CPS.

Finally, our results add to existing literature which finds that occupational mobility is much curtailed in low-wage jobs and other precarious types of employment.[2, 48, 17][2]. However, by providing individual mobility scores for each occupation, we can look beyond these trends to identify bright spots occupations in the labor market that provide low-wage workers with dependable access to sustainable employment down the line.

5.3 Next Steps

This analysis makes a number of simplifying assumptions that could be verified and potentially corrected for in further work:

1) The Occupation-Specific Networks (OSNs) were created based on three parameters that determine which transitions to keep when modelling career paths. Further analysis could investigate how robust these findings are to different parameter values. In particular, lowering the transition probability cutoff (ϕ) could lead to more complex and complete OSNs.

2) In developing indicators that describe career paths, we made the simplifying assumption that the probability of a transition is independent of the transitions that came before it. However, our method for computing relative path probability could be updated to make the probability of any given transition conditional on past employment history.

3) Instead of using the median annual wage to estimate occupation salary, further analysis could better account for the type of wage growth that comes from experience by assigning wages in higher percentiles of the distribution to occupations that are further away from the origin occupation in the OSN.

4) Since the intention of the OSNs is to model career paths available from a starter job, it may be interesting to investigate whether different models are derived if only transitions that originate from the first job in a resume are considered to model the first step in the career path, and similarly, only transitions that originate from the nth job in a resume are considered to model the nth step in the career path.

5) The resume data that is at the core of this thesis is likely not representative of the U.S.

[2]Our findings also generally agree with a ranking of industries by mobility by Escobari et al., 2021[17], with few exception that could probably be explained by the fact that we segment occupations by sustainable and unsustainable occupations.

population. Future work could strategically sample and weigh resumes so that the data is more reflective of the labor force.[3]

Beyond these methodological modifications, our analysis could also be leveraged to answer different questions:

1) Future work could reproduce our analysis and fold in other demographic features to investigate how mobility prospects may vary for different gender and race/ethnicity groups. This would require using a different data source such as the CPS.

2) Future work could also explore how our measures of mobility relate to job requirements using alternate skill classification systems such as Autor, Levy and Murnane's (2003) framework of routine versus non-routine skills and manual versus cognitive skills, as well as classifying skills as general and specific, as in Garg et al. (2019)[4, 18]. Finally, other dimensions of the O*NET content model, such as Work Activities or Abilities, could also be incorporated.

3) We saw throughout this paper that our mobility indicators were not always relevant depending on the type of occupation being studied. One potential next step might be to think more deeply about how to improve some of our measures, particularly those capturing wage change, or to combine their strengths and weaknesses into one "super-indicator".

3) Our analysis could also be leveraged to study how the increasing rate of occupational change seen in recent years might be affecting upward mobility prospects.

4) Similarly, our methods could also be re-purposed to evaluate the long-term impact of internships, apprenticeships, or certifications.

Finally, our method could be operationalized by incorporating our mobility scores into career advice tools. In particular, there are a number of existing tools that suggest job transitions based on skills proximity. These products could be improved by leveraging our measures to estimate the longer term upward mobility prospects of potential destination occupations as well as the feasibility of that transition.

[3] See Escobari et al., 2021[17] for a potential methodology.

Chapter 6

Glossary

Skill growth – The idea that career growth is driven by human capital investments that increase the scope of a worker's skill set.

Skill transfer – The idea that career growth can be driven by workers transitioning to occupations with similar skills requirements as their current job, but greater promise of security and better wages.

Employment profile – An employment profile is a digital resume pieced together from various public online sources that links educational, certification, and professional experience over time to unique individuals (EBG, 2022)[16]

Sustainable and Unsustainable occupations – An occupation is *sustainable* if it pays a living wage and has non-negative projected employment change over 2020-30. A living wage is any annual wage that is greater than or equal to MIT's 2019 Living Wage of $68,808[25]. An occupation is *unsustainable* if it has a negative projected employment change OR a median annual wage of less than MIT's living wage.[1]

Better occupations – An occupation q is better than an occupation p if it has higher median annual wages.

Occupation transition – A job change from occupation p to occupation q. In the social

[1]These definitions are adapted from methodology from a report by the World Economic Forum and the Boston Consulting Group, (WEF and BCG, 2018)[50]

profiles data, two consecutive professional records p and q represent an occupational transition from p to q. Note that *within-occupation transitions* are possible and represent a job change between two jobs in the same O*NET occupation.

Transition weight – Traditionally, the weight of a transition from occupation p to occupation q would represent the number of times this transition has been observed in the data. In this analysis, we re-scale these weights so that they represent the share of people in occupation p who end up in occupation q. As such, if N_p represents all the neighbors of a node p:

$$\sum_{q \in N_p} w_{(p,q)} = 1$$

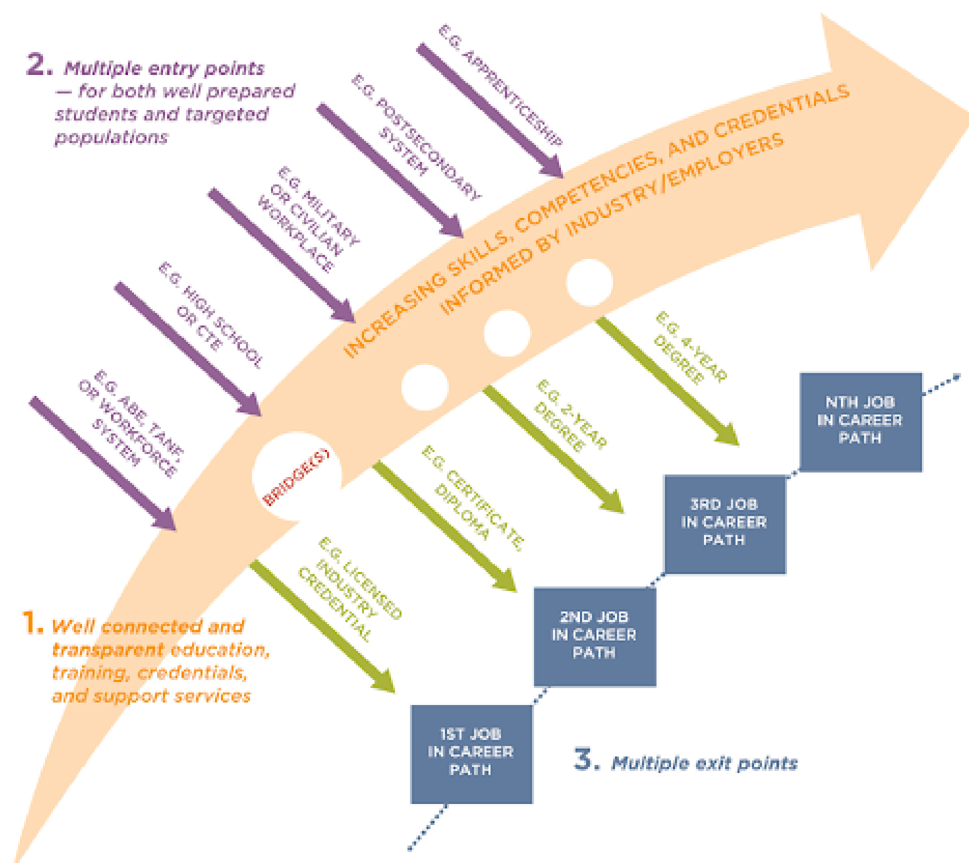
This allows us to interpret the weights as the probability that an individual in an occupation p will transition to occupation q.

Occupation-Specific Network (OSN) – Networks that use occupation transitions and transition weights to model the most likely career paths available to an individual starting their career from a specific occupation p.

