It's Not Just Who You Know:
Skillsets, Coordination, and Employment Mobility in the US Civil Service

Joshua R. Bruce
Department of Sociology
Duke University
417 Chapel Drive
Box 90088
Durham, NC 27708
joshua.bruce@duke.edu

September 2018

Abstract

When and why are some skillsets more valuable than others? This paper addresses the role of skillsets as bundles of coordinative capabilities in the US civil service. Building on recent advances in personnel economics and studies of knowledge in team performance, this paper theorizes the role of skillsets in employment mobility by stressing the value to employers of employees best suited to coordination roles in their organizations. A novel method for skillset identification is introduced, leveraging the availability of job documentation and natural language processing software. After identifying employees' skillsets and skill-based linkages among coworkers, panel regression models of 2.7 million person-year records, covering a subset of federal employees between 1979 and 2014, indicate that civil servants best positioned to coordinate workplace tasks are more highly compensated. Furthermore, this effect is found to depend in part on the supply of alternative personnel with relevant capabilities, and on the complexity of the organization in which civil servants work. As organizational complexity (i.e., need for coordinative capabilities) increases, so too does the magnitude of later salary growth. Limitations of the analysis are discussed, as well as future directions for research on the nature of work, employment, mobility, and organizational performance.

It's Not Just Who You Know:
Skillsets, Coordination, and Employment Mobility in the US Civil Service

What makes a person's skillset valuable? One branch of scholarship on this question, within sociology and organizational theory, focuses on skill-related determinants of organizational outcomes, such as product development (de Vaan, Stark, and Vedres 2015; Vedres and Stark 2010) and organizational learning (Zappa and Robins 2016). This line of research is insightful for understanding how employees' skillsets influence organizational performance, yet individual-level outcomes, which are an important component of intragenerational mobility and economic inequality (Byun, Frake, and Agarwal 2018; Kalleberg and Mouw 2018), are rarely addressed. A second line of research in personnel economics theorizes individual-level outcomes in labor markets as a function of skill-based human capital (Gibbons and Waldman 2006; Lazear 2009). Despite the profusion of formal economic models, there has been little empirical work testing their validity. Thus, there remains an enduring gap in our understanding of how skillsets relate to employment outcomes for workers due to a lack of research on the person-level mechanisms that drive well-documented aggregate patterns (Kalleberg and Mouw 2018; Rosenfeld 1992).

Several scholars have begun confronting this issue, both within economics and sociology (e.g., Deming 2017; Leung 2014). This paper joins their efforts by combining recent insights on labor market processes and organizational performance to develop a theory of contingent skillset value for individual outcomes. The model put forth is grounded in core tenets of human capital theory, which are then expanded by a social capital-informed perspective on skills as context-dependent resources. Whereas human capital models have historically viewed skills as held by atomized individuals, this paper emphasizes social-situational determinants of skillset value and empirically demonstrates how the mechanism of skills-in-context affects individual mobility. In short, this paper theorizes that when employees hold skills in common with their coworkers, they are able to facilitate information translation in the workplace and coordination among their coworkers. This communicative role is theorized to be especially valuable when few others possess the requisite skillset to understand the work being done by coworkers, which leads to downstream mobility for uniquely translational employees and when workplace complexity is greatest. The theoretical argument is tested in the context of the US civil service using an unprecedented administrative dataset on the careers of federal employees from 1974 to 2014.

Given the focus on civil servants, an important scope condition of the theory developed is its focus on full-time, salaried employees in quasi-internal labor markets.[1] Notwithstanding considerable discussion of the demise of such occupations and careers, Bureau of Labor Statistics (BLS) data show a consistent increase in the proportion of employees compensated by salary, rather than an hourly wage, since the mid-1990s.[2] Furthermore, in the first quarter of 2017, just under 40% of American workers were employed by organizations with 1,000 or more employees, a share that has increased every year since 2003.[3] While there is no doubt that non-standard work is an important feature of modern labor markets, the 'typical' career still exists for many employees in large organizations,[4] and this paper speaks to their employment experiences.

The results presented confirm the theoretical argument: increasingly sharing skills with coworkers positively predicts later promotion. Skills are measured using a novel application of natural language processing to a corpus of context-specific job descriptions. Furthermore, the presence of alternative skillset paths between coworkers, which represent sources of skill redundancy, is shown to reduce the positive benefit of skillset connectedness. Having identified these factors, the paper explores contextual features that make connective skillsets more or less valuable, especially the complexity of the workplace. Predicted marginal effects demonstrate that connective skillsets are increasingly valuable as the number of skillsets in a workplace goes up; in other words, as it becomes harder to coordinate employees, the ability to do so is increasingly rewarded. These results are shown to be robust to multiple model specifications.

This paper contributes to theories of social capital, human capital, and employment mobility by theorizing a mechanism that enables workplace communication and coordination. This mechanistic account shows that not only does opportunity (i.e., social capital) matter, the ability to capitalize on social capital is also an important component of how people get ahead in large organizations by capturing the value present in their informational networks. This capability is represented by the human capital a worker accumulates during their tenure in the labor market, which may have differential value across workplaces and over time.

---

[1] This is an important difference from some recent, related scholarship, which explicitly focuses on spot labor markets and non-standard employment (e.g., Leung 2014, 2017).
[2] See Table 10 of BLS Report 1061: Characteristics of minimum wage workers, 2015, available at: https://www.bls.gov/opub/reports/minimum-wage/2015/home.htm (last accessed January 21, 2018).
[3] See Table F, "National Business Employment Dynamics Data by Firm Size Class" from the BLS, available at: https://www.bls.gov/web/cewbd/table_f.txt (last accessed July 14, 2018).
[4] See BLS report on "Contingent and Alternative Employment Arrangements," available at: https://www.bls.gov/news.release/conemp.toc.htm (last accessed July 13, 2018).

This paper also contributes to the empirical analysis of employment dynamics. First, it establishes a novel method of measuring skills in career history data that, to the author's knowledge, has not been used before. This method enables a more granular and context-specific approach to assessing the skills acquired on the job, which are shown to be instrumental in how people achieve upward employment mobility. Second, it presents a large-scale longitudinal study of workplace dynamics in a context that represents a substantial segment of the US workforce: federal government employment represented 1.8% of total US employment in 2016, while state and local government personnel, many of whom work in similar labor contexts, accounted for an additional 12.4% of workers in the same year.[5] This paper thereby adds to empirical knowledge on skills, occupations, careers, and mobility by developing and microanalytically testing a theory of individual-level career dynamics.

The paper proceeds by briefly reviewing economic models of human capital, which are then integrated with skill-based sociological theories on organizational performance, extending the sources of returns to human capital to include social determinants of mobility. The following section discusses the civil service in greater detail, highlighting the government's emphasis on coordinative skillsets as a source of value. The data, measurement strategy, and analytical methods are then introduced, and regression results are presented. The paper concludes by discussing implications of the results and generalizability, limitations of the current study, and questions to be addressed in future research.

SKILLS AS HUMAN CAPITAL

Modern empirical research on workplace mobility and skills emerged largely from the seminal work of Gary Becker and his contemporaries (cf. Becker 1993; for a recent review, see: Kalleberg and Mouw 2018). Following their research, personnel economists mostly focused on explaining employment outcomes as processes of skill accumulation, skill signaling, and organizational learning (about employees' skills and effort in applying them). In the canonical model, time spent learning on the job in a firm confers skills whose value is highest in that firm; skills are transferable between firms but (almost) always at a discount (Becker 1993). Becker's human capital model achieved popularity in part because it lent itself to analyzing who (workers

---

[5] See: BLS data, "Employment by Major Industry Sector, 2006, 2016, and Projected 2026," *Employment by Major Industry Sector*, available at: https://www.bls.gov/emp/ep_table_201.htm (last accessed September 9, 2018).

or employers) ought to pay for skill acquisition in an economically rational system. However, despite the theoretical convenience and straightforward policy prescriptions, irregularities in empirical analyses raise concerns about the accuracy of Becker's model in capturing the observed world (Gibbons and Waldman 1999). In one prominent example, Baker, Gibbs, and Holmstrom (1994) find substantial deviations from theoretically-predicted wage dynamics in a firm's internal labor market.[6] They conclude by emphasizing the need for more data to empirically validate the profusion of human capital theories.

Two related, influential concepts emerged in response to these irregularities. The first is task-specific human capital, based on the proposition that "human capital accumulated in one job will typically lose value in another job that requires a different mix of skills" (Gibbons and Waldman 2006:63). Whether an employee moves across firms, occupations, or industries is theoretically immaterial (p. 90); the focal mechanism is the similarity of the skillset required between two positions, even two associated positions in the same firm.[7] Lazear (2009) proposes a similar mechanism in his "skill-weights" approach to human capital, theorizing that skills necessary in a job are drawn on to different degrees between firms. In both formalizations, changes in the demands placed on workers generate wage differences despite static skillsets.

This line of theorizing is core to the model developed herein. However, this paper argues that the economic models take a much too atomistic view of employees and skillsets. Most workers are not in a continual state of change between jobs and firms, particularly among the full-time workforce of professional services organizations like the federal government. Moreover, despite considerable scholarly attention on interfirm employment mobility, a

---

[6] Other scholars argue against firm-specific human capital, noting that frictions in skill transferability arise at other, more important analytical levels. Occupation-specific and industry-specific human capital have been proposed as better levels of aggregation, given high levels of skill transferability between firms. Despite the profusion of studies, empirical contradictions remain. I limit my discussion of these measures largely because the concept of task-specific human capital captures many of the same processes in a more refined manner (Gibbons and Waldman 2006:75–76).

