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Abstract

We use a unique corpus of job descriptions for C-suite positions to document skills requirements in top managerial occupations across a large sample of firms. A novel algorithm maps the text of each executive search into six separate skill clusters reflecting cognitive, interpersonal, and operational dimensions. The data show an increasing relevance of social skills in top managerial occupations, and a greater emphasis on social skills in larger and more information intensive organizations. The results suggest the need for training, search and governance mechanisms able to facilitate the match between firms and top executives along multiple and imperfectly observable skills.

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1 Introduction

The role of top executives in shaping organizational performance has been the subject of intense scrutiny. Existing studies have linked managerial effectiveness to observable personal characteristics, career trajectories, psychological traits, and behaviors of individuals hired in these positions.[1] However, much less is understood about the concrete skills requirements needed to succeed in these top managerial positions. Lack of evidence about the specific skills valued in managerial labor markets is problematic on two levels. First, it limits the understanding of *how* top managers actually contribute to firm performance and, in particular, whether different managerial skills may matter differently across organizations and over time. Second, it provides little guidance to shape the appropriate skill formation in potential future candidates for these occupations.

In this article we use a large corpus of detailed and previously unexplored job descriptions for C-suite positions spanning a time period of 17 years to study which skills are demanded in managerial labor markets. We classify the information contained in these documents using methods borrowed from machine learning, which allow us to map unstructured, free-text data into distinct clusters of skill requirements. We use the data to examine the variation in the demand for different managerial skills which provides, to the best of our knowledge, the first direct evidence on C-suite skill requirements.[2] Finally, we provide a stylized model to interpret the variation in the demand for executive *Social skills*—a skill cluster that experiences sustained growth over time and is relatively most likely to be included in CEO job descriptions—across firms and test the implications of the model by matching the information provided in the job descriptions with firm-level observable characteristics.[3]

Our analysis is based on novel and rich data on thousands of firm-level searches for executive positions (e.g. CEO, CFO, CIO, etc.) conducted by a large sample of firms around the globe. These documents, which are private and typically unavailable to researchers,[4]

[1]Bertrand and Schoar (2003) document the presence of managerial "fixed effects", i.e. systematic performance differentials that can be attributed to individual managers. Custódio et al. (2013) discuss the rising importance of "generalist" CEOs (i.e. executives that gained experience in a variety of industries prior to appointment vs. specialized managers). Frydman (2019) documents, in addition to the relevance of generalist experience, the sustained increase in CEOs with business degrees. Custódio and Metzger (2013) document the importance of CEOs' industry specific knowledge in the context of M&A activities, while Benmelech and Frydman (2015) focus on CEOs with military experience. Bandiera et al. (2020) study the behavior of CEOs and its relationship with firm performance. Kaplan et al. (2012) study the characteristics and psychological traits of candidate and hired executives in the context of a sample of companies involved in buyout and venture capital transactions. Kaplan and Sorensen (2021) use the same psychological assessments for a broader sample of CEO candidates.

[2]In a spirit similar to this paper, Adams et al. (2018) study the skill sets of board members in a large sample of U.S. firms. Our study differs from this earlier study on multiple dimensions. First, we study the skill requirements of C-suite executives, rather than board members. Second, we study the skills sought after by firms, rather than the skills of hired individuals. Third, we use a novel classification approach to determine the skills requirements, which we describe in more detail below.

[3]Bandiera et al. (2015) also study the matching between middle managers, firms and incentives in the context of the Italian labor market, but they do not directly observe the demand for managerial skills.

[4]The documents are not publicly posted and are only circulated directly to candidates that the headhunter identifies as potentially suitable.

were provided to us by one of the world's largest headhunting companies. Headhunters play an increasingly important role in filling top-level managerial positions and are often engaged even when a suitable internal candidate already exists. When our headhunter partner begins a search with a client firm, the first step is the drafting of a job specification that gives a comprehensive description of the skills and responsibilities sought in an ideal candidate. The client firm's Board takes the lead in generating the content of the specification, in collaboration with the headhunter. Its text therefore closely reflects the perceived needs of the firm at the time of the search. We use the universe of texts that our partner holds to measure skill demand in a broad sample of firms.