Appendix A

Methods

Figure A-1: Three Essential Features of Career Pathways



Note: From the Alliance for Quality Career Pathways at the Center for Law and Social Policy. (2014). *Shared vision, strong systems: The alliance for quality career pathways framework version 1.0.* June, 2014. Retrieved from http://www.clasp.org/resources-and-publications/files/aqcp-framework-version-1-0/AQCP-Framework.pdf.[1] As cited in: Elsey, Bonnie, Laura Lanier, and Jessie Stadd. "Career Pathways Toolkit: An Enhanced Guide and Workbook for System Development." U.S. Department of Labor, Employment and Training Administration, Manhattan Strategy Group. Accessed January 5, 2021. https://lincs.ed.gov/professional-development/resource-collections/profile-957.

Table A.1: O*NET Skill Types

Skill Type	Skill
Basic	Monitoring
	Learning Strategies
	Active Learning
	Speaking
	Active Listening
	Science
	Writing
	Critical Thinking
	Reading Comprehension
	Mathematics
Complex Problem Solving	Complex Problem Solving
Resource Management	Time Management
	Management of Material Resources
	Management of Personnel Resources
	Management of Financial Resources
Social	Service Orientation
	Coordination
	Social Perceptiveness
	Instructing
	Persuasion
	Negotiation
Systems	Judgment and Decision Making
	Systems Evaluation
	Systems Analysis
Technical	Equipment Maintenance
	Repairing
	Equipment Selection
	Installation
	Troubleshooting
	Operation and Control
	Operations Monitoring
	Quality Control Analysis
	Technology Design
	Programming
	Operations Analysis

Source: Source: 'Skills Search'. ONET Online. Accessed January 18, 2022

A.1 Estimating The Rate of Occupational Change

When creating the OSN, the path length cutoff parameter θ is meant to capture the number of occupational transitions that can reasonably be achieved in a single career. As such, determining a reasonable value for this parameter requires an estimation of the rate of occupational change (ROC) over the length of an individual career

Analysis of Full-Career employment profiles: Perhaps the most obvious way to approach this challenge is to count the number of occupational transitions that are observed in employment profiles that reflect a full career. To determine the standard length of a full career, we can compute the time between the start of the "prime working age" (25, as defined by the BLS) and the average retirement age (around 60 over 2002-2014, as determined by a Gallup survey), which comes to 36 years [41, 30].[1] Having determined the length of a full career, we can then subset the universe of employment profiles to those with a career length of 36 years or more, where career length is defined as the difference in years between the end date of the ultimate record and the start date of the first record. Finally, we can compute the median number of cross-occupational transitions observed in these full-career profiles and take this as our parameter.

Adjusting for Increased ROC over Time: One potential objection to this method is that it reflects the behavior or a particular subset of individuals who entered the labor market anywhere between 1970 and 1987. However, a number of analyses suggest that the rate of occupational change (ROC) has increased in recent years and that "job-hopping" has become the "'New Normal' for millennials" (Meister, 2012). As such, the parameter estimated with our first method might severely underestimate the expected number of occupational transitions observed today. What's more, these older employment profiles might be less granular simply because they have more ground to cover, such that some transitions might be altogether omitted. Indeed, table A.1 below, which shows the average yearly ROC for employment profiles by the decade that they first entered the labor market, suggests that profiles of people who started working in 2010-2020 had over 8 times more occupational transitions in a year than profiles of people who started working in 1960-1970.

[1] Although a number of groups may not fit this mold, in particular women who disproportionately leave the labor market to assume parental responsibilities (Parker, 2015), a one-size-fits all approach is accepted here because we cannot differentiate between these groups in the data[39].

Table A.2: Yearly Rate of Occupational Change by Decade of Entry, All Records

Decade of Entry	ROC	n
(1960, 1970]	0.08	1,044
(1970, 1980]	0.09	31,829
(1980, 1990]	0.10	119,568
(1990, 2000]	0.14	290,608
(2000, 2010]	0.26	632,392
(2010, 2020]	0.65	663,466

Note: Within-occupation transitions not included in calculations.

Therefore, a second method for estimating the path length cutoff parameter might be to multiply the cutoff arrived at using the full-career employment profiles by the factor increase in yearly ROC for employment profiles who entered the labor market between 2010-2020 and those that that entered the labor market between 1970-1990.

Adjusting for Early Career Bias: Still, this second method has its own potential share of flaws. In particular, the employment profiles of individuals who entered the labor market between 2010-2020 only reflect the first 10 years of work. This early career period is likely characterized by a heightened ROC as individuals strive to find their niche and have not accumulated enough occupation-specific knowledge to make job-switching too costly. To check the validity of this hypothesis, the table below shows the average yearly ROC for up to the first ten years of the career by the decade of labor market entry. Note that for people who entered the labor market in (2010, 2020], the early career and the full career period are the same.

Table A.3: Yearly Rate of Occupational Change by Decade of Entry, Early and Full-Career

Decade of Entry	Full Career ROC	Early Career ROC	n
(1960, 1970]	0.08	0.08	1,044
(1970, 1980]	0.09	0.09	31,829
(1980, 1990]	0.10	0.11	119,568
(1990, 2000]	0.14	0.15	290,608
(2000, 2010]	0.26	0.26	632,392
(2010, 2020]		0.65	663,466

Note: Within-occupation transitions not included in calculations.

As it turns out, our hypothesis does not bear out in the data. The ROC is fairly constant between the two periods, although the early-career ROC is slightly higher than the full-career ROC for people who entered the labor market in (1980, 1990] and (1990, 2000]. If we wanted to correct for this slight increase, a third method to estimate θ might be to multiply the cutoff arrived at using the full-career employment profiles by the factor increase in early career transitions from the reference decades 1970-1990[2] to the current decade 2010-2020.

Using a Subset of Recent employment profiles: Finally, a fourth method might be to focus on employment profiles with a labor market entry date that is more recent, but goes back far enough to provide information on behavior beyond the early career stage. Multiplying the number of years in a career by an average of the yearly ROC from profiles with an entry date between (1990, 2000] and (2000, 2010] gives us such a cutoff.

Results and conclusions:

The parameters estimated using each of the four approaches are shown below. Reassuringly, the latter three methodologies all converge towards similar numbers of expected occupational transitions over the course of a career (a range of 6-7, averaging at 6.89), making the decision to set the path length cutoff to 7 relatively straightforward.

Table A.4: Expected Number of Transitions in a Career

Method	**Transitions**
Full CVs	1.00
Relative Increase	7.00
Early Career Adjustment	6.44
Modern CVs	7.23

Note: Early career is defined as the first 10 years after labor market entry.

It should be noted that although this analysis was conducted using all of the employment profiles regardless of educational attainment, the table and figure below show that the difference in yearly ROC between the two groups is small. As such, the same parameter is used for both analyses.

[2]The early-career ROC across the two groups is simply the average of the early-career ROC for (1960, 1970] and the early-career ROC for (1970, 1980].