[7] A central concern for Gibbons and Waldman (2006) is explaining cohort effects in long-term wages. Baker et al. (1994) document consistent wage differences across cohorts that appear unrelated to cohorts' demographic and educational composition. Gibbons and Waldman argue that cohorts with lower long-term wages entered employment during an economic downturn, pushing more employees into low-skill jobs where human capital accumulates slower. In other words, these individuals started with both a lower intercept (a recession pushed starting wages down) and then experienced reduced slopes (lower-quality jobs conferred human capital at a slower rate). Given that the labor market conditions in place at the time when an individual is hired do not change, this phenomenon is partially captured in my use of individual fixed effects. Gibbons and Waldman (2006:90–92) are also circumspect about the ability of their model to capture wage dynamics in ILMs, which is surprising given their direct response to Baker et al., who consider the firm in their study to be at least partially characteristic of ILMs (1994:923).

substantial portion of intragenerational wage inequality emerges while employees remain with the same employer (Mouw and Kalleberg 2010; see also Kalleberg and Mouw 2018). Thus, the wage value of employees' skills frequently changes despite their remaining stationary (i.e., in the same job at the same employer), highlighting the need for a more expansive theory of wage dynamics and skill value.

This paper builds on the task-specific and skill-weights approaches by theorizing a complementary process: changes in context that occur regardless of change in a given individual's human capital, job, or employer. This approach emphasizes the linkage between an employees' skillset (i.e., the total amount of work-related knowhow an employee has gathered up to some point in their career) and the employment context. Changes in skillset value come from an employee's skill-based fit with their coworkers, providing a potentially continuous source of contextual change, whether or not the focal employee moves to a new position.

Skill-based fit in the workplace influences workers' compensation because the vast majority of work is rarely completed in isolation, especially in large professional services organizations (Thompson 1967). Human capital acquisition alone does not matter if it does not fit the labor context, which may change for a variety of reasons having little to do with any single individual's skillset or the emphasis placed on enacting skills learned on the job (e.g., due to the differential adoption of technology between divisions in an organization [Acemoglu and Restrepo 2018; Bartel, Ichniowski, and Shaw 2007]). This line of theorizing motivates an analytical turn away from the specialist-generalist debate toward a focus on how employee skills match their work environments, which may be accomplished equally well by specialists or generalists.[8] The basis for this theory is an understanding that human capital is best captured by skills, which have variable worth to employers due to contextual differences that may vary across firms (thereby yielding firm-specific human capital effects) or within the same firm over time. The next section explicates this argument in a mechanistic account of how skill-based fit leads to employment mobility.

---

[8] This study is nonetheless indebted to the theoretical and empirical work on the generalist/specialist debate. For example, Teodoridis, Bikard, and Vakili (2018) demonstrate that specialization can be broken apart into those with domain-relevant specialization or not, which have distinct implications for scientific achievement. I go beyond domain-relevance to address skill-level complementarities between employees' skillsets.

SKILLS IN ORGANIZATIONS

Organizational scholars (in sociology, economics, and business administration) have long been concerned with the coordinative role employee knowledge plays in organizational performance (Okhuysen and Bechky 2009). Within organizations, the need for coordination stems from the specialization of tasks;[9] increasing division of labor leads to greater need for coordination to achieve organizational objectives (Becker and Murphy 1992; Kogut and Zander 1996; Simon 1957). Simon (1957:103), theorizing organizational coordination, wrote: "In any large organization—the Federal government is an excellent example—the task of relating the activities of one individual or unit to those of others becomes one of the greatest importance, complexity, and difficulty." Building on Simon, Thompson (1967:54–55) subdivided intra-organizational coordination into three types of interdependence between actors—pooled, sequential, and reciprocal—each increasingly difficult to carry out successfully. To successfully coordinate interdependent tasks, Thompson (1967:56) argued that organizations employ three strategies: standardization, coordination by plan, and coordination by mutual adjustment. The final strategy, which is integral to completing reciprocally interdependent work, entails communication of the evolving state of affairs between coworkers in an ongoing manner (1967:62). Coworkers must possess sufficient shared workplace-specific knowledge to enable absorption, processing, acting on, and transmission of relevant information between themselves, thereby achieving mutual adjustment.

'Knowledge' is used here synonymously with skills, meaning what employees are capable of doing at work without further training or education.[10] In human capital models, skills are built up through formal education and on-the-job learning that takes place when completing tasks (Becker 1993; Gibbons and Waldman 2006). Similarly, in research on knowledge and workplace interactions, the source of knowledge shared between coworkers is typically co-participation on teams, projects, or in divisions of an organization (e.g., Hansen 1999; de Vaan et al. 2015). In this latter literature, increasing skill overlap between coworkers (i.e., more experience working together) enables mutual comprehension of complex information, which increases the quality of organizational output.

---

[9] The prototypical mechanisms for overcoming coordination problems have been identified as markets, hierarchies (i.e., organizations), and their hybrid combinations (Williamson 1975).

[10] For a different perspective on communication and mobility in the workplace, see: Goldberg et al. (2016).

The core mechanism leading from skills to value can be broken out into two processes (Vedres and Stark 2010; de Vaan et al. 2015). First, subsets of a team who worked together previously are able to draw on their common knowledge, generated during prior co-working, to communicate complex information effectively with each other in an environment of technical uncertainty and disconnected knowledge bases. When teams are made up of people who have worked on different projects, they hold different technical skillsets and knowledge, generating tension when there is difficulty in communicating complex ideas without a shared lexicon. Individuals who worked together previously, thereby possessing common knowledge, are able to bridge these tension-causing gaps in the new setting (called "structural folding") and act as translators between intra-organizational groups.

The degree of divergence in team members' knowledge, their "cognitive distance," is the second part of the mechanism, complementing structural folding to produce novel, high quality products (de Vaan et al. 2015). As knowledge complexity increases within a team, a greater amount of tension is generated by the lack of mutual interpretability. The greater the tension overcome by structural folding, the higher the propensity for successful creativity. Stated differently, increased value is generated when a sub-group within an organization is able to bridge the skillsets of otherwise disconnected coworkers, especially if those disconnected coworkers have highly disparate skillsets.

One context where these processes come to light is in interdisciplinary academic research groups. Interpersonal communication and comprehension are more difficult when collaborators are from distant academic disciplines, which decreases their scholarly output. However, if such scholars are able to bridge the cognitive gaps between themselves, their final output has a greater likelihood of making a scholarly impact (Leahey, Beckman, and Stanko 2017). In organizations, employees with skills that bridge gaps between their coworkers' skillsets enable the transmission of information that makes organizations and teams more successful, overcoming a major impediment to organizational success imposed by specialization, much as connective agents, such as consultants, link technology suppliers and adopters, facilitating innovation diffusion and organizational learning (Attewell 1992; Valentine 2018).

Beyond organizations and their constituent divisions, there is little empirical work on how skillsets, as connective elements in the workplace, lead to individual-level outcomes. Deming's (2017) analysis suggests that communication and coordination in the workplace make

some occupations more economically valuable than others, but the analysis is limited by highly aggregated, cross-sectional data, leaving substantial questions about how connective mechanisms operates inside organizations and over individuals' careers, which may feature multiple occupations that confer skills not captured in cross-sectional data. de Vaan et al. (2015) provide a window on how coordination, achieved through the language of common experience, leads to high organizational performance. The next section links these perspectives, going beyond co-participation in teams and single occupational categories to show how employees' skillsets are a contingent resource that leads to individual employment mobility.

Opportunities versus Capabilities

Skills are theorized to enable coordination in organizations, making them a complement to network-based social capital. In Granovetter's (1973) influential theory, social capital represents the resources, especially information, available to a person by virtue of who they know and how strongly they are connected to these others. Burt's seminal work (e.g., 1992, 1997) extends Granovetter's theorizing to empirical analyses of employees in organizations, looking at the value realized by individuals from their structural opportunities to communicate across groups of otherwise disconnected people (i.e., to occupy brokerage positions spanning structural holes). The key resource tapped into by people in these network positions is non-redundant information. "People whose networks bridge the structural holes between groups have an advantage in detecting and developing rewarding opportunities. Information arbitrage is their advantage…. brokerage across the structural holes between groups provides a vision of options otherwise unseen" (Burt 2004:354). In a word, social capital provides *opportunity*.

However, a lingering incompleteness in the study of social capital comes from the ubiquitous emphasis on social capital as opportunity. Scholars have shown copious evidence that opportunity, measured typically by brokerage, is positively related to both firm- and individual-level outcomes (for a review, see Burt 2000). What remains insufficiently studied, and where this paper focuses its attention, is on individuals' *capabilities* to translate network opportunity into employment outcomes. In the words of Burt (2004:354), "Networks do not act, they are a context for action. The next phase of work is to understand the information arbitrage by which people acting as brokers harvest the value buried in structural holes." This is not a recent problem, as pointed out by Gould and Fernandez (1989:98, note 4), who note that most measures of social

capital indicate a "necessary but not sufficient condition for actual brokerage behavior." Byun, Frake, and Agarwal (2018) report one of the first studies to empirically address this problem, finding that lobbyists with more diverse experiences are better positioned to take advantage of expansions in their social network resources (i.e., increases in social capital).

Building on Byun et al.'s (2018) work, this paper theorizes that context-specific skillsets, not just breadth of experience, provide employees' the capacity to capture value from gaps that exist between their coworkers' skillsets. The capacity to extract value from social connections comes from sharing skills that enables a person to arbitrate between others who have difficulty communicating workplace-relevant information, even if they already know each other.[11] In settings where specialization is prevalent, as is the case in many hierarchical organizations, coworkers often face what psychologists have labeled the "curse of knowledge." The curse of knowledge operates when people feel they know what they want to communicate in a given scenario due to their own deep expertise, yet they lack the terminology of their communication partners' expertise to convey this information (Heath and Staudenmayer 2000). This point is integral to theories of technology and coordination problems in organizations and teams (Becker and Murphy 1992; Teodoridis 2018) and can stem from multiple factors (Ferreira and Sah 2012; Lyons 2017). Beyond skillset diversity, this theory argues that connective individuals are valuable to organizations precisely because of their translational capacity (Jones 2011; Obstfeld 2005), which is conditional on their connections to the skillsets of others working in the same time and place as the focal individual. This leads to the core hypothesis in this paper:

> *Hypothesis 1: Greater skillset connectivity with coworkers leads to upward employment mobility for the focal employee.*

In addition to skillset connectivity, another feature of the skillset network in the workplace is critical to the value of any focal employee's skills: skillset redundancy. Possessing a connective skillset is hypothesized to generate value for the focal employee, but this is conditional on the degree to which others are also capable of filling the communicative role in