We propose a novel classification approach to derive economically interpretable measures from the unstructured text of this corpus. Our approach involves two steps. First, we define a comprehensive vector of skills requirements that are relevant for Chief Executives. We obtain this by collecting the numerous textual descriptions of skills from the O*NET entry for the *Chief Executive* occupation, and clustering them into six broad categories using a k-means algorithm. Second, we express each job description in the search corpus in terms of the relative demand for each skill cluster by comparing the similarity of the language included in the document with the text associated with each of the O*NET clusters.

Both the clustering of O*NET skills into groups and the comparison of job texts to O*NET texts require the quantification of linguistic relatedness. We compute this via a language embedding model estimated from an auxiliary corpus of all Harvard Business Review articles from its inception in 1922 to the present day. This large, domain-specific corpus allows us to obtain semantic relationships between words in the context of business and management. We then apply the model to measure similarity in the O*NET and job search corpora, an approach known as *transfer learning*.

The clusters that emerge from O*NET capture interpretable structure in skills. Two categories relate to cognitive skills, *Monitoring of Performance* and *Information Skills*; two relate to functional and operational skills, *Financial and Material Resources* and *Administrative Tasks*; and two relate to interpersonal skills, *Human Resources* and *Social Skills*.[5] These clusters map into well-known aspects of leadership, such as problem solving embodied in the cognitive clusters, or motivation and empathy embodied in the soft skills clusters. But these categories also contain more subtle distinctions within them. For example, within soft skills, *Human Resources* focuses on interpersonal skills relevant for motivating employees, while *Social Skills* refer primarily to the ability to establish empathy, persuade and listen to others.

To characterize these novel measures of demand for executive skills across firms, we first examine their variation across different C-suite positions. On average, firms demand a greater range of skills from the CEO than from other more specialized C-suite positions. Among these specialized positions, we observe a natural relationship between job title and skill demand (e.g. *Human Resources* is the relatively most common skill in CHRO job

[5]These labels are assigned by us after examining the content of the skill clusters.

texts). This is consistent with Guadalupe et al. (2013) who argue that functional managers in the C-suite specialize in different tasks according to function-specific characteristics. Comparing CEOs and CFOs, we find a greater emphasis on interpersonal skills for CEOs and functional skills for CFOs. In personality assessments there are notable differences between CEOs and CFOs (Kaplan and Sorensen 2021) which our results show might plausibly be driven by firms seeking distinct skill sets for the two positions.

We see less variation in skill demand across countries and industries, although non-US firms on average demand more *Financial and Material Resources*. We do see, however, strikingly different trends over time across different skill clusters. In particular, *Social Skills* experienced sustained growth throughout the sample, while the demand for *Financial and Material Resources* sharply declined over time.

The growth of the *Social Skills* cluster is especially interesting, in our view, in that its growing relevance mirrors broader trends in the general labor market as documented in Deming (2017). Additionally, this skill is the most likely to be included in CEO job descriptions relative to other C-suite positions. We use a stylized model in the spirit of Garicano (2000) to further study the relationship between the demand for social skills and firms' characteristics. In this framework, vertical communication between the workforce and the C-suite raises productivity, but communication is costly. Whereas Garicano (2000) conceives of this cost as arising due to technological reasons, we view them as also depending on managerial social skills.[6] In the model, greater social skills in the C-suite become more important when the volume of problems needed to be solved rises, and when the interaction between workers and C-suite becomes more important for production. These are situations which increase the demand for and the value of executive time, which is limited, and social skills allow a relaxation of managerial time constraints.