Figure A-2: The Rate of Occupational Change by Decade of Entry

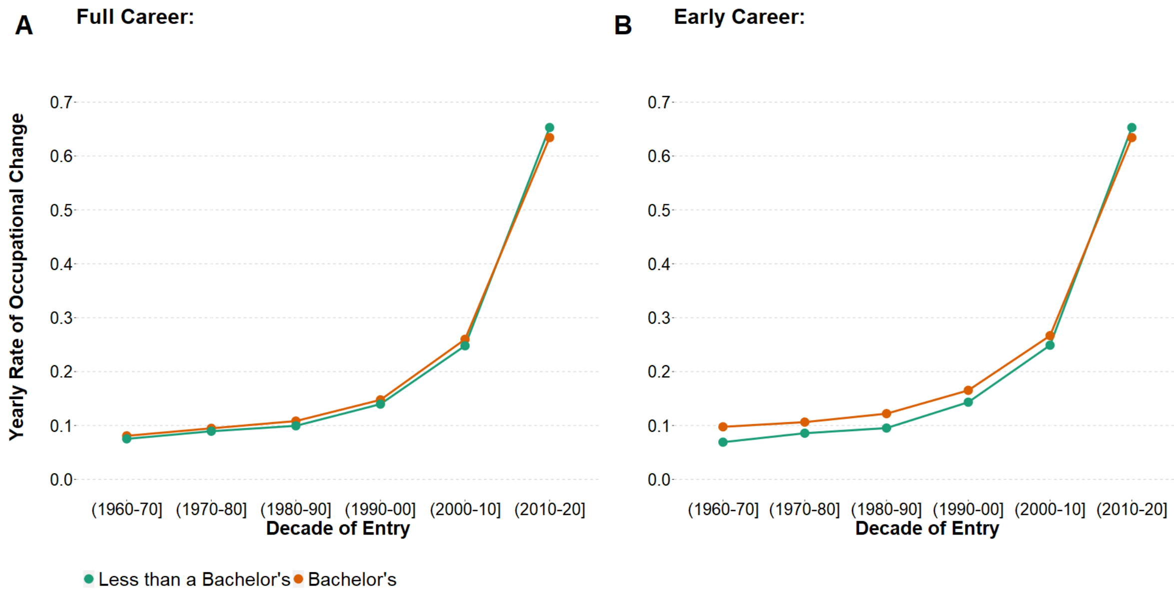


Table A.5: Yearly Rate of Occupational Change by Decade of Entry and Highest Educational Attainment

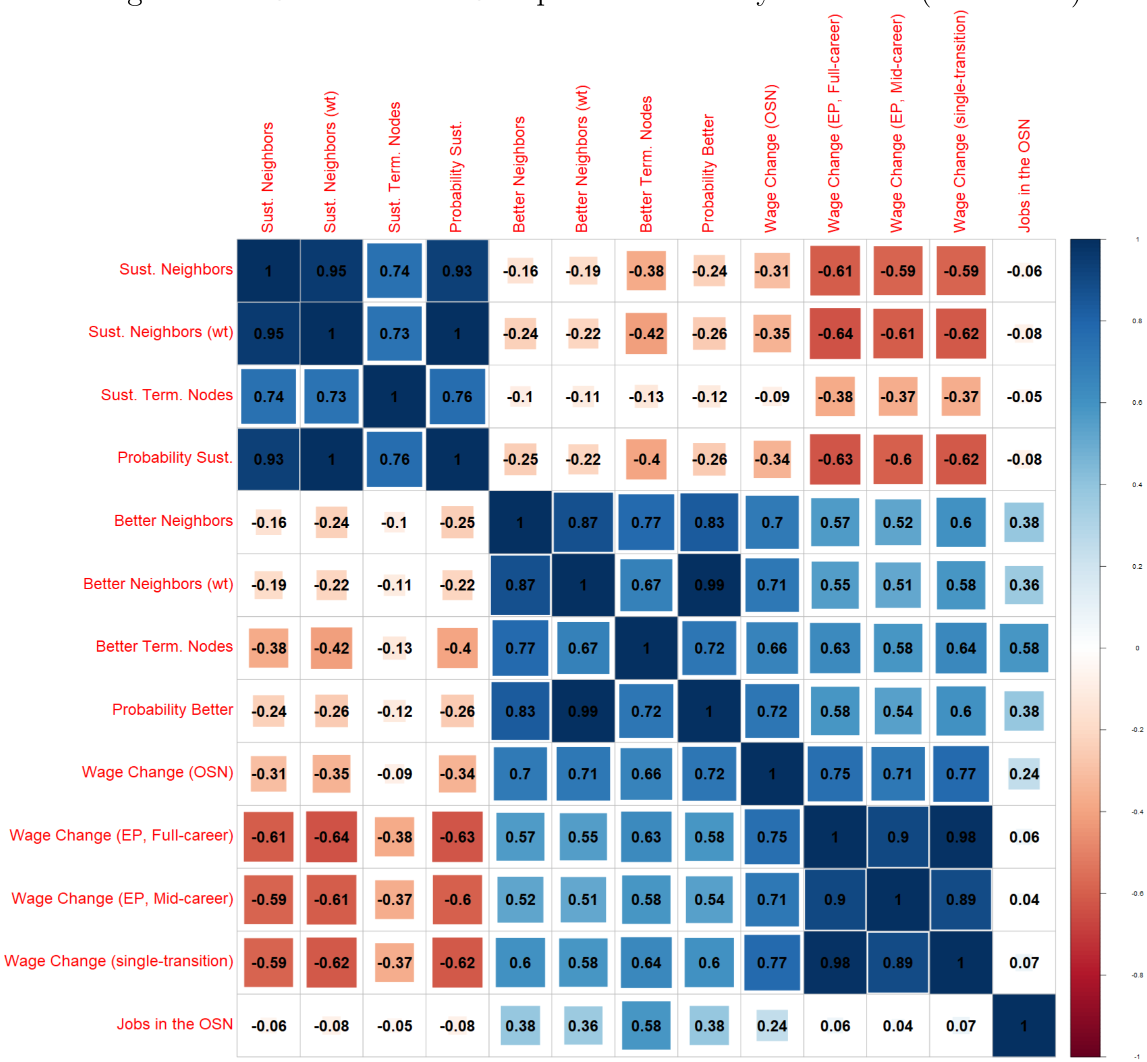
	Less than a Bachelor's:		Bachelor's:	
Decade of Entry	**All**	**Early Career**	**All**	**Early Career**
(1960, 1970]	0.08	0.07	0.08	0.10
(1970, 1980]	0.09	0.09	0.09	0.11
(1980, 1990]	0.10	0.10	0.11	0.12
(1990, 2000]	0.14	0.14	0.15	0.17
(2000, 2010]	0.25	0.25	0.26	0.27
(2010, 2020]		0.65		0.63

Note: Early career is defined as the first 10 years after labor market entry.

Appendix B

Results

Figure B-1: Correlation of Occupational Mobility Measures (Bachelor's)



Note: Network-based indicators that evaluate a job's proximity to sustainable occupations: 1) The share of neighbor nodes that are sustainable (*Sust. Neighbors*), 2) The weighted share of neighbor nodes that are sustainable (*Sust. Neighbors (wt)*), 3) The share of terminal nodes that are sustainable (*Sust. Term. Nodes*), 4) The probability of reaching a sustainable occupation (*Probability Sust.*).

Network-based indicators that evaluate a job's proximity to better (higher-wage) occupations: 1) The share of neighbor nodes that are better occupations (*Better Neighbors*), 2) The weighted share of neighbor nodes that are better occupations (*Better Neighbors (wt)*), 3) The share of terminal nodes that are better occupations (*Better Term. Nodes*), 4) The probability of reaching a better occupation (*Probability Better*).

Indicators that evaluate a job's wage growth potential: 1) The average, probability weighted wage growth over the OSN (*Wage Change, OSN*), 2) The average wage growth over employment profiles that start with the occupation of interest (*Wage Change (EP, Full-career)*), 3) The average wage growth at the mid-career point over employment profiles that start with the occupation of interest (*Wage Change (EP, Mid-career)*), 4) The average wage growth over transitions that start with the occupation of interest (*Wage Change (single-transition)*).

Network-based indicators that evaluate a job's career flexibility: 1) The number of occupations in the network other than the occupation of interest (*Jobs in the Network*).

Figure B-2: Mobility Indicator Distribution by Highest Educational Attainment, Weighted by Occupation Prevalence

Note: The distribution of occupational mobility scores are weighted by the prevalence of that occupation in the employment profiles data. The Probability of Reaching a Sustainable Job, The Probability of Reaching a Better Job, and the Number of Jobs in the OSN (or Network) are all derived from the Occupation-Specific Networks. The Mid-Career Wage Change is derived from the longitudinal employment profiles data.