---

[11] The opportunity to connect people is of course structurally limited by being present in some meaningful organizational unit, which is incorporated in my measurement approach by focusing on individuals in the same organizational divisions at the same time.

the workplace without drawing on the focal employee's skillset. As exclusivity diminishes (i.e., as more skillsets can be drawn on to solve coordination issues), the likelihood of promotion based on skills is hypothesized to decline. In network terminology, this boils down to *transitivity*, or the extent to which a focal actor's connections are also connected to each other. Applied to skillsets in a workplace, transitivity measures the degree to which an employee's skill-based connections also possess other overlapping skills; in other words, how redundant is the focal employee's skillset. This is a critical feature because it qualitatively changes the strategic value of the focal employee's skillset. Brokerage-based theorizing argues that individual value emerges when no other actor has the opportunity to exercise control over information. Positions of importance may be used manipulatively or collaboratively (Obstfeld 2005), but either produces value by demonstrating that the individual is integral to communication in the workplace. The same logic can be applied to the capacity for translation; as others possess the skills necessary to communicate effectively with a focal actors' connections, the focal actor loses valuable exclusivity. This results in the following hypothesis:

> *Hypothesis 2: Increasing skillset redundancy will reduce the likelihood of later promotion.*

A final concern represents the demand for coordination. What features of the workplace make it more or less difficult to coordinate, which may in turn influence the organizational value placed on connected skillsets? As organizations grow in size and complexity, search costs within the organization increase as communication becomes more difficult (Garicano 2000), often due to an increase in specialization (Becker and Murphy 1992). This process has been documented in scientific teams, and has led to the rise in co-authorship as a way to process increasingly voluminous and diverse information (Jones 2011). As such, it is hypothesized that employees with the most-connected skillsets, relative to their immediate coworkers, will see a greater return to their skills in more complex work environments. Stated formally:

> *Hypothesis 3: Employees working in contexts with a greater number of distinct employee skillsets will see a greater positive return to their own skillset connectedness.*

THE CIVIL SERVICE CONTEXT

The three hypotheses are tested in the context of the US federal civil service, which is one of the largest quasi-internal labor markets (ILM) in the United States (cf. DiPrete 1989). The civil service is a "quasi" ILM in the sense that each organizational unit is its own ILM, which is linked to other ILMs by common promotion ladders and information sharing systems. The civil service is divided at two major levels: agencies and sub-agency bureaus. Agencies are the highest-level organizational unit, such as the Department of Labor, which encompass bureaus, such as the Bureau of Labor Statistics. Some agencies do not contain sub-dividing bureaus (e.g., the Environmental Protection Agency). Within bureaus, personnel are assigned to occupations based on the primary set of tasks they are expected to carry out. Work is performed at geographic locations, called duty stations, around the United States, and employees are assigned to the duty station where they perform the majority of their work.

When a person is initially hired into the civil service, they are placed on a wage ladder, typically the General Schedule (GS) pay scale, which is the most common pay ladder in the civil service and the focus of my analysis.[12] An employee's initial position on the 15-level pay ladder is determined formulaically by the mixture of their education, prior work experience, and any military history. Movement up the scales is based in part on time spent working at each level, but there is no guarantee of upward mobility; personnel often remain at the same level for many years. Criteria for progressing up the GS scale are documented by the Office of Personnel Management (OPM) with input from the relevant agency or bureau; OPM's authority is granted by Title 5 of the US Code to oversee promotion guidelines. The GS pay scale is used throughout the non-military civil service, along with a common pension system, reducing barriers to inter-organizational mobility by personnel. The systematization of "ports of entry," or typical entry levels, and pay ladders are two defining characteristics of ILMs (Althauser 1989; Doeringer and Piore 1971), which we see continuing to operate in the civil service.

Work in the civil service is further divided within bureaus into occupational groups and individual occupations. Occupational groups collect occupations that represent broadly defined

---

[12] Other important pay scales include the Foreign Service pay scale, used to compensate Foreign Service Officers in the Department of State, and the Senior Executive Service pay scale which compensates the highest-level managers in the federal government. These and other employees not compensated on the GS scale are not included in the sample analyzed below but are included in variable creation if they work alongside GS employees. For more, see OPM's webiste "Pay & Leave: Pay Systems: General Schedule," available at: https://www.opm.gov/policy-data-oversight/pay-leave/pay-systems/general-schedule/ (last accessed December 19, 2017).

fields, such as the "Social Science, Psychology, and Welfare Group," which includes such occupations as sociologists, social psychologists, economists, workforce analysts, and others. Occupations are assigned based on the types of tasks the employee is expected to spend most of their time carrying out, which are detailed in each occupation's job description. Within occupations, employees are compensated according to a grade level that is determined by one or more supervisors. Movement up grade levels within an occupation is determined by how an employee scores on (up to nine) distinct factors applied to all positions, which are detailed in OPM's *Classifier's Handbook*.[13] Two of the nine factors, relating to physical ability to perform work and work conditions, are largely irrelevant to professional service work conducted by the mostly white-collar full-time workers on the GS pay scale.

The remaining seven promotion factors emphasize the degree to which an employee has mastery of the skills necessary to complete their work, their ability to do work without direct supervision, and the capacity of the employee to draw on and coordinate disparate areas of knowledge to achieve their objectives. This final element—coordination—is common across the highest levels of many factors, underscoring the importance of skills-as-translational resources in the civil service. One factor, assessing "complexity" of an employee's position, awards the most points for work that is "characterized by breadth and intensity of effort and involve[s] several phases pursued concurrently or sequentially with the support of others within or outside the organization." The highest level of another factor, evaluating the types of connections an employee possesses, stresses that "persons contacted [in carrying out the job] typically have diverse viewpoints, goals, or objectives requiring the employee to achieve a common understanding of the problem and a satisfactory solution by convincing them, arriving at a compromise, or developing suitable alternatives." Each of these statements emphasizes the value placed on the capacity to connect and usefully interpret disjoint bodies of information, coordinating and communicating across disconnected groups.

In addition to emphasizing the capability to coordinate, official guidance is also explicit in its deference to managerial decision makers, encouraging managers to determine grade levels (i.e., salary) in light of each employee's unique capacity to carry out work. In the *Introduction to the Position Classification Standards*,[14] OPM guidance states:

---

[13] Available at https://www.opm.gov/fedclass/clashnbk.pdf (last accessed August 18, 2018)
[14] Available at https://www.opm.gov/fedclass/gsintro.pdf (last accessed August 18, 2018)

> *While it is the position which is classified, the relationship of the employee to the position can be recognized when the performance of the incumbent broadens the nature or scope and effect of the work being performed.... Such changes affect the difficulty of work or the responsibility and authority given the employee and can be recognized in the position classification decision* [i.e., salary grade].

The capabilities to coordinate employees and to make sense of diverse and complex information are defining features of the most valued work carried out in the federal civil service. Skillsets that link otherwise disconnected employee knowhow in the workplace thereby make one valuable as a translator and coordinator. Furthermore, promotion decision makers have the authority to reward these skillsets with increased pay in the form of higher GS grade levels, establishing the linkage between employment context, skillsets, translational capabilities, and mobility in the federal civil service context. The remainder of this paper lays out the empirical strategy for testing this argument using data on the employment history of civil servants.

DATA, MEASURES, AND ANALYTICAL APPROACH

Data on federal employees come from civil service personnel records provided by OPM. These records consist of annual employment snapshots for nearly all federal employees, including their occupation, length of service with the federal government, agency and bureau of employment, pay scale and grade, supervisory status, and a unique identification number that is consistent across fiscal years. All of the following variable creation and model estimation draws from this same source, but the data are substantially reduced in the estimation phase.

Specifically, while the raw data cover 1974-2014, the analysis is limited to the careers of employees hired in 1979 or later, following major civil service reform legislation that changed how promotion and pay were determined for most personnel.[15] Employees of the Department of Defense are excluded, as are employees in security and national defense-related positions (e.g., US Marshals). Records are dropped for any employees who worked at any time in two bureaus (Internal Revenue Service and Social Security Administration), or if they ever worked in any

---

[15] Civil Service Reform Act, Public Law 95-454 (1978); see:
https://www.law.cornell.edu/topn/civil_service_reform_act_of_1978 (last accessed August 21, 2018)

bureau of the Department of Veterans Affairs. The analysis is further limited to employees who worked at government bureaus with at least 50 employees in every observation year; to employees only compensated on the GS pay scale during their entire records in the data; and to those who never held a politically appointed position (i.e., exclusively career civil servants). The data are reduced in these ways to avoid concerns of omitted variable bias that may emerge due to political features in some civil servants' careers, data limitations for personnel working in financially sensitive parts of the government, or for military-adjacent workplaces where it is not possible to control for the skillsets of military personnel as accurately as non-Department of Defense employees. The complete set of careers analyzed represent 287,635 unique individuals across 2.73 million person-year records (average of 9.5 records per person); all personnel with only one year of service are dropped due to the panel estimation strategy discussed below.

While the careers analyzed are subject to these limitations, the variable creation approach laid out below makes use of all standard-career compensated employees in the raw data from 1974 onward (i.e., all personnel with a positive value for income earned, in a non-seasonal position, and with a valid occupation code). This includes up to five years of work history for the coworkers of employees whose careers are included in the analytical frame beginning in 1979. All personnel are included in the variable creation phase because these represent the skillsets that the analyzed personnel interact with, even if those skillsets are held by people who have had more varied work experiences making them unsuitable for analysis.

Measuring Skills

The emphasis in this paper is on skills as connective elements between people, who possess bundles of skills (skillsets) accumulated over their work history. Measuring skills has been achieved by a variety of approaches in the past. In many labor-economic studies, human capital is measured by how long an individual has worked in a given job/firm/occupation/industry, with considerable variation in the specificity used to delineate categories within these levels of analysis.[16] Deming (2017) improves on this approach by breaking down occupations into a limited set of skills, defined in the US Department of Labor's Occupational Information Network (O*NET) database.[17] The O*NET data is based on surveys of people working in each occupation

---

[16] For a review of the difficulties in comparing terminology and measurement of skills, see Spenner (1990).
[17] O*NET data and documentation available at: https://www.onetonline.org/

and occupational experts, providing a nationally representative picture of the skills used in roughly 1,000 occupations. However, a shortcoming of the O*NET data, suggested by Lazear's (2009) skill-weights theory, is that different types of organizations likely draw on the skills that typify an occupation in unique ways, and there may be idiosyncratic skills in some occupations that are not well captured in the highly generalized O*NET framework. Aggregate measures also leave researchers blind to the skills accumulated by workers who have held more than one occupation. An alternative approach, favored by team-focused researchers, treats everyone who worked on a project as possessing the same skill experience (de Vaan et al. 2015). This approach is hard to justify in the case of the federal government, where personnel are rigidly categorized in separate occupations based on their primary work activities and the number of people working together is much larger than small teams.