Overall, we find supportive evidence for both predictions of the model. Conditional on a host of firm and search characteristics, the demand for social skills is higher in larger firms and, using the sub-sample of repeated searches for the same firm, it also varies significantly *within* firms according to size. Furthermore, conditional on firm size, the demand for social skills is also greater in firms that are publicly listed, MNEs, and are involved in M&A activities, which we use as proxies for the need to deal with a greater scope of problems. To examine the role of an increase in the value of C-suite communication, we consider the relationship between the demand for social skills in the C-suite and skills that firms look for in their workforce. Specifically, we focus on a particular channel that the management literature has long emphasized increases the value of C-suite communication: the extent to which workforce skills are specialized in information processing activities. The argument is that the shift towards information-intensive work requires executives to exert additional effort in communication in order to coordinate employees and achieve organizational alignment (Drucker 2007). To study this prediction, we match firms from the executive search

[6]The idea that social skills facilitate problem exchange is also present in Deming (2017) who models the horizontal exchange of problems within a team of workers rather than the vertical exchange of problems within an organizational hierarchy.

database to their online job postings provided by Burning Glass Technologies. Various indicators of information technology skills in firm-level demand in non-executive occupations correlate strongly with executive social skills. This provides the first direct evidence (to our knowledge) supporting the influential ideas of Drucker (2007) about the effective skills needed to manage knowledge workers. The correlations we observe between social skills and problem volume and workforce skills, respectively, are nearly all absent for the other skills in the job descriptions.[7]

While the primary contribution of this paper stands in the creation and analysis of novel measures of skill requirements for top managerial positions for a large sample of firms and over time, our results also contribute to the broader understanding of managerial labor markets, and in particular of the process through which firms and managers are matched. First, the data suggest that firms exert considerable effort in articulating the managerial skills needed in new hires, and that the skills demanded vary considerably across organizations. This suggests that managerial effectiveness (especially in cases in which the assignment process is efficient) may reflect the quality of the *match* between firms and managers, rather than solely the characteristics and behaviors of individuals. Second, whereas the existing theoretical literature on firm-executive matching typically conceives of top managers as vertically differentiated according to a single "ability" factor (Gabaix and Landier 2008, Tervio 2008), our results show that assessing match quality requires a richer skills-based approach. Third, the demand for executive skills is increasingly focused on "softer" aspects of managerial capabilities such as social skills, which may be harder to assess in reality relative to cognitive and operational skills. The growth in the importance of soft skills over time thus calls for investments in screening and high quality governance approaches to overcome possible matching frictions.[8]

Finally, universities and other academic institutions play an important role in the formation of executive skills via business education. Business education has traditionally focused on developing cognitive skills, but our work shows that increasing the ability to relate to others is an important skill to develop for meeting market demand. Recent evidence has shown that interventions that impart hard skills to managers lead to material gains in performance (Bloom et al. 2013, Custodio et al. 2021) and a natural question that arises from our work is whether soft skills can also be transferred via training.

Related Literature This paper relates to several literatures. As mentioned above, Deming (2017) is a seminal contribution that shows a growing importance of social skills in the labor market. The analysis in Deming (2017) shows that occupations that are more intensive in social skills have a growing share in the overall labor market. We instead show that

[7]For example, *Human Resources*, the other soft-skill cluster, is not related to firm size nor positively related to any of the other firm characteristics, with the exception of a firm being publicly traded. On the other hand, we do find that managerial cognitive skills are positively related to workers' IT skills.

[8]Dessein and Prat (2019) model explicitly the interaction between heterogeneous managerial talent, screening and governance imperfections, and organizational capital.

social skills are growing *within* the Chief Executive occupation. Moreover, we link cross sectional variation in social skill demand to firm characteristics, which are not explicitly considered in Deming (2017).

Hoffman and Tadelis (2020) draw on personnel data from a large technology firm to show that non-C-suite managers' interpersonal skills reduce employee turnover. Kaplan et al. (2012) show that two factors explain variation in personal evaluation surveys of CEO candidates, one that captures general ability and another that contrasts interpersonal skills with execution skills. Subsequent firm performance is positively correlated with general and execution ability. In contrast, Kaplan and Sorensen (2021) further show that Boards are in fact more likely to appoint C-suite executives with higher interpersonal skills. One interpretation is that Boards overweight such skills in their appointment decisions. Our evidence shows that Boards explicitly include social language in job specifications *prior to the screening and interview process*, and that this varies systematically with proxies for the need for internal coordination.