Figure B-3: Mobility Indicator Distribution by Occupation Type (Bachelor's)

Note: The distribution of occupational mobility scores are not weighted by the prevalence of the occupations in the employment profiles data. The Probability of Reaching a Sustainable Job, The Probability of Reaching a Better Job, and the Number of Jobs in the OSN (or Network) are all derived from the Occupation-Specific Networks. The Mid-Career Wage Change is derived from the longitudinal employment profiles data.

Table B.1: Unsustainable occupations with the highest probability of reaching a sustainable occupation, by highest educational attainment

Group	Occupation	Industry	Probability
Less than a Bachelor's	Nuclear Engineers (310)	Utilities	0.73
	Chemical Technicians (453)	Manufacturing	0.64
	Occupational Health and Safety Technicians (1,609)	Manufacturing	0.60
	Health Educators (2,723)	Health Care and Social Assistance	0.51
	Instructional Coordinators (367)	Educational Services	0.51
	Graduate Teaching Assistants (8,862)	Educational Services	0.50
	Licensed Practical and Licensed Vocational Nurses (1,156)	Health Care and Social Assistance	0.47
	Computer Network Support Specialists (7,473)	Professional, Scientific, and Technical Services	0.46
	Railroad Conductors and Yardmasters (737)	Transportation and Warehousing	0.46
	Tax Examiners and Collectors, and Revenue Agents (2,876)	Government	0.45
Bachelor's	Social Science Research Assistants (1,067)	Educational Services	1.00
	First-Line Supervisors of Food Preparation and Serving Workers (25,930)	Accommodation and Food Services	0.74
	Nuclear Engineers (732)	Utilities	0.71
	Graduate Teaching Assistants (34,933)	Educational Services	0.70
	Chemical Technicians (956)	Manufacturing	0.66
	Licensed Practical and Licensed Vocational Nurses (678)	Health Care and Social Assistance	0.66
	Environmental Science and Protection Technicians, Including Health (1,584)	Professional, Scientific, and Technical Services	0.64
	Food Science Technicians (473)	Manufacturing	0.62
	Computer Network Support Specialists (7,304)	Professional, Scientific, and Technical Services	0.61
	Tax Preparers (4,972)	Professional, Scientific, and Technical Services	0.61
	Tutors (23,481)	Educational Services	0.61

Notes: The number in parentheses represents the number of times this occupation appears in the data.

Table B.2: Sustainable occupations with the highest probability of reaching a better occupation, by highest educational attainment

Group	Occupation	Industry	Probability
Less than a Bachelor's	Biologists (1,097)	Government	0.68
	Sustainability Specialists (204)	Government	0.65
	Electronics Engineers, Except Computer (5,553)	Manufacturing	0.54
	Security Management Specialists (1,717)	Government	0.54
	Web Administrators (956)	Professional, Scientific, and Technical Services	0.50
	Business Continuity Planners (909)	Government	0.49
	Budget Analysts (1,020)	Government	0.47
	Validation Engineers (4,599)	Manufacturing	0.46
	Logistics Managers (6,329)	Transportation and Warehousing	0.41
	Transportation, Storage, and Distribution Managers (303)	Transportation and Warehousing	0.40
Bachelor's	Web Administrators (2,225)	Professional, Scientific, and Technical Services	0.80
	Security Management Specialists (3,673)	Government	0.72
	Biologists (2,386)	Government	0.63
	Business Continuity Planners (1,822)	Government	0.61
	Financial Quantitative Analysts (477)	Finance and Insurance	0.58
	Sustainability Specialists (702)	Government	0.57
	Transportation, Storage, and Distribution Managers (416)	Transportation and Warehousing	0.55
	Budget Analysts (2,773)	Government	0.53
	Education Administrators, Elementary and Secondary School (14,976)	Educational Services	0.53
	Environmental Compliance Inspectors (2,030)	Government	0.50

Notes: The number in parentheses represents the number of times this occupation appears in the data.

Table B.3: Sustainable occupations with the highest expected wage change at mid-career, by highest educational attainment

Group	Occupation	Industry	Expected Wage Change
Less than a Bachelor's	Food Scientists and Technologists (145)	Manufacturing	0.66
	Sustainability Specialists (204)	Government	0.59
	Auditors (9,820)	Professional, Scientific, and Technical Services	0.36
	Commercial and Industrial Designers (7,984)	Manufacturing	0.30
	Urban and Regional Planners (1,219)	Government	0.29
	Chiropractors (133)	Health Care and Social Assistance	0.28
	Environmental Compliance Inspectors (971)	Government	0.27
	Accountants (26,913)	Professional, Scientific, and Technical Services	0.26
	Social and Community Service Managers (6,865)	Health Care and Social Assistance	0.26
	Environmental Scientists and Specialists, Including Health (764)	Government	0.24
	Postsecondary Teachers, All Other (9,764)	Educational Services	0.24
Bachelor's	Auditors (39,250)	Professional, Scientific, and Technical Services	0.51
	Commercial and Industrial Designers (23,868)	Manufacturing	0.45
	Investment Underwriters (787)	Finance and Insurance	0.42
	Food Scientists and Technologists (569)	Manufacturing	0.41
	Accountants (91,941)	Professional, Scientific, and Technical Services	0.39
	Social and Community Service Managers (13,698)	Health Care and Social Assistance	0.38
	Environmental Compliance Inspectors (2,030)	Government	0.35
	Epidemiologists (179)	Government	0.35
	Financial Quantitative Analysts (477)	Finance and Insurance	0.34
	Urban and Regional Planners (3,142)	Government	0.34

Notes: The number in parentheses represents the number of times this occupation appears in the data.

Table B.4: Sustainable occupations with the most jobs in the network, by highest educational attainment

Group	Occupation	Industry	Number of Jobs
Less than a Bachelor's	Robotics Engineers (138)	Professional, Scientific, and Technical Services	14
	Budget Analysts (1,020)	Government	13
	Auditors (9,820)	Professional, Scientific, and Technical Services	12
	Clinical Research Coordinators (2,578)	Professional, Scientific, and Technical Services	12
	Security Managers (1,088)	Government	12
	Accountants (26,913)	Professional, Scientific, and Technical Services	11
	Aerospace Engineers (519)	Manufacturing	11
	Financial Analysts (16,174)	Finance and Insurance	11
	Financial Managers, Branch or Department (39,926)	Finance and Insurance	11
	Hospitalists (318)	Health Care and Social Assistance	11
	Treasurers and Controllers (16,045)	Finance and Insurance	11
Bachelor's	Mining and Geological Engineers, Including Mining Safety Engineers (365)	Professional, Scientific, and Technical Services	18
	Petroleum Engineers (1,380)	Mining, Quarrying, and Oil and Gas Extraction	18
	Computer Network Architects (395)	Professional, Scientific, and Technical Services	17
	Chemical Engineers (15,809)	Manufacturing	16
	Industrial Engineers (12,006)	Manufacturing	16
	Manufacturing Engineers (18,613)	Manufacturing	16
	Validation Engineers (10,885)	Manufacturing	16
	Mechatronics Engineers (327)	Professional, Scientific, and Technical Services	12
	Financial Examiners (1,360)	Finance and Insurance	11
	Makeup Artists, Theatrical and Performance (959)	Information	11
	Robotics Engineers (349)	Professional, Scientific, and Technical Services	11