The issue of skill measurement is resolved by turning to government documentation of work responsibilities for employees in 610 distinct occupations. Any time an occupational title is created in the federal government, OPM publishes a 1-3 paragraph description of the primary work functions expected of people working in that occupation; these are then printed in OPM handbooks. Occupational descriptions were collected from the most recent edition of the OPM *Handbook of Occupational Groups and Families* (2009), with now-defunct occupational categories filled in from older handbooks where necessary. These descriptions were then analyzed using a natural language processing algorithm developed by computational linguistics researchers to label the parts of speech (e.g., nouns, verbs) in each occupational description (Manning et al. 2014).[18] The verbs identified in each description were extracted, constituting the general activities that make up each occupation's core skills.[19] Each employee thereby accrues a year-specific skillset of the verbs identified based on the occupation(s) they have worked in up to and including the focal fiscal year, capturing any expansion of skillsets beyond a single occupation.

---

[18] Stanford CoreNLP algorithm implemented in R; see: https://stanfordnlp.github.io/CoreNLP/ (last accessed July 24, 2018).
[19] The CoreNLP algorithm identifies multiple types of each part of speech. I specifically retain five types of verbs: base, gerund/present participle, past participle, third-person singular, and non-third-person singular. Verbs are also converted to a common root word to avoid differences in tense. Terms that are ubiquitous across descriptions (i.e., those occurring in more than 100 descriptions) are dropped, as they largely stem from the uniform language used in each description. Terms that only occur in a single description are also dropped, as they provide no connective information (i.e., they are network isolates).

In every year, each employee may share connections with other employees in their bureau by virtue of common skills. This can occur in two ways: First, employees who have ever worked in the same occupation(s) in the past will share overlap in the skills from their common experiences, even if they no longer share the same occupational title. Second, skills that occur in multiple occupations' descriptions link those occupations.[20] This is represented using a bipartite network of employee skillsets and skills.[21] The two-mode nature of the data is an important feature of this study and differentiates it from most studies of social capital in organizations, which typically transform two-mode networks into one-mode representations that are simpler to analyze, collapsing the source of the connection between two actors (in this case, skills; in others, co-membership in groups) into a weight on the tie between them or a binary indicator of whether or not two people are linked at all. This simplifying tactic is susceptible to significantly misrepresenting the connectivity present in a network, especially when using typical measures of social capital, such as Burt's (2004) measure of network constraint (Burchard and Cornwell 2018; Opsahl 2013). As such, the measurement approach used avoids these documented shortcomings when creating variables.

[FIGURE 1 ABOUT HERE]

Figure 1 presents an example of the two-mode network structure. Every blue circle (N = 465) in the graph represents a distinct skillset present in the Bureau of Labor Statistics in 2005, while every pink square (N = 216) represents a unique skill. Skillsets are only connected to each other by virtue of sharing common skills. The histogram presents the degree distribution of the number of skills each skillset contains. The majority of skillsets have less than twelve skills, and

---

[20] For example, financial managers and accountants share the term "interpret," as do 17 other occupations in the civil service, including foreign law specialists, computer operators, and construction control technicians. Obviously, many of these occupations draw from different knowledge domains, but the skill of interpretation is applied in some capacity in all of them. It is this generalized sense of overlap captured in the skillset-overlap network.

[21] Bipartite, or two-mode, networks are defined by the fact that there are two classes of nodes (in this case, skillsets and individual skills), and connections only occur between nodes that are in the other class (i.e., a tie exists between an employee's skillset and a skill, but never from a skill to another skill). This is recorded in a 2x2 incidence matrix, where rows index the unique skillsets of every employee in a bureau in a given year and columns index the verbs identified in all of the occupational descriptions associated with the work experiences of those employees. The values in each cell are the number of times a skill occurs in the occupational descriptions associated with the row's skillset. E.g., if an employee worked in occupations A and B, and those occupations' descriptions mention verb Q once each, the cell corresponding to row: skillset A+B and column: verb Q would have a value of two.

the 75th percentile is at sixteen skills. Separate networks like this are constructed for each of the 3,212 bureau-year combinations, and independent variables discussed below are then created from these networks.

[TABLE 1 ABOUT HERE]

Variables

The dependent, independent, and control variables are all time-varying measures calculated for each person-year record, with many calibrated to the specific bureau an employee works in. Table 1 presents their definitions. Variables based on coworkers' skillsets are calculated based on all compensated employees' career histories in the bureau in each relevant year, regardless of those coworkers' pay scales or when they began working for the government; i.e., while only a subset of employees' careers (those hired in 1979 or later) are analyzed in the modeling stage, all employees are referenced in terms of the skills present in each workplace when creating variables. Table 2 presents descriptive statistics for these variables while Table 3 presents their correlations.

[TABLE 2 ABOUT HERE]

[TABLE 3 ABOUT HERE]

     Dependent variable. The primary dependent variable in this analysis is movement up GS grades, which indicates upward employment mobility in the civil service. This is measured by the grade level in the subsequent year for every person-year record in the data. Civil servants in many geographic locations receive a location-based pay supplement to compensate them for living in more expensive places. These are separate from GS grade, which makes the use of grade comparable across geographies in a way that compensation is not.

     Primary independent variables. There are three key independent variables in this analysis. First, an employee's connectedness to others measures their ability to act in a translational role. This is operationalized as the person-year two-mode degree centrality in the skillsets-skills network specific to the employing bureau in that year; i.e., the year-specific count

of skillsets an employee shares at least one skill with in the bureau where that person works. This variable is standardized into five bureau-year quintile categories in order to make the value comparable across bureaus that have substantial differences in the number of skillsets present; the intuition is that it matters if you are more connected than your immediate peers, not more or less connected in absolute terms than people in different bureaus or time periods. This non-parametric specification also allows the magnitude of the effect to vary between levels without making monotonicity assumptions. The more coworkers' skillsets an employee is connected to, the more important they are hypothesized to be in the organizational context, predicting a positive and increasing coefficient at higher skillset connectivity quintiles.

Second, greater redundancy in translational capability is hypothesized to have a negative effect on employment mobility. This is captured by the proportion of an employees' connections who are also share at least one skill in common (i.e., network transitivity); e.g., if person A shares skills with only persons B and C, but B and C do not share skills, this value is 0; if B and C do share a skill in common, the value is 1.

A third key variable captures the complexity of the bureau in which each person works every year. This is operationalized with a dummy variable indicating whether or not the bureau is in the top half of the distribution of the number of skillsets present in every bureau (i.e., if the number of skillsets in the bureau is greater than 2,089, the median value of the number of unique skillsets in each bureau). This variable is coded 1 for complex bureaus, 0 otherwise.

Control variables. Several variables are included to control for other time-varying employment features: a count of the number of occupations each person has held up to and including the focal year, the number of bureaus the person has worked in, and the number of occupational groups the person has worked in. The first two variables are proxies for communication-based social capital that emerges as people work in more contexts; prior research has demonstrated that moving through roles in an organization exposes employees to greater opportunities to establish social connections (Kleinbaum 2012), leaving them with networks containing more structural holes. The third measure is important for capturing the coherence of jobs an individual has worked in (i.e., category spanning), which may influence manager perceptions of competency (Leung 2014). For example, economists and workforce analysts are both in the social science occupational group, suggesting their jobs are inherently related. However, a biologist who moves into workforce analysis would span two occupational groups

(natural/biological and social sciences), raising questions about the coherence of their experience, which may weigh down their likelihood of promotion. Models also include variables accounting for length of tenure with the federal government (an important determinant of salary grade eligibility) and supervisory status, which is an important source of increased pay.

Analytical Approach

Model estimation is conducted by ordinary least squares (OLS) panel regression, predicting salary grade in the subsequent year as a function of the above variables. All models include individual fixed effects, which are important in accounting for time-invariant individual characteristics that may influence mobility, such as race, ethnicity, gender, or sociability. OLS is used because the outcome variable (grade in the subsequent period) has a sufficiently normal distribution (mean = 10.56, median = 11, SD = 2.78) with limited heaviness in the tails of the distribution (Kurtosis = 2.45). The values of the salary grade variable are also roughly comparable (i.e., one-unit of change is interpretively equivalent, whether it is from 7 to 8 or 10 to 11, etc.). All models include robust standard errors clustered by individual to account for within-panel error correlation, and listwise deletion is used to address missingness.

EMPIRICAL RESULTS

Table 4 presents the main results: five panel OLS regression models predicting salary grade in the following year for each person-year record. Model 1 establishes a baseline for each control variable. Model 2 includes the main predictor variable—skillset connectedness—broken out by quintiles. Model 3 adds a continuous measure of skillset redundancy. Model 4 includes a dummy variable for organizational complexity, which is then interacted with indicator variables for skillset connectedness quintiles in Model 5.

[TABLE 4 ABOUT HERE]

Coefficients on the control variables are stable across all models. First, becoming a supervisor has an average predicted effect of .59 on salary grade across all models. Similarly, as employees remain in the civil service longer, their grade level rises. The number of bureaus and number of occupations worked in both exhibit positive effects for employees' salary grades. This

coheres with Kleinbaum's (2012) finding that as employees move throughout an organization, they accrue higher social capital, which should lead to positive pecuniary benefits. Relatedly, the coefficient for the number of occupational groups worked in is negative. This comports with Leung's (2014) argument that moving across unrelated disciplines, rather than through multiple roles in a coherent trajectory within a single domain, can have a negative impact on evaluations of an employee, in this case, reducing their promotion likelihood.