McCann et al. (2015) present a model in which agents have both communication and cognitive skills and sort into managerial and worker positions. Individuals with high communication skills become managers in equilibrium, and those with lower communication skills become workers. Team size increases in managerial communication skill, and there is positive assortative matching on cognitive skill between workers and managers. Our findings that social skills are more present in larger firms, and that executive and workforce information skills are positively correlated, support both predictions. More broadly, we are unaware of any previous empirical work that relates the skills of workers to the skills of top managers.

The paper also relates to the literature studying how the shift towards information-intensive tasks (which we proxy with the demand for IT skills among workers) affects firm organizations (Bloom et al. (2014), Babina et al. (2020)). Relative to prior contributions, we are the first to document the relationship between information-intensive skills among workers and skill requirements at the top of the hierarchy.

Finally, our paper makes a methodological contribution: the overall measurement strategy is generic and can be applied in other situations in which a researcher wishes to measure skill content from job descriptions. Dictionary methods in which researchers use keyword counts to measure content have traditionally dominated the analysis of text in economics and finance (e.g. Baker et al. 2016) and have also been used to measure the skill content of job descriptions (e.g. Deming and Kahn 2018). Our method is more automated, retains interpretability, and draws on semantic relationships derived from the entire HBR vocabulary to measure content rather than a small number of search terms. We make publicly available our HBR embedding model for researchers who wish to measure skill content in other settings, or who require language similarity comparisons in business contexts more generally.[9]

[9] It can currently be downloaded at `https://bit.ly/3xBiFGN`, and we are currently planning a website

The rest of the paper proceeds as follows. Section 2 provides institutional background on the headhunting industry and an overview of the main corpus. Section 3 describes how we map job text to skill vectors. Section 4 documents basic facts about how skills vary across firms, while section 5 focuses specifically on the role of executive social skills in facilitating problem exchange. Section 6 concludes.

2 Executive Search Database

The analysis presented in the paper is based on a corpus of documents provided to us by a global executive search firm. In this section we provide a brief overview of the industry, as well as of the key steps involved in an executive search, to help contextualize the data we employ in the analysis. We then describe the firms included in the corpus and the documents in detail.

2.1 Institutional Background

Executive search firms specialize in filling vacancies for managerial positions, including those at the very top of firms' hierarchies (what we call C-suite positions in the remainder of the paper).[10] The sector emerged in the post-war boom, and experienced sustained growth over time, reaching worldwide revenues of more than \$15bn in 2018 (from \$3bn in 1991). The industry is currently dominated by five "generalist" firms that account for about a third of total industry revenues. Our partner is included in this set of top firms. Generalist firms work with a variety of firms, industries, and countries, as opposed to niche firms that focus on narrow sectors or C-suite positions (for example, some companies focus exclusively on technology sectors).

The use of executive search firms is widespread across large firms, in both developed and developing economies, even when an internal candidate is under consideration.[11] Typically, when a vacancy opens, a headhunter "pitches" the services offered by his or her company, in most cases in competition with other search firms. According to our partner, the selection of a specific company is generally based on the consultant's past record, personal connections with a large enough pool of suitable candidates, and/or specific industry expertise. If the contract is won, the search process typically takes three months to a year. The client forms a Board committee to oversee the search. One of the first tasks assigned to the committee is the drafting of a document in which the Board makes explicit what they want the new hire to achieve, and the required competencies. Importantly, while the headhunter helps shape this document (for example, suggesting a certain structure), the content of this document primarily reflects the perspectives and beliefs of the Board committee. As

that will allow researchers to interact with the model.

[10] This section draws extensively from The Economist (2020).