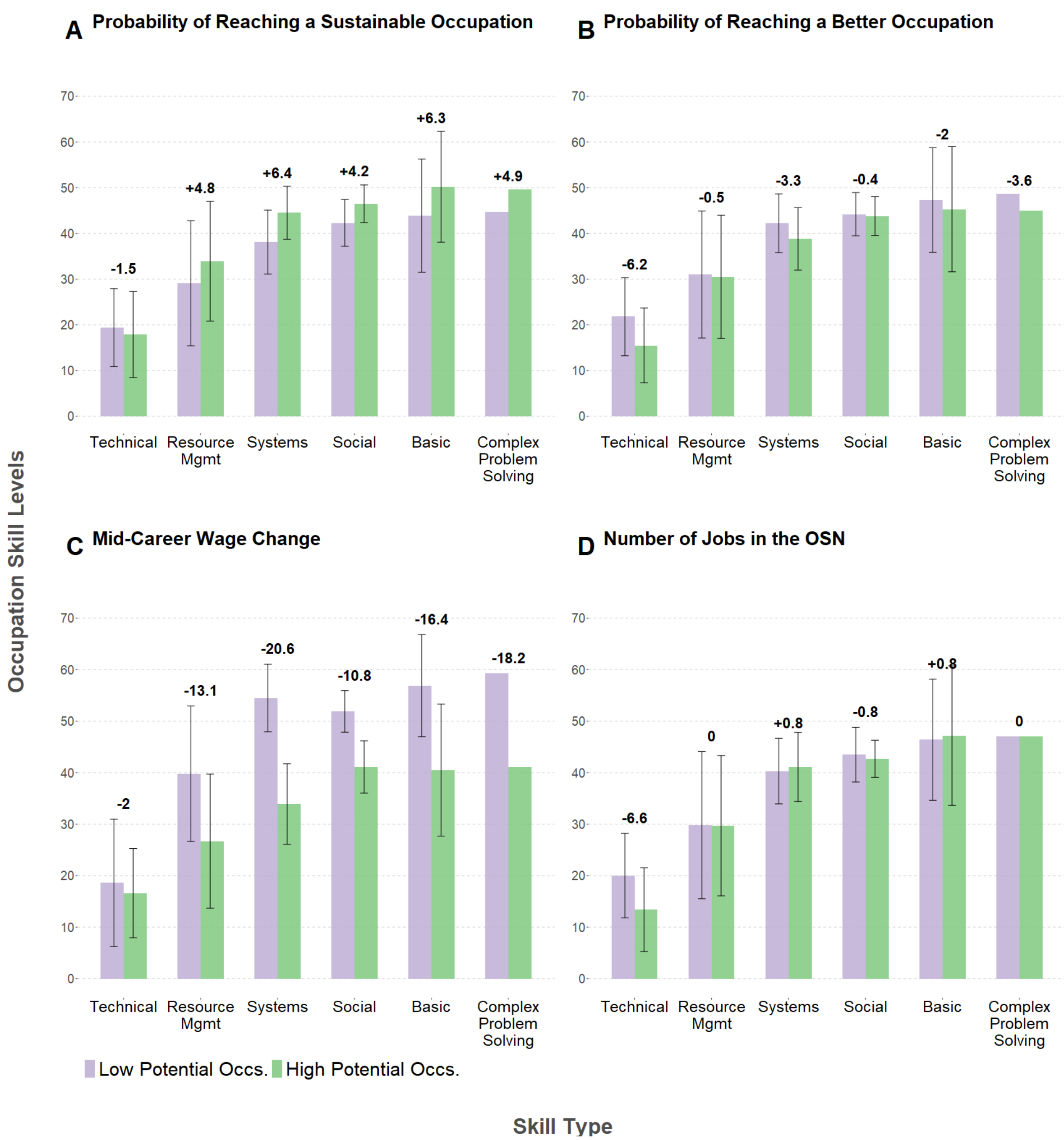
Notes: The number in parentheses represents the number of times this occupation appears in the data.

Table B.5: Unsustainable occupations with the most jobs in the network, by highest educational attainment

Group	Occupation	Industry	Number of Jobs
Less than a Bachelor's	Payroll and Timekeeping Clerks (9,374)	Professional, Scientific, and Technical Services	14
	Tellers (14,685)	Finance and Insurance	14
	Bill and Account Collectors (5,997)	Administrative and Support Services	13
	Dishwashers (3,469)	Accommodation and Food Services	13
	Loan Counselors (854)	Finance and Insurance	13
	Tax Preparers (2,154)	Professional, Scientific, and Technical Services	13
	Billing, Cost, and Rate Clerks (11,642)	Health Care and Social Assistance	12
	Credit Analysts (5,159)	Finance and Insurance	12
	Mixing and Blending Machine Setters, Operators, and Tenders (339)	Manufacturing	12
	Proofreaders and Copy Markers (332)	Information	12
	Sales Agents, Financial Services (17,458)	Finance and Insurance	12
	Tax Examiners and Collectors, and Revenue Agents (2,876)	Government	12
Bachelor's	Tool and Die Makers (164)	Manufacturing	19
	Nuclear Engineers (732)	Utilities	13
	Tellers (20,677)	Finance and Insurance	12
	Bill and Account Collectors (4,121)	Administrative and Support Services	11
	Credit Authorizers (2,649)	Finance and Insurance	11
	Legal Support Workers, All Other (2,482)	Government	11
	Payroll and Timekeeping Clerks (8,155)	Professional, Scientific, and Technical Services	11
	Printing Press Operators (934)	Manufacturing	11
	Real Estate Brokers (457)	Real Estate and Rental and Leasing	11
	Tax Preparers (4,972)	Professional, Scientific, and Technical Services	11

Notes: The number in parentheses represents the number of times this occupation appears in the data.

Figure B-4: Differences in the skill requirements of unsustainable occupations that are either high or low-mobility potential (Bachelor's)



Note: The bolded number above each set of bars indicates the difference in skill centrality levels between the occupations with high mobility potential and occupations with low mobility potential. The averages across occupation types are not weighted by the prevalence of the occupations in the employment profiles data. Occupations were binned differently for each indicator: for the *mid-career wage change* and the *number of jobs in the OSN*, the high-mobility potential occupations are in the upper quartile of the distribution of scores across the unsustainable occupations, and the low-mobility potential occupations are in the lower quartile. With respect to the *probability of reaching a sustainable job*, the high-mobility potential occupations have a score of 0.3 or more, and low-mobility potential occupations have a score of 0.05 or less. Finally, with respect to the *probability of reaching a better job*, the high-mobility potential occupations have a score of 0.5 or more, and the low-mobility potential occupations have a score of 0.10 or less. The last two indicators were partitioned manually because they did not have enough spread across the unsustainable occupations to properly create quartiles.

Table B.6: Skill differences between unsustainable occupations in the top and bottom of rankings by the probability of reaching a sustainable job

Less than a Bachelor's	**Top-Bottom** difference	p-value	**Bachelor's**	**Top-Bottom** difference	p-value
Learning Strategies	11.4	***	Mathematics	8.8	***
Systems Evaluation	11.3	***	Systems Analysis	7.2	***
Systems Analysis	11.2	***	Reading Comprehension	6.9	***
Mgmt of Personnel Resources	10.7	***	Systems Evaluation	6.9	***
Reading Comprehension	9.9	***	Operations Analysis	6.8	***
Writing	9.9	***	Critical Thinking	6.6	***
Operations Analysis	9.0	**	Writing	6.5	***
Negotiation	8.9	***	Science	6.3	*
Instructing	8.8	***	Speaking	6.0	***
Speaking	8.7	***	Active Listening	6.0	***
Active Learning	8.6	***	Mgmt of Financial Resources	5.9	***
Critical Thinking	8.5	***	Negotiation	5.9	***
Mgmt of Financial Resources	8.4	**	Active Learning	5.6	***
Active Listening	8.3	***	Learning Strategies	5.4	***
Persuasion	8.1	***	Persuasion	5.3	***
Mgmt of Material Resources	8.0	**	Programming	5.2	***
Monitoring	7.9	***	Judgment and Decision Making	5.0	***
Complex Problem Solving	7.7	***	Complex Problem Solving	4.9	***
Coordination	7.3	***	Mgmt of Personnel Resources	4.8	**
Mathematics	7.2	***	Instructing	4.6	**
Time Mgmt	7.2	***	Monitoring	4.6	***
Judgment and Decision Making	7.1	***	Mgmt of Material Resources	4.4	**
Social Perceptiveness	6.8	***	Social Perceptiveness	3.9	**
Science	6.5		Time Mgmt	3.9	***
Service Orientation	4.7	*	Coordination	3.3	**
Programming	3.1	*	Service Orientation	2.4	.
Technology Design	1.7		Technology Design	1.7	
Quality Control Analysis	-1.5		Quality Control Analysis	0.5	
Operations Monitoring	-3.1		Operations Monitoring	-1.2	
Installation	-5.1	*	Operation and Control	-3.1	
Operation and Control	-5.7		Troubleshooting	-3.6	
Troubleshooting	-6.6	*	Installation	-3.9	*
Equipment Selection	-8.3	**	Equipment Selection	-5.5	**
Equipment Maintenance	-9.5	**	Repairing	-6.8	**
Repairing	-9.6	**	Equipment Maintenance	-7.1	**