Models 2-5 add additional variables testing the hypotheses discussed above. The sample of individuals and records is identical across all models, enabling comparability of model fit statistics. In each additional model, the coefficients on being more skill-connected increase at every quintile (all coefficients relative to the 1st connectedness quintile). Employees at the highest level of connectedness (i.e., the 5th quintile) experience an average predicted increase of .20 in the following year's grade level. To put the .20 increase in context, being in the highest connectedness quintile is worth approximately 34% of the increase in pay expected for becoming a supervisor (.20/.59). The coefficients are significant ($p < .001$) and increase uniformly in every model, strongly supporting Hypothesis 1.

Turning to Models 3 and 4, the negative and significant coefficient on Skillset Redundancy indicates a lower predicted grade in the following period. However, the magnitude on this coefficient is smaller than the positive benefit experienced at the 2nd quintile of connectedness (again, relative to the 1st quintile), reducing the predicted increase in pay by 59% of the increase from greater coordinative capability (i.e., .032/.054). The negative sign supports Hypothesis 2, but the relatively smaller magnitude of this effect suggests that, on average, the benefit of greater connectedness more than compensates for any decline due to increased skillset redundancy.

Model 4 reports a positive direct effect of working in more complex bureaus, indicating that employees of larger, more complex organizations earn more on average than those at less-complex organizations. This main effect holds but is slightly reduced in Model 5, which explores the value of skillset connectedness across organizational environments. In each of the four interactions, the first two coefficients are small in size and weakly or non-significant. The two highest levels of connectedness (i.e., the 4th and 5th quintile interactions) show positive and significant coefficients. The main effects of connectedness remain positive and significant in

Model 5. Taken together, this suggests that being more connected has extra value in complex environments.

[FIGURE 2 ABOUT HERE]

This point is illustrated in Figure 2, which plots the marginal predicted effects of each skillset connectedness quintile in the two cases: simpler and more complex bureaus. The marginal effect estimation holds all other variables at their mean effects, while incorporating both the direct and interactional effects for the specified variables. On the left, for less-complex bureaus, the average effect of being more connected grows at higher levels. However, only the most-connected quintile stands out as considerably compensated relative to the other levels. In more complex bureaus, indicated on the right end of the x-axis, being in the 4th or 5th quintiles has a markedly higher predicted effect on the next year's salary grade, while the 2nd and 3rd quintiles are not substantially different from the 1st quintile reference group. In all, the evidence from Model 5, which is collectively represented in Figure 2, demonstrates support for Hypothesis 3, showing that being more connected is indeed more valuable as the workplace becomes more complex and coordinative skillsets are in higher demand.

Robustness Checks

Employer and industry effects. In addition to individual-specific time-invariant features that may affect promotion, which are accounted for in the models presented in Table 4 by including individual fixed effects, other contextual features may influence promotion beyond the time-varying variables included. To address this concern, Model 5 is re-estimated with indicator variables for the bureau of employment and the occupational group that each person works in. Bureau variables control for time-invariant organizational features, such as Executive Branch authority, while occupational-group variables roughly approximate for industry effects (e.g., people in the medical field may face different labor market opportunities than social scientists). In models including these two sets of controls individually and together, all results remain materially unchanged (models presented in Table A1 in the Appendix).

Human capital accumulation as determinant of promotion. Another potential source of concern relates to the mis-identification of the skill-based advantage as a meaningful predictor of

promotion. It could be argued that, as individuals accumulate more skills that enable them to better coordinate in the workplace, there are simultaneously accumulating more human capital, which itself may be rewarded. This feature is partially controlled for by including the number of occupations held but is better accounted for when considering the number of skills accumulated. As such, Model 5 in Table 4 is again re-estimated with a variable counting the number of skills accumulated (see Table A2 in the Appendix). The results are again substantively unchanged, lending support to the argument that the influence of skill connectedness operates independently of the quantity of human capital any individual possesses.

      Domain knowledge versus generalized skills. A more substantive critique might argue that focusing on verbs as generalized skills misses the true connective elements that matter in the workplace. Rather than skills, domain-specific knowledge may play an important role, more so or entirely in place of skills that apply across domains. This concern runs counter to the theory laid out by Deming (2017) and others who focus on skills applicable across occupations; de Vaan et al. (2015) are agnostic on the issue of domain knowledge versus generalized skills (given that their case is likely drawing on a very circumscribed, and thus common, body of knowledge). This potential issue is addressed by repeating the identification strategy discussed above for pulling out verbs in occupational descriptions, but now identifying nouns. Each person's noun-based connectivity is calculated as it is in the verb-specific networks, again divided into bureau-year specific quintiles. Model 5 is then re-estimated including these variables, presented in Table 5 as Model 6 (the same control variable specification is used in both models, but coefficients are omitted for brevity; results are materially unchanged). Model 6 demonstrates that, while adding additional nouns-as-knowledge has a small, positive affect (β = .003, $p < .001$), connectivity through nouns has an increasingly negative relationship with later promotion. The main results based on verbs-as-skills and organizational complexity remain materially unchanged. This provides additional support for the argument that generalized skills, not domain-specific knowledge, are the driving force behind workplace coordination across skillsets, which organizations reward through raises.

[TABLE 5 ABOUT HERE]

DISCUSSION

The coordination problem of how to effectively transfer knowledge from one person to another is a classic concern in the social sciences. Economists historically favor market-based mechanisms (i.e., pricing) to facilitate information transmission between buyers and sellers (e.g., Hayek 1945). Organizational theorists, examining dynamics inside organizations rather than between atomized market actors, focus on the processes of within-organization coordination where pricing is not applicable (Okhuysen and Bechky 2009; Thompson 1967). Skill-based complementarities emerge from common experiences shared by coworkers, and teams with members that link disparate bodies of expertise are particularly successful in creative and scientific production (Leahey et al. 2017; de Vaan et al. 2015). This paper combines recent empirical research and formal models of personnel mobility from economics (Deming 2017; Gibbons and Waldman 2006; Lazear 2009) with organizational theories of workplace dynamics and performance to articulate a microanalytic model of employment mobility. The evidence presented consistently indicates that workers with coordinative skillsets—those most able to facilitate knowledge-based communication in the workplace—are compensated at higher levels downstream, even after controlling for numerous personal and organizational factors. The positive benefit of coordinative skillsets is greater in environments with increased knowledge complexity among personnel, further reinforcing the argument that contextual features matter for understanding who gets ahead in the workplace.

The theory and context are closely linked, and concerns over information asymmetries discussed in other studies (Ferguson and Hasan 2013; Leung 2014; Merluzzi and Phillips 2016) are less concerning here, as civil servants typically work in the same organizational division for many years. This contextual feature motivates the scope conditions discussed at the beginning of the paper. Despite narrowing the field of potential application for the theory developed, the results are likely to speak to a number of organizations beyond federal and state governments. Specifically, large organizations with skilled, diversely-trained workforces where employees work collaboratively are likely to experience many of the same dynamics. The video game and academic research sectors are both examples in the literature cited, where skillset connectivity has been linked to organizational performance. More broadly, innovation-focused organizations with large workforces are likely to experience similar dynamics; Miles et al. (2009) call these "I-form" organizations. I-form organizations "must have, or be able to develop, the capability to

continually create, share, and apply knowledge" (Miles et al. 2009:61). These internal needs are related to the ability of organizations to absorb and make use of external knowledge, a primary concern in strategic management (Cohen and Levinthal 1990). The promotion dynamics in such organizations are an important component of intragenerational mobility, especially as knowledge-based organizations achieve primacy over traditional manufacturing firms in the modern economy. These dynamics may become further exacerbated as large firms subsume others, as is currently happening at an increasing race in the latest wave of merges and acquisitions; 2017 saw more merges and acquisitions in the US than any year since 1985.[22]

Coordination is and remains a challenging problem, which must be overcome as specialization increases and novel ideas become "harder to find." Bloom et al. (2017) argue the US economy has only maintained high rates of innovative achievement, upon which economic growth depends, because of tremendous increases in scientific effort that offset declines in productivity. One key element in the productive use of knowledge is the efficient coordination of people who know different things. The analysis presented here suggests that the government is already rewarding those people with the skillsets that bring communicative capacity, but it does not speak to numerous other large, hierarchical organizations, which will require their own in-depth analyses. As firms merge or diversify internally, the need for cross-functional communication, and thus, for appropriately-skilled communicators, will only grow. This presents an important opportunity for economic mobility among workers with relevant skillsets, and conversely, a lack of opportunity for groups that are shut out of career paths that generate coordinative skillsets.

A limitation of this study—and an impetus for future research—stems from this final point. The modeling approach used obscures any individual time-invariant predictors of acquiring the skillsets that lead to mobility, such as race or gender.[23] Future work will need to analyze who the people are in these positions, and whether they come from typically advantaged categories of employees. The evidence is mounting that task-based explanations are integral to understanding economic outcomes in the labor market (Byun et al. 2018; Deming 2017; Williams and Bol 2018). The argument here is that skillsets are particularly valuable because of

---

[22] According to the Institute for Mergers, Acquisitions and Alliances; see: https://imaa-institute.org/m-and-a-us-united-states/ (last accessed August 28, 2018).
[23] The data do not include race, ethnicity, or gender of civil servants, which future analyses will need to consider.

their role in enabling coordination. Additional research is needed to address who has access to these positions, and what paths took them there, gathering the requisite skills along the way.

An explicit goal of this paper was to decompose oft-cited aggregate patterns into their constituent, individual-level and context-dependent elements, thereby uncovering mechanisms that drive employment mobility (Kalleberg and Mouw 2018; Rosenfeld 1992). Robust evidence suggests that "who you know" matters for getting ahead at work (Burt 2000; Kleinbaum 2012). Here, the strategy was to identify skills closely linked to the employment context. The results show that what you know and how it connects to what your coworkers know are important elements in promotion. Future research will build on these advances to consider the sources of and barriers to accessing skills necessary for mobility in labor markets, as well as the organizational consequences of incentive systems for employees with coordinative skillsets.

REFERENCES

Acemoglu, Daron and Pascual Restrepo. 2018. "Artificial Intelligence, Automation and Work." Working Paper No. 24196, National Bureau of Economic Research, Cambridge, MA.

Althauser, Robert P. 1989. "Internal Labor Markets." *Annual Review of Sociology* 15:143–61.