Notes: Unsustainable occupations only. Signif. codes: *** (p <= 0.001), ** (p <= 0.01), * (p <= 0.05), . (p <= 0.1).
Notes: The averages are not weighted by the prevalence of the occupations in the employment profiles data. High-mobility potential (Top) occupations are those with a probability of 0.3 or more, and the low-mobility potential occupations (bottom) are those with a score of 0.05 or less. This indicator was partitioned manually because it did not have enough spread across the unsustainable occupations to properly create quartiles

Table B.7: Skill differences between occupations in the top and bottom of rankings by the number of jobs in the OSN

Less than a Bachelor's	**Top-Bottom**		**Bachelor's**	**Top-Bottom**	
	difference	p-value		difference	p-value
Mathematics	3.9	*	Mathematics	10.1	***
Mgmt of Financial Resources	1.7		Persuasion	3.2	
Negotiation	0.3		Reading Comprehension	3.1	.
Programming	-0.4		Mgmt of Financial Resources	3.1	
Persuasion	-0.5		Negotiation	3.0	
Time Mgmt	-0.6		Active Listening	2.4	
Service Orientation	-0.9		Operations Analysis	2.4	
Reading Comprehension	-1.2		Speaking	2.4	
Active Listening	-1.2		Programming	1.9	
Speaking	-1.3		Writing	1.6	
Active Learning	-1.4		Critical Thinking	1.5	
Mgmt of Material Resources	-1.4		Systems Analysis	1.1	
Judgment and Decision Making	-1.6		Judgment and Decision Making	1.1	
Coordination	-1.8	.	Active Learning	0.3	
Critical Thinking	-1.9		Time Mgmt	0.2	
Writing	-1.9		Systems Evaluation	0.2	
Complex Problem Solving	-1.9		Complex Problem Solving	0.0	
Systems Analysis	-2.3		Coordination	-1.6	
Systems Evaluation	-2.4		Mgmt of Material Resources	-1.6	
Operations Analysis	-2.6		Mgmt of Personnel Resources	-1.9	
Social Perceptiveness	-2.6	.	Social Perceptiveness	-2.5	
Mgmt of Personnel Resources	-3.2	*	Technology Design	-2.6	
Technology Design	-3.5	**	Monitoring	-2.9	*
Monitoring	-3.5	***	Service Orientation	-3.1	.
Learning Strategies	-3.6	*	Learning Strategies	-4.0	*
Installation	-3.6	.	Instructing	-4.0	*
Instructing	-4.1	**	Science	-6.1	.
Quality Control Analysis	-6.3	**	Installation	-6.4	***
Equipment Selection	-6.7	**	Quality Control Analysis	-7.3	*
Science	-7.7	**	Operations Monitoring	-8.2	**
Operations Monitoring	-8.2	***	Equipment Selection	-9.1	***
Repairing	-8.3	**	Operation and Control	-10.3	**
Equipment Maintenance	-8.8	**	Troubleshooting	-10.7	***
Troubleshooting	-9.6	***	Repairing	-10.8	***
Operation and Control	-10.1	***	Equipment Maintenance	-11.3	***

Notes: Unsustainable occupations only. Signif. codes: *** (p <= 0.001), ** (p <= 0.01), * (p <= 0.05), . (p <= 0.1).
Notes: The averages are not weighted by the prevalence of the occupations in the employment profiles data. High-mobility potential (Top) occupations are in the upper quartile of the distribution of number of jobs in the network across the unsustainable occupations, and the low-mobility potential occupations (bottom) are those in the lower quartile.

Table B.8: Difference in skill change between paths that start in occupations and end in either sustainable or unsustainable occupations

Less than a Bachelor's	**(Δ Sustainable) - (Δ Unsustainable)**		**Bachelor's**	**(Δ Sustainable) - (Δ Unsustainable)**	
	difference	p-val		difference	p-val
Mgmt of Financial Resources	21.7	***	Mgmt of Financial Resources	20.4	***
Mgmt of Material Resources	19.1	***	Operations Analysis	19.1	***
Operations Analysis	18.8	***	Mgmt of Personnel Resources	18.0	***
Mgmt of Personnel Resources	17.7	***	Mgmt of Material Resources	17.1	***
Systems Evaluation	13.9	***	Systems Evaluation	16.6	***
Systems Analysis	12.5	***	Systems Analysis	15.1	***
Monitoring	11.7	***	Complex Problem Solving	11.1	***
Negotiation	11.6	***	Monitoring	11.1	***
Coordination	11.1	***	Coordination	10.8	***
Social Perceptiveness	10.5	***	Learning Strategies	10.8	***
Complex Problem Solving	10.3	***	Judgment and Decision Making	10.5	***
Judgment and Decision Making	10.2	***	Active Learning	9.9	***
Learning Strategies	10.0	***	Science	9.7	***
Time Mgmt	10.0	***	Instructing	9.1	***
Active Learning	9.8	***	Mathematics	9.0	***
Persuasion	9.8	***	Time Mgmt	8.7	***
Science	9.4	***	Writing	8.3	***
Reading Comprehension	9.2	***	Persuasion	8.2	***
Instructing	9.1	***	Negotiation	8.1	***
Writing	8.9	***	Reading Comprehension	8.1	***
Critical Thinking	8.4	***	Social Perceptiveness	8.1	***
Speaking	7.5	***	Critical Thinking	7.8	***
Active Listening	6.3	***	Programming	6.0	***
Mathematics	5.4	***	Speaking	5.8	***
Operations Monitoring	5.1	***	Service Orientation	5.2	***
Technology Design	5.1	***	Quality Control Analysis	4.8	***
Programming	4.7	***	Active Listening	4.6	***
Service Orientation	4.5	***	Technology Design	4.5	***
Quality Control Analysis	4.0	***	Operations Monitoring	3.7	***
Troubleshooting	0.7		Troubleshooting	-0.6	
Operation and Control	-0.4		Installation	-0.7	.
Installation	-2.2	***	Operation and Control	-1.3	
Equipment Selection	-5.9	***	Equipment Selection	-3.9	***
Repairing	-7.6	***	Repairing	-5.3	***
Equipment Maintenance	-8.0	***	Equipment Maintenance	-5.9	***

Signif. codes: *** (p <= 0.001), ** (p <= 0.01), * (p <= 0.05), . (p <= 0.1).
The difference columns shows the difference in skill requirement changes between career paths that start in unsustainable occupations and end in sustainable occupation, and career paths that start and end in unsustainable occupations. To do this, cumulative changes in centrality are computed for each skill over each career path in an occupation's OSN. Those changes are then aggregated by whether paths end in a sustainable or unsustainable occupation, weighing the averages by the path probability, but not by the occupation prevalence in the employment profiles data.