Attewell, Paul. 1992. "Technology Diffusion and Organizational Learning: The Case of Business Computing." *Organization Science* 3(1):1–19.

Baker, George, Michael Gibbs, and Bengt Holmstrom. 1994. "The Wage Policy of a Firm." *The Quarterly Journal of Economics* 109(4):921–55.

Bartel, Ann, Casey Ichniowski, and Kathryn Shaw. 2007. "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills." *The Quarterly Journal of Economics* 122(4):1721–58.

Becker, Gary S. 1993. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. 3rd ed. Chicago: The University of Chicago Press.

Becker, Gary S. and Kevin M. Murphy. 1992. "The Division of Labor, Coordination Costs, and Knowledge." *Quarterly Journal of Economics* 107(4):1137–60.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb. 2017. "Are Ideas Getting Harder to Find?" Working Paper No. 23782, National Bureau of Economic Research, Cambridge, MA.

Burchard, Jake and Benjamin Cornwell. 2018. "Structural Holes and Bridging in Two-Mode Networks." *Social Networks* 55:11–20.

Burt, Ronald S. 2004. "Structural Holes and Good Ideas." *American Journal of Sociology* 110(2):349–399.

Burt, Ronald S. 1992. *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Burt, Ronald S. 1997. "The Contingent Value of Social Capital." *Administrative Science Quarterly* 42(2):339–65.

Burt, Ronald S. 2000. "The Network Structure Of Social Capital." *Research in Organizational Behavior* 22:345–423.

Byun, Heejung, Justin Frake, and Rajshree Agarwal. 2018. "Leveraging Who You Know by What You Know: Specialization and Returns to Relational Capital." *Strategic Management Journal* 39(7):1803–33.

Cohen, Wesley M. and Daniel A. Levinthal. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35(1):128–52.

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *The Quarterly Journal of Economics* 132(4):1593–1640.

DiPrete, Thomas Albert. 1989. *The Bureaucratic Labor Market: The Case of the Federal Civil Service*. New York: Plenum Press.

Doeringer, Peter B. and Michael J. Piore. 1971. *Internal Labor Markets and Manpower Analysis*. Lexington, MA: Heath.

Ferguson, John-Paul and Sharique Hasan. 2013. "Specialization and Career Dynamics Evidence from the Indian Administrative Service." *Administrative Science Quarterly* 58(2):233–56.

Ferreira, Daniel and Raaj K. Sah. 2012. "Who Gets to the Top? Generalists versus Specialists in Managerial Organizations." *The RAND Journal of Economics* 43(4):577–601.

Garicano, Luis. 2000. "Hierarchies and the Organization of Knowledge in Production." *Journal of Political Economy* 108(5):874–904.

Gibbons, Robert and Michael Waldman. 1999. "Careers in Organizations: Theory and Evidence." Pp. 2373–2437 in *Handbook of Labor Economics*, vol. 3, Part B, edited by D. Card and O. Ashenfelter. Amsterdam: North-Holland.

Gibbons, Robert and Michael Waldman. 2006. "Enriching a Theory of Wage and Promotion Dynamics inside Firms." *Journal of Labor Economics* 24(1):59–107.

Goldberg, Amir, Sameer B. Srivastava, V. Govind Manian, William Monroe, and Christopher Potts. 2016. "Fitting In or Standing Out? The Tradeoffs of Structural and Cultural Embeddedness." *American Sociological Review* 81(6):1190–1222.

Gould, Roger V. and Roberto M. Fernandez. 1989. "Structures of Mediation: A Formal Approach to Brokerage in Transaction Networks." *Sociological Methodology* 19:89–126.

Granovetter, Mark. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78(6):1360–1380.

Hansen, Morten T. 1999. "The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge across Organization Subunits." *Administrative Science Quarterly* 44(1):82–111.

Hayek, F. A. 1945. "The Use of Knowledge in Society." *The American Economic Review* 35(4):519–30.

Heath, Chip and Nancy Staudenmayer. 2000. "Coordination Neglect: How Lay Theories of Organizing Complicate Coordination in Organizations." *Research in Organizational Behavior* 22:153–91.

Jones, Benjamin F. 2011. "As Science Evolves, How Can Science Policy?" *Innovation Policy and the Economy* 11:103–31.

Kalleberg, Arne L. and Ted Mouw. 2018. "Occupations, Organizations, and Intragenerational Career Mobility." *Annual Review of Sociology* 44.

Kleinbaum, Adam M. 2012. "Organizational Misfits and the Origins of Brokerage in Intrafirm Networks." *Administrative Science Quarterly* 57(3):407–52.

Kogut, Bruce and Udo Zander. 1996. "What Firms Do? Coordination, Identity, and Learning." *Organization Science* 7(5):502–18.

Lazear, Edward P. 2009. "Firm-Specific Human Capital: A Skill-Weights Approach." *Journal of Political Economy* 117(5):914–40.

Leahey, Erin, Christine M. Beckman, and Taryn L. Stanko. 2017. "Prominent but Less Productive: The Impact of Interdisciplinarity on Scientists' Research." *Administrative Science Quarterly* 62(1):105–39.

Leung, Ming D. 2014. "Dilettante or Renaissance Person? How the Order of Job Experiences Affects Hiring in an External Labor Market." *American Sociological Review* 79(1):136–58.

Leung, Ming D. 2017. "Learning to Hire? Hiring as a Dynamic Experiential Learning Process in an Online Market for Contract Labor." *Management Science*.

Lyons, Elizabeth. 2017. "Team Production in International Labor Markets: Experimental Evidence from the Field." *American Economic Journal: Applied Economics* 9(3):70–104.

Manning, Christopher D. et al. 2014. "The Stanford CoreNLP Natural Language Processing Toolkit." Pp. 55–60 in *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations*.

Merluzzi, Jennifer and Damon J. Phillips. 2016. "The Specialist Discount: Negative Returns for MBAs with Focused Profiles in Investment Banking." *Administrative Science Quarterly* 61(1):87–124.

Miles, Raymond E., Grant Miles, Charles C. Snow, Kirsimarja Blomqvist, and Hector Rocha. 2009. "The I-Form Organization." *California Management Review* 51(4):61–76.

Mouw, Ted and Arne L. Kalleberg. 2010. "Do Changes in Job Mobility Explain the Growth of Wage Inequality among Men in the United States, 1977-2005?" *Social Forces* 88(5):2053–77.

Obstfeld, David. 2005. "Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation." *Administrative Science Quarterly* 50(1):100–130.

Okhuysen, Gerardo A. and Beth A. Bechky. 2009. "Coordination in Organizations: An Integrative Perspective." *Academy of Management Annals* 3:463–502.

Opsahl, Tore. 2013. "Triadic Closure in Two-Mode Networks: Redefining the Global and Local Clustering Coefficients." *Social Networks* 35(2):159–67.

Rosenfeld, Rachel A. 1992. "Job Mobility and Career Processes." *Annual Review of Sociology* 18:39–61.

Simon, Herbert A. 1957. *Administrative Behavior: A Study of Decision-Making Processes in Administrative Organization*. 2d ed. New York, NY: Macmillan.

Spenner, Kenneth I. 1990. "Skill: Meanings, Methods, and Measures." *Work and Occupations* 17(4):399–421.

Teodoridis, Florenta. 2018. "Understanding Team Knowledge Production: The Interrelated Roles of Technology and Expertise." *Management Science* 64(8):3625–48.

Teodoridis, Florenta, Michaël Bikard, and Keyvan Vakili. 2018. "Creativity at the Knowledge Frontier: The Impact of Specialization in Fast- and Slow-Paced Domains." *Administrative Science Quarterly*.

Thompson, James D. 1967. *Organizations in Action: Social Science Bases of Administrative Theory*. New York: McGraw-Hill.

de Vaan, Mathijs, David Stark, and Balazs Vedres. 2015. "Game Changer: The Topology of Creativity." *American Journal of Sociology* 120(4):1144–94.

Valentine, Melissa A. 2018. "Renegotiating Spheres of Obligation: The Role of Hierarchy in Organizational Learning." *Administrative Science Quarterly* 63(3):570–606.

Vedres, Balázs and David Stark. 2010. "Structural Folds: Generative Disruption in Overlapping Groups." *American Journal of Sociology* 115(4):1150–90.

Williams, Mark and Thijs Bol. 2018. "Occupations and the Wage Structure: The Role of Occupational Tasks in Britain." *Research in Social Stratification and Mobility* 53:16–25.

Williamson, Oliver E. 1975. *Markets and Hierarchies: Analysis and Antitrust Implications: A Study in the Economics of Internal Organization*. New York: Free Press.

Zappa, Paola and Garry Robins. 2016. "Organizational Learning across Multi-Level Networks." *Social Networks* 44:295–306.

Table 1. Primary Variables and Definitions

Variable Name	Definition
Dependent Variable	
Salary Grade at Time +1	The employee's General Schedule pay grade in the fiscal year following the focal fiscal year.
Primary Independent Variables	
Skill Connectivity Quintile	A categorical variable with five levels corresponding to the quintile in the distribution of how many unique skillsets the focal employee shares at least one skill with compared to all employees in the same bureau-year.
Skillset Redundancy	The proportion of the skillsets that an employee shares at least one skill with that also share at least one skill with each other (i.e., network transitivity).
Complex Bureau Dummy	A dichotomous variable indicating whether or not the focal employee works in a bureau that has more than the median number of skillsets present in the workplace (0 = less than or equal to 2,089 skillsets in the bureau; 1 = more than 2,089 skillsets in the bureau).
Control Variables	
Supervisory Dummy	Is the employee in a supervisory position in the current fiscal year? (0 = no, 1 = yes)
Length of Service Category	Categorical variable with seven levels indicating the number of years of employment the focal employee has with the federal government (<1-4 years; 5-9 years; 10-14 years; 15-19 years; 20-24 years; 25-29 years; 30+ years).
Num. Bureaus Worked In	Continuous count variable of the number of bureaus (e.g., National Institutes of Health) the focal employee has worked in, up to and including the focal year.
Num. Occupational Groups Worked In	Continuous count variable of the number of occupational groups (e.g., Medical, Hospital, Dental, and Public Health Group) the focal employee has worked in, up to and including the focal year.
Num. Occupations Held	Continuous count variable of the number of occupations (e.g., Physician's Assistant) the focal employee has held, up to and including the focal year.

Note. All variables relating to an employee's skillset and work history are person-year specific; all variables relating to the bureau are bureau-year specific.

Table 2. Descriptive Statistics

Variable	Mean	SD	Median	Min.	Max.	Categorical
Salary Grade at Time +1	10.546	2.780	11	1	15	N
Supervisory Dummy	0.112	0.315	0	0	1	Y
Length of Service Category	2.641	1.561	2	1	7	Y
Num. Bureaus Worked In	1.262	0.596	1	1	7	N
Num. Occupational Groups Worked In	1.171	0.400	1	1	5	N
Num. Occupations Held	1.409	0.634	1	1	7	N
Skill Connectivity Quintile	3.007	1.414	3	1	5	Y
Skillset Redundancy	0.760	0.381	0.942	0	1	N
Complex Bureau Dummy	0.498	0.500	0	0	1	Y

Note. All statistics reported for 2,731,993 complete observations used in primary analysis.

Table 3. Correlation Matrix of Outcome and Predictor Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Salary Grade at Time +1	1								
2. Supervisory Dummy	0.268	1							
3. Length of Service Category	0.272	0.204	1						
4. Num. Bureaus Worked In	0.154	0.128	0.248	1					
5. Num. Occupational Groups Worked In	0.046	0.058	0.195	0.105	1				
6. Num. Occupations Held	0.022	0.069	0.288	0.228	0.629	1			
7. Skill Connectivity Quintile	0.061	0.026	0.156	0.075	0.339	0.518	1		
8. Skillset Redundancy	-0.053	-0.073	-0.044	-0.178	-0.033	-0.081	-0.059	1	
9. Complex Bureau Dummy	0.107	0.086	0.027	0.185	-0.006	0.036	-0.001	-0.370	1

Note. All correlations reported for 2,731,993 complete observations used in primary analysis.

Table 4. Panel OLS Regression Models Predicting Salary Grade at Time +1

	Model 1	Model 2	Model 3	Model 4	Model 5
Supervisor Dummy	0.598**	0.596**	0.595**	0.594**	0.594**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Length of Service[a]					
5-9 Years	0.875**	0.875**	0.874**	0.871**	0.871**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
10-14 Years	1.333**	1.333**	1.333**	1.325**	1.326**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
15-19 Years	1.617**	1.620**	1.619**	1.609**	1.610**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
20-24 Years	1.810**	1.814**	1.813**	1.801**	1.803**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
25-29 Years	1.975**	1.980**	1.980**	1.965**	1.967**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
30+ Years	2.116**	2.122**	2.122**	2.106**	2.108**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Num. Bureaus Worked In	0.395**	0.403**	0.398**	0.398**	0.399**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Num. Occupational Groups Worked In	-0.296**	-0.302**	-0.302**	-0.299**	-0.296**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Num. Occupations Held	0.992**	0.934**	0.933**	0.928**	0.923**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Skill Connectivity Quintiles					
2nd Quintile [b]		0.053**	0.053**	0.054**	0.045**
		(0.004)	(0.004)	(0.004)	(0.005)
3rd Quintile [b]		0.062**	0.062**	0.063**	0.072**
		(0.005)	(0.005)	(0.005)	(0.006)
4th Quintile [b]		0.126**	0.126**	0.126**	0.083**
		(0.006)	(0.006)	(0.006)	(0.007)
5th Quintile [b]		0.203**	0.202**	0.202**	0.172**
		(0.007)	(0.007)	(0.007)	(0.009)
Skillset Redundancy			-0.037**	-0.032**	-0.031**
			(0.002)	(0.002)	(0.002)
Complex Bureau Dummy				0.189**	0.144**
				(0.008)	(0.010)
Complex Bureau Dummy ×					
2nd Skill Connectivity Quintile [b]					0.018*
					(0.007)
3rd Skill Connectivity Quintile [b]					-0.015
					(0.008)
4th Skill Connectivity Quintile [b]					0.113**
					(0.010)
5th Skill Connectivity Quintile [b]					0.082**
					(0.012)
Constant	7.995**	7.984**	8.021**	7.930**	7.949**
	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)
Individual Fixed Effects	YES	YES	YES	YES	YES
Within-R^2	0.527	0.528	0.528	0.528	0.529
AIC	6441372.6	6436976.2	6436352.3	6432867.8	6431713.7
BIC	6441500.8	6437155.7	6436544.6	6433073.0	6431970.2

Note. All models fit with 2,731,993 observations for 287,635 unique individuals; robust standard errors in parentheses.

* $p < .01$; ** $p < .001$ (two-tailed)

[a] Reference category is <1 - 4 Years of government employment.

[b] Reference category is 1st Skillset Connectivity Quintile.

Table 5. Comparing Knowledge Domain versus Skillset Connectivity in
Panel OLS Regression Models Predicting Salary Grade in Time +1

	Model 5	Model 6
Skill Connectivity Quintiles		
2nd Quintile [b]	0.045**	0.091**
	(0.005)	(0.005)
3rd Quintile [b]	0.072**	0.164**
	(0.006)	(0.007)
4th Quintile [b]	0.083**	0.198**
	(0.007)	(0.008)
5th Quintile [b]	0.172**	0.303**
	(0.009)	(0.010)
Skillset Redundancy	-0.031**	-0.031**
	(0.002)	(0.002)
Complex Bureau Dummy	0.144**	0.148**
	(0.010)	(0.010)
Complex Bureau Dummy ×		
2nd Skill Connectivity	0.018*	0.041**
Quintile [b]	(0.007)	(0.007)
3rd Skill Connectivity	-0.015	-0.010
Quintile [b]	(0.008)	(0.008)
4th Skill Connectivity	0.113**	0.091**
Quintile [b]	(0.010)	(0.010)
5th Skill Connectivity	0.082**	0.060**
Quintile [b]	(0.012)	(0.012)
Num. Skills Accumulated		0.003**
		(0.000)
Knowledge Domain Connectivity		
2nd Quintile [c]		-0.122**
		(0.004)
3rd Quintile [c]		-0.200**
		(0.006)
4th Quintile [c]		-0.228**
		(0.007)
5th Quintile [c]		-0.289**
		(0.009)
Constant	7.949**	7.967**
	(0.011)	(0.011)
Individual Fixed Effects	YES	YES
All control variables in Table 4 also included		
N	2,731,993	2,731,993
Within-R^2	0.529	0.530
AIC	6431713.742	6425093.949
BIC	6431970.152	6425414.462

Note. All models fit with 2,731,993 observations for 287,635 unique
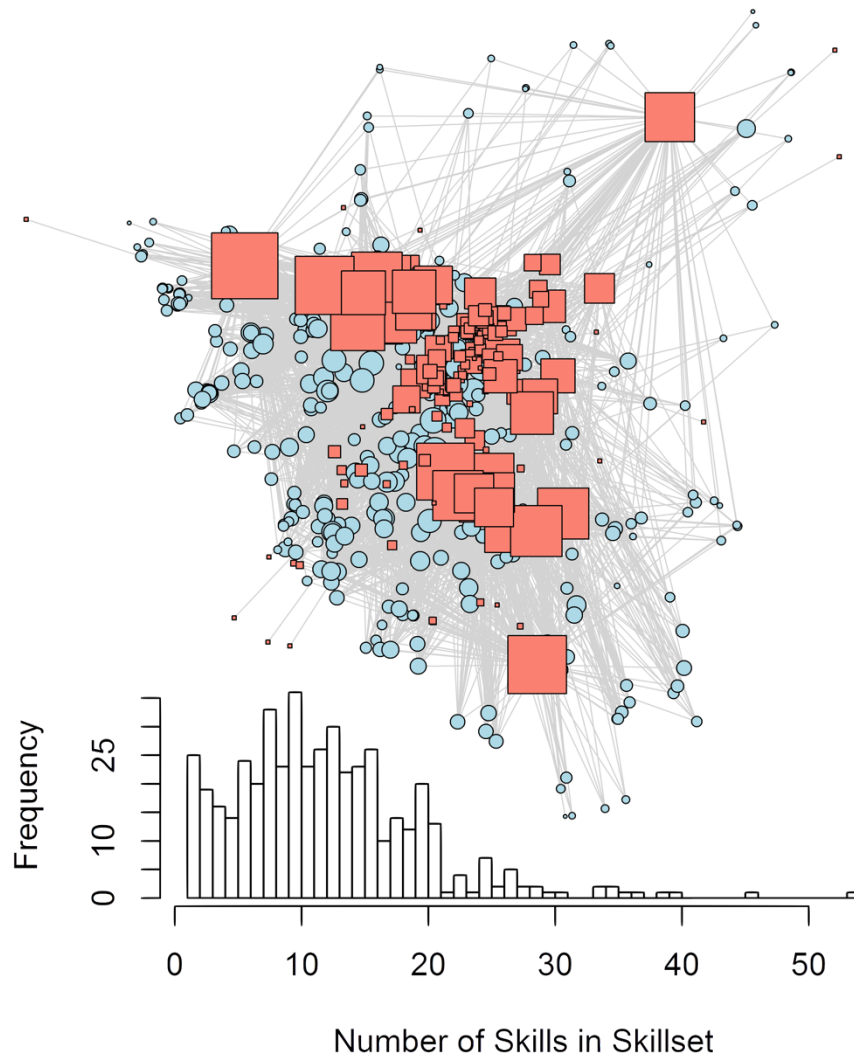individuals; robust standard errors reported in parentheses.
* $p < .01$; ** $p < .001$ (two-tailed)
[b] Reference category is 1st Skillset Connectivity Quintile.
[c] Reference category is 1st Knowledge Domain Connectivity Quintile.

Figure 1. Example Two-Mode Network of Skills and Skillsets

Note. Top panel displays an example two-mode network of skills (pink squares, N = 216) and skillsets (blue circles, N = 465) in the Bureau of Labor Statistics in fiscal year 2005. Node size is scaled by the square root of the number of connections (i.e., degree); graph layout performed by multidimensional scaling. The histogram shows the distribution of the number of skills connected to each skillset (i.e., one-mode degree).