Table B.9: Regression Results: Determinants of the Probability Reaching a Sustainable Occupation (College)

	Occupational Characteristics	Job Transition Characteristics	Skills Characteristics	Workforce Characteristics
	(1)	(2)	(3)	(4)
const	0.371***	0.635***	0.589***	15.137**
	(0.039)	(0.146)	(0.152)	(6.147)
Occ. Predicted Growth	0.510***	0.559***	0.480***	0.507***
	(0.113)	(0.109)	(0.123)	(0.129)
Occ. Wage	0.170***	0.149***	0.145***	0.147***
	(0.028)	(0.029)	(0.030)	(0.032)
Occ. Requires College	0.183***	0.138***	0.079*	0.025
	(0.042)	(0.041)	(0.047)	(0.051)
Occ. is a first job		-0.799***	-0.509*	-0.089
		(0.264)	(0.292)	(0.494)
Occ. is a last job		-0.319	-0.645*	-0.708*
		(0.346)	(0.356)	(0.366)
Within-Occ Transition Share		0.120	0.172	0.173
		(0.141)	(0.142)	(0.145)
Number of Jobs in OSN		0.054***	0.048***	0.049***
		(0.013)	(0.015)	(0.015)
% of workers with a BA				0.334
				(0.368)
% of workers with education				-0.658
beyond HS				(0.975)
Industry Dummies	Yes	Yes	Yes	Yes
Skill Centrality Variables			Yes	Yes
Decade Dummies				Yes
Region Dummies				Yes
Observations	495	495	470	470
R^2	0.517	0.549	0.633	0.654
Adjusted R^2	0.495	0.525	0.580	0.593
Residual Std. Error	0.275	0.267	0.252	0.248
F Statistic	35.233***	38.958***	27.744***	25.017***

Standard errors are heteroskedasticity robust. Numerical variables were re-scaled using Z-score normalization.

*p<0.1; **p<0.05; ***p<0.01

Table B.10: Regression Results: Determinants of the Probability of Reaching a Better Occupation (College)

	Occupational Characteristics	Job Transition Characteristics	Skills Characteristics	Workforce Characteristics
	(1)	(2)	(3)	(4)
const	0.304***	0.603***	0.524***	1.953
	(0.034)	(0.095)	(0.107)	(4.636)
Occ. Predicted Growth	-0.499***	-0.367***	-0.262**	-0.167
	(0.127)	(0.103)	(0.110)	(0.113)
Occ. Wage	-0.101***	-0.082***	-0.083***	-0.077***
	(0.011)	(0.011)	(0.017)	(0.017)
Occ. Requires College	0.006	-0.017	0.001	-0.037
	(0.027)	(0.024)	(0.032)	(0.035)
Occ. is a first job		-0.538***	-0.279	0.663**
		(0.170)	(0.199)	(0.326)
Occ. is a last job		-0.416*	-0.316	-0.246
		(0.218)	(0.242)	(0.246)
Within-Occ Transition Share		-0.488***	-0.508***	-0.543***
		(0.074)	(0.075)	(0.079)
Number of Jobs in OSN		0.088***	0.089***	0.090***
		(0.013)	(0.013)	(0.013)
% of workers with a BA				0.891***
				(0.254)
% of workers with education				0.065
beyond HS				(0.604)
Industry dummies	Yes	Yes	Yes	Yes
Skill Centrality Variables			Yes	Yes
Decade of Entry dummies				Yes
Region dummies				Yes
Observations	495	495	470	470
R^2	0.218	0.425	0.506	0.539
Adjusted R^2	0.184	0.394	0.434	0.457
Residual Std. Error	0.236	0.203	0.196	0.192
F Statistic	12.248***	12.550***	7.458***	7.988***

Standard errors are heteroskedasticity robust. Numerical variables were re-scaled using Z-score normalization.

*p<0.1; **p<0.05; ***p<0.01

Table B.11: Regression Results: Determinants of the Change in Mid-Career Wages (Bachelor's)

	Occupational Characteristics	Job Transition Characteristics	Skills Characteristics	Workforce Characteristics
	(1)	(2)	(3)	(4)
const	0.640***	0.539***	0.797***	-9.170
	(0.037)	(0.166)	(0.178)	(8.617)
Occ. Predicted Growth	0.131	0.225	0.025	-0.023
	(0.193)	(0.193)	(0.197)	(0.211)
Occ. Wage	-0.377***	-0.336***	-0.279***	-0.262***
	(0.035)	(0.036)	(0.037)	(0.030)
Occ. Requires College	-0.217***	-0.184***	-0.018	-0.119*
	(0.044)	(0.044)	(0.050)	(0.065)
Occ. is a first job		0.694**	-0.142	0.159
		(0.330)	(0.345)	(0.614)
Occ. is a last job		-0.203	-0.311	-0.250
		(0.447)	(0.493)	(0.530)
Within-Occ Transition Share		-0.385**	-0.432***	-0.264
		(0.170)	(0.160)	(0.173)
Number of Jobs in OSN		0.049***	0.043*	0.033*
		(0.018)	(0.023)	(0.019)
% of workers with a BA				0.205
				(0.591)
% of workers with education				-3.145**
beyond HS				(1.270)
Industry dummies	Yes	Yes	Yes	Yes
Skill Centrality Variables			Yes	Yes
Decade of Entry dummies				Yes
Region dummies				Yes
Observations	495	495	470	470
R^2	0.681	0.701	0.757	0.788
Adjusted R^2	0.667	0.685	0.722	0.751
Residual Std. Error	0.366	0.356	0.335	0.317
F Statistic	40.772***	39.890***	29.400***	26.411***

Standard errors are heteroskedasticity robust. Numerical variables were re-scaled using Z-score normalization.