Figure 2. Marginal Predicted Effect of Skillset Connectivity Quintile
by Bureau Complexity Indicator
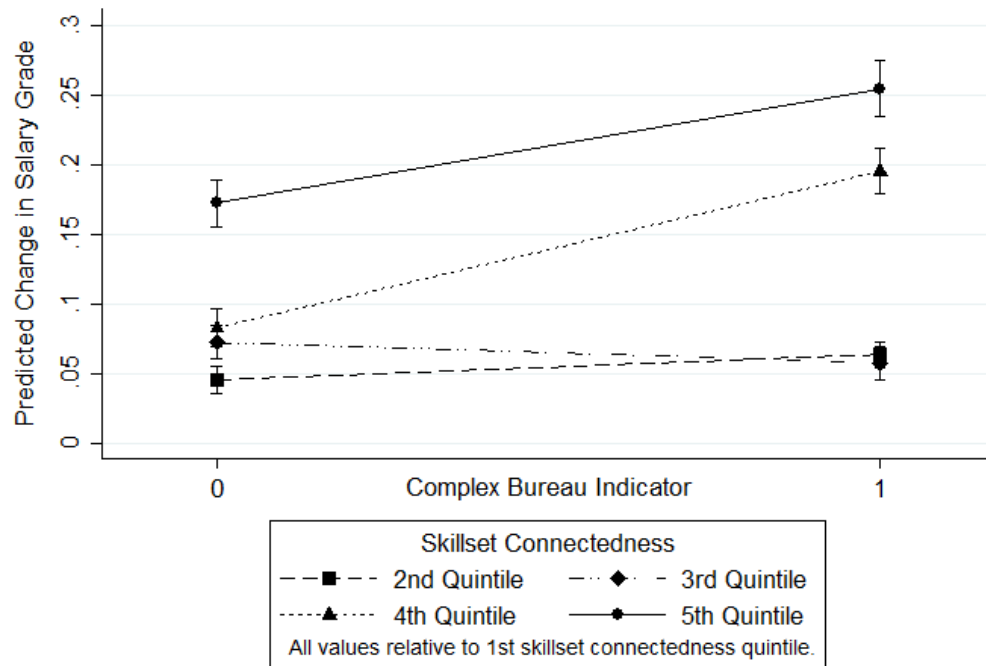
It's Not Just Who You Know:

Skillsets, Coordination, and Employment Mobility in the US Civil Service

APPENDIX: ROBUSTNESS CHECKS

1. Occupational Group Effects & Bureau Effects

One potential source of omitted variable bias may stem from institutional features that consistently drive promotion outside of the time-varying explanations considered in the main paper. To address this potential concern, I re-estimate Model 5 from Table 3 to include bureau indicator variables, which capture the time-invariant effects of these units of employment.

Similar to bureau-specific effects, there are reasons to be concerned about the effects of occupational groups. Specifically, those in some groups, which are roughly analogous to industries, may experience different labor market opportunities outside the federal government. In most cases, the unique opportunities are likely captured already by controlling for individual effects, but as an added precaution, I also re-estimate Model 5 from Table 3 with occupational group indicator variables.

Table A1 presents the results of these models. Model 5 is the same as presented in Table 3 in the main paper. Model A1 adds occupational group fixed effects, Model A2 adds bureau fixed effects, and Model A3 includes both. Across all models, the main results remain substantively unchanged.

Table A1. Alternative Fixed-Effects Specifications

	Model 5	Model A1	Model A2	Model A3
Supervisor Dummy	0.594***	0.616***	0.581***	0.603***
	(0.005)	(0.005)	(0.005)	(0.005)
Length of Service Category [a]				
5-9 Years	0.871***	0.861***	0.859***	0.850***
	(0.003)	(0.003)	(0.003)	(0.003)
10-14 Years	1.326***	1.316***	1.307***	1.299***
	(0.004)	(0.004)	(0.004)	(0.004)
15-19 Years	1.610***	1.606***	1.592***	1.589***
	(0.005)	(0.005)	(0.005)	(0.005)
20-24 Years	1.803***	1.806***	1.789***	1.792***
	(0.006)	(0.006)	(0.006)	(0.006)
25-29 Years	1.967***	1.980***	1.960***	1.972***
	(0.008)	(0.008)	(0.008)	(0.008)
30+ Years	2.108***	2.134***	2.118***	2.142***
	(0.011)	(0.011)	(0.011)	(0.011)
Num. Bureaus Worked In	0.399***	0.399***	0.200***	0.198***
	(0.004)	(0.004)	(0.008)	(0.008)
Num. Occupational Groups Worked In	-0.296***	-0.241***	-0.272***	-0.219***
	(0.009)	(0.010)	(0.009)	(0.010)
Num. Occupations Held	0.923***	0.927***	0.922***	0.927***
	(0.006)	(0.006)	(0.006)	(0.006)
Skill Connectivity Quintile [b]				
2nd Quintile	0.045***	0.027***	0.048***	0.030***
	(0.005)	(0.005)	(0.005)	(0.005)
3rd Quintile	0.072***	0.044***	0.078***	0.050***
	(0.006)	(0.006)	(0.006)	(0.006)
4th Quintile	0.083***	0.049***	0.089***	0.055***
	(0.007)	(0.007)	(0.007)	(0.007)
5th Quintile	0.172***	0.134***	0.185***	0.146***
	(0.009)	(0.008)	(0.009)	(0.008)
Skillset Redundancy	-0.031***	-0.030***	-0.016***	-0.014***
	(0.002)	(0.002)	(0.001)	(0.001)
Complex Bureau Dummy	0.144***	0.128***	0.269***	0.241***
	(0.010)	(0.010)	(0.011)	(0.011)
Complex Bureau Dummy ×				
2nd Skill Connectivity Quintile [b]	0.018**	0.032***	0.017*	0.031***
	(0.007)	(0.007)	(0.007)	(0.007)
3rd Skill Connectivity Quintile [b]	-0.015	-0.000	0.012	0.026**
	(0.008)	(0.008)	(0.008)	(0.008)
4th Skill Connectivity Quintile [b]	0.113***	0.097***	0.144***	0.129***
	(0.010)	(0.010)	(0.010)	(0.010)
5th Skill Connectivity Quintile [b]	0.082***	0.088***	0.115***	0.120***
	(0.012)	(0.012)	(0.012)	(0.012)
Constant	7.949***	7.578***	8.481***	8.054***
	(0.011)	(0.018)	(0.074)	(0.071)
Occupation Group FEs	No	Yes	No	Yes
Bureau FEs	No	No	Yes	Yes
Individual Fes	Yes	Yes	Yes	Yes
N	2,731,993	2,731,993	2,731,993	2,731,993
Within-R^2	0.529	0.536	0.535	0.542
AIC	6431713.742	6389675.584	6395586.938	6355359.596
BIC	6431970.152	6390214.047	6397612.584	6357667.293

Note. All models fit with 2,731,993 observations for 287,635 unique individuals; models include individual fixed effects; robust standard errors reported in parentheses.
* $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed)
[a] Reference category is <1 - 4 Years of government employment.
[b] Reference category is 1st Skillset Connectivity Quintile.

2. Increase in Skills as Increase in Human Capital Leading to Promotion

Another concern may be that, as individuals add skills as they work in multiple occupations, their on-the-job human capital necessarily increases. This could influence the likelihood of promotion through the increased connectedness measure (though it is worth noting, an increase in connectedness need not occur because someone adds to their skillset; it is conditional on skills having some overlap with other skillsets in the workplace).

Table A2 compares Model 5 from Table 3 in the main paper to Model 4A, which adds a count variable of the number of skills accumulated. The coefficient is positive and significant, which is in keeping with general human capital theory. The main results do not materially change across the coefficients discussed in the paper.

Table A2. Accumulation of Skills

	Model 5	Model A4
Supervisor Dummy	0.594***	0.594***
	(0.005)	(0.005)
Length of Service Category [a]		
5-9 Years	0.871***	0.871***
	(0.003)	(0.003)
10-14 Years	1.326***	1.326***
	(0.004)	(0.004)
15-19 Years	1.610***	1.612***
	(0.005)	(0.005)
20-24 Years	1.803***	1.805***
	(0.006)	(0.006)
25-29 Years	1.967***	1.970***
	(0.008)	(0.008)
30+ Years	2.108***	2.112***
	(0.011)	(0.011)
Num. Bureaus Worked In	0.399***	0.392***
	(0.004)	(0.004)
Num. Occupational Groups Worked In	-0.296***	-0.291***
	(0.009)	(0.009)
Num. Occupations Held	0.923***	0.884***
	(0.006)	(0.007)
Skill Connectivity Quintile [b]		
2nd Quintile	0.045***	0.044***
	(0.005)	(0.005)
3rd Quintile	0.072***	0.068***
	(0.006)	(0.006)
4th Quintile	0.083***	0.075***
	(0.007)	(0.007)
5th Quintile	0.172***	0.160***
	(0.009)	(0.009)
Skillset Redundancy	-0.031***	-0.030***
	(0.002)	(0.002)
Complex Bureau Dummy	0.144***	0.151***
	(0.010)	(0.010)
Complex Bureau Dummy ×		
2nd Skill Connectivity Quintile [b]	0.018**	0.021**
	(0.007)	(0.007)
3rd Skill Connectivity Quintile [b]	-0.015	-0.013
	(0.008)	(0.008)
4th Skill Connectivity Quintile [b]	0.113***	0.105***
	(0.010)	(0.010)
5th Skill Connectivity Quintile [b]	0.082***	0.068***
	(0.012)	(0.012)
Num. Skills Accumulated		0.010***
		(0.001)
Constant	7.949***	7.933***
	(0.011)	(0.011)
N	2,731,993	2,731,993
Within-R^2	0.529	0.529
AIC	6431713.742	6430813.202
BIC	6431970.152	6431082.433

Note. All models fit with 2,731,993 observations for 287,635 unique individuals; models include individual fixed effects; robust standard errors reported in parentheses.
* $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed)
[a] Reference category is <1 - 4 Years of government employment.
[b] Reference category is 1st Skillset Connectivity Quintile.