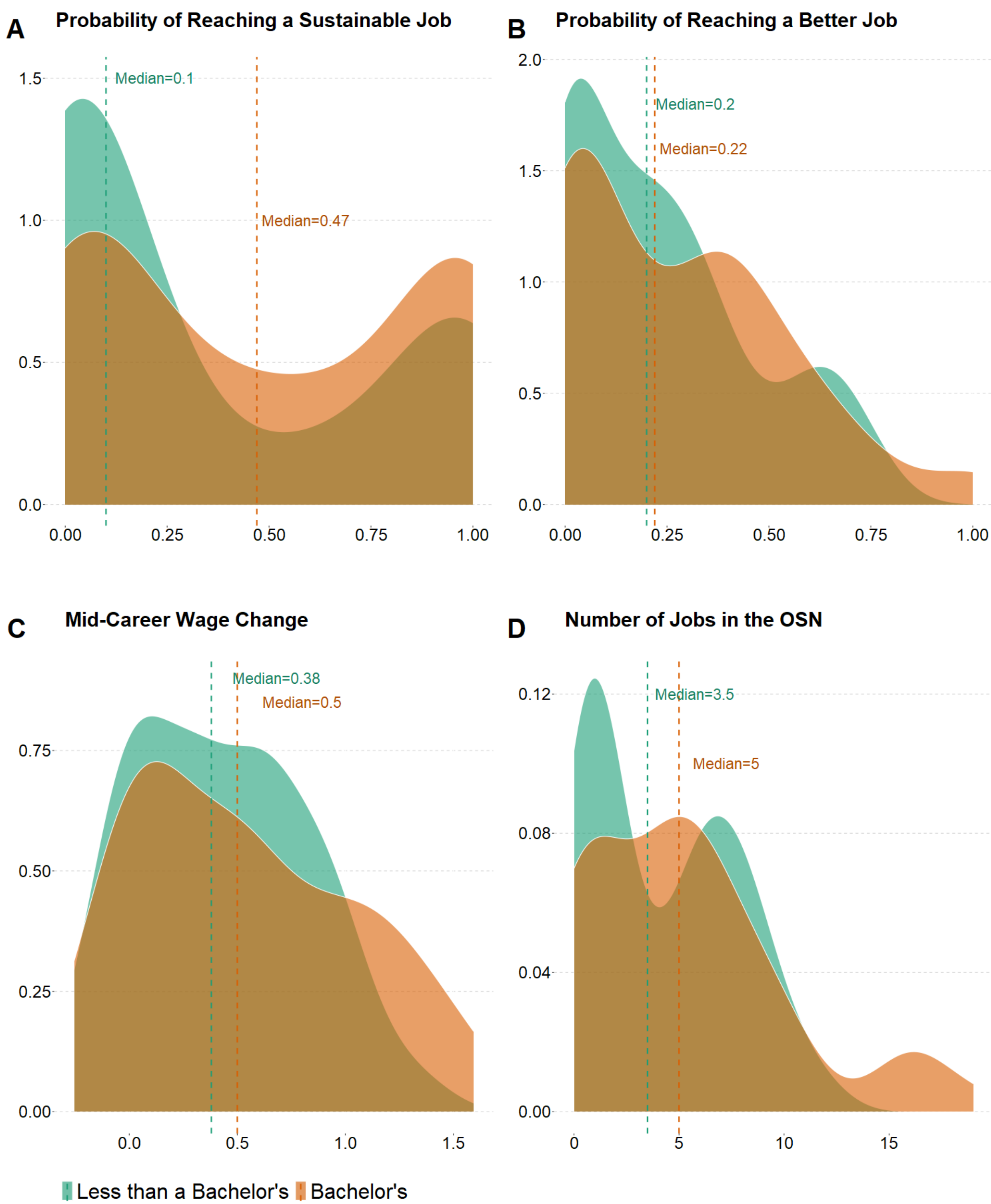
*p<0.1; **p<0.05; ***p<0.01

Table B.12: Share of occupational transitions that involve a human capital investment, by whether the industries of the origin and destination occupations match

		Less than a Bachelor's			Bachelor's		
Origin Industry	Destination Industry Match	n	% Involving Education	% Involving Certification	n	% Involving Education	% Involving Certification
Accommodation and Food Services	No	101,283	0.09	0.02	138,706	0.22	0.04
	Yes	61,552	0.06	0.02	53,052	0.21	0.03
Administrative and Support Services	No	46,100	0.06	0.03	64,346	0.10	0.05
	Yes	19,823	0.03	0.03	33,416	0.04	0.05
Agriculture, Forestry, Fishing, and Hunting	No	2,280	0.14	0.03	3,830	0.29	0.04
	Yes	343	0.08	0.03	520	0.17	0.06
Arts, Entertainment, and Recreation	No	8,005	0.08	0.03	20,171	0.20	0.05
	Yes	1,982	0.04	0.05	3,822	0.09	0.09
Construction	No	35,637	0.06	0.04	27,114	0.15	0.05
	Yes	25,323	0.03	0.04	8,990	0.08	0.06
Educational Services	No	103,106	0.06	0.02	184,880	0.13	0.04
	Yes	51,800	0.03	0.02	71,160	0.10	0.04
Finance and Insurance	No	132,908	0.05	0.02	221,313	0.08	0.04
	Yes	80,801	0.03	0.02	155,085	0.04	0.05
Government	No	77,421	0.05	0.04	140,368	0.11	0.06
	Yes	30,850	0.03	0.05	56,655	0.06	0.08
Health Care and Social Assistance	No	137,325	0.06	0.03	177,809	0.14	0.04
	Yes	125,085	0.06	0.04	117,649	0.12	0.08
Information	No	17,582	0.05	0.03	41,492	0.08	0.03
	Yes	8,160	0.02	0.01	27,663	0.03	0.01
Manufacturing	No	110,609	0.05	0.03	140,100	0.09	0.05
	Yes	79,547	0.04	0.03	108,546	0.04	0.05
Mining, Quarrying, and Oil and Gas Extraction	No	838	0.04	0.03	840	0.07	0.04
	Yes	191	0.03	0.03	285	0.02	0.04
Other Services	No	34,604	0.05	0.03	62,708	0.08	0.04
	Yes	15,349	0.03	0.03	22,802	0.04	0.03
Professional, Scientific, and Technical Services	No	206,724	0.04	0.03	387,475	0.06	0.05
	Yes	297,014	0.02	0.05	588,867	0.04	0.06
Real Estate and Rental and Leasing	No	35,011	0.05	0.04	35,390	0.10	0.05
	Yes	24,096	0.02	0.04	17,951	0.04	0.05
Retail Trade	No	232,386	0.07	0.02	318,907	0.16	0.04
	Yes	145,193	0.05	0.02	158,425	0.12	0.03
Transportation and Warehousing	No	56,365	0.06	0.02	45,963	0.16	0.04
	Yes	25,493	0.03	0.02	11,679	0.11	0.04
Utilities	No	2,463	0.05	0.04	1,586	0.12	0.06
	Yes	694	0.03	0.04	237	0.09	0.06
Wholesale Trade	No	107,073	0.04	0.02	199,335	0.06	0.04
	Yes	84,249	0.02	0.02	216,488	0.02	0.03

Notes: An occupation transition involves an educational any time two consecutive professional records are separated by an educational record in the employment profile data.

Figure B-5: Distribution of the Mobility Indicators Across Manufacturing Occupations, by Highest Educational Attainment



Note: The distribution of occupational mobility scores do not take into account the prevalence of occupations in the employment profiles data.

Figure B-6: Weighted Distribution of the Mobility Indicators Across Manufacturing Occupations, by Highest Educational Attainment

Note: The distribution of occupational mobility scores is weighted by occupation prevalence in the employment profiles data.

Figure B-7: Distribution of the Mobility Indicators Across Manufacturing Occupations, by Occupation Type (Less than a Bachelor's)

Note: The distribution of occupational mobility scores do not take into account the prevalence of occupations in the employment profiles data.

Figure B-8: Distribution of the Mobility Indicators Across Manufacturing Occupations, by Occupation Type (Bachelor's)

Note: The distribution of occupational mobility scores do not take into account the prevalence of occupations in the employment profiles data.

Table B.13: Gateway manufacturing occupations into sustainable manufacturing occupations:

Group	**Origin**			**Destination**
	Occupations	Sustainable	n size	Top Destination
Less than a Bachelor's	Commercial and Industrial Designers	Yes	7,984	Mechanical Engineers
	Manufacturing Production Technicians	No	6,095	First-Line Supervisors of Production and Operating Workers
	Materials Engineers	Yes	533	Manufacturing Engineers
	Chemical Engineers	Yes	4,703	Manufacturing Engineers
	Validation Engineers	Yes	4,599	Software Quality Assurance Engineers and Testers
	Mechanical Drafters	No	3,732	Drafters, All Other
	Industrial Engineers	Yes	3,494	Validation Engineers
	First-Line Supervisors of Production and Operating Workers	No	21,096	General and Operations Managers
	Purchasing Agents, Except Wholesale, Retail, and Farm Products	No	19,234	Purchasing Managers
	Inspectors, Testers, Sorters, Samplers, and Weighers	No	14,659	Quality Control Systems Managers
Bachelor's	Mechanical Engineers	Yes	39,912	Commercial and Industrial Designers
	Purchasing Agents, Except Wholesale, Retail, and Farm Products	No	33,502	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products
	Electronics Engineers, Except Computer	Yes	26,153	Managers, All Other
	Commercial and Industrial Designers	Yes	23,868	Mechanical Engineers
	First-Line Supervisors of Production and Operating Workers	No	18,960	General and Operations Managers
	Manufacturing Engineers	Yes	18,613	Mechanical Engineers
	Chemical Engineers	Yes	15,809	Mechanical Engineers
	Logisticians	Yes	13,031	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products
	Industrial Engineers	Yes	12,006	Manufacturing Engineers
	Validation Engineers	Yes	10,885	Software Developers, Applications

Notes: Calculations are weighted by path probability and origin occupation count.

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