[11] According to the Economist (2020), 80-90% of Fortune 250 or FTSE 100 companies resort to executive search firms, while almost half of companies in the next tier also do so.

such, the document provides a unique insight into the firm-specific job skills that the new appointee is expected to possess, the main activities that the person is expected to engage in, and the goals that the Board expects the new appointee to pursue.[12] The job description document forms the basis of the executive search campaign, and is the primary source of data for our analysis (we provide more details on the structure and the content of the documents in the next subsection).

When the headhunting begins, recruiters use multiple sources to generate a list of suitable candidates for the position, including public and private databases of profiles, or informal suggestions from the headhunter's network. Potential candidates are vetted extensively through interviews with former colleagues, clients, ex-bosses or past employees, or public sources of information on past performance. The headhunters then contact these potential candidates to further vet the possible match and gauge their interest in the position. Eventually, a handful of interested candidates are vetted more thoroughly through a combination of interviews with the Board committee, formal assessments, simulations, and in-depth background checks performed by specialists. The typical compensation for a successful search has for a long time been proportional to the first year compensation of the selected candidate (typically one third of it, including bonuses), but most recently (given the increase in C-suite pay) it has been capped between \$500,000 and \$1m.[13]

While there is existing empirical evidence on the search and selection process for executives that focuses on the characteristics of hired candidates (Kaplan et al. 2012, Kaplan and Sorensen 2021, Cziraki and Jenter 2020), our data allows us to study with unprecedented detail the demand for executive skills that are made explicit in the job descriptions. This is important to isolate demand for CEO skills from their supply and any frictions in the matching process. We describe the sample of firms included in the analysis and the features of these documents in more detail below.

2.2 Sample

Our sample consists of the universe of executive searches for top managerial positions (C-suite level) conducted by one of the top-five global headhunters. Besides the job description, each document also provides additional information: (1) Start and end dates for each executive search campaign; (2) Location of the branch office of the headhunter the search contract was awarded to; (3) Title of the executive position to be filled and, lastly, (4) Name of the client firm and a unique search identifier.

[12]A possible concern is that the documents may include "boiler-plate" language enforced by the headhunter's organization. While some standardization in language is certainly possible, headhunting firms typically take the form of partnerships, in which individual headhunters work in a regime of substantial autonomy from the parent organization. The company who gave us access to the data, specifically, reassured us that they have not enforced standardized language in the job descriptions. The absence of standardization is also evident from the variation that we observe across documents, which is described in more detail below.

[13]This excludes ancillary revenues that may be generated by other services provided by executive search companies, i.e. leadership development, Board training etc.

The sample we analyze has 4,622 searches conducted by 3,794 firms.[14] The number of firms is smaller than the number of documents since some companies perform multiple searches across different C-suite positions or, in some instances, for the same title but in different years. We exploit this within-firm variation in some of our analysis later in the paper.

Table A.1 shows summary statistics for the documents, including number of job description documents by position and year of search. The majority of the sample consists of job descriptions for CEO positions (43%), followed by a sizeable number of CFO searches (36%), with the remainder being other specialized C-suite positions (Chief Information, Human Resources and Marketing Officers). The sample contains executive search data from years 2000-2017. The number of searches ranges from 133 in year 2003 to 375 in year 2015.

We name-matched the firms included in the sample with external data sources to retrieve additional information on the firms conducting these searches. Specifically, we matched the data with CapitalIQ, Orbis, and Dun and Bradstreet for firm size (number of employees), primary industries of activity (at the 4 digit SIC code level), country of HQ location, publicly listed status, and involvement in M&A activities, all measured as averages in the the three years prior to the search). Tables A.1 and A.2 show basic summary statistics on the sample of firms included in the analysis. 57% of the sample is accounted for by US firms, 29% are European and UK firms, while the remainder of searches originate from firms based in Latin America, Asia and Oceania. These frequencies are similar when we consider the location of the search, though the two differ for 17% of the searches.[15] The firms included in the sample are on average large (1,500 employees at the median, standard deviation 55,000). 26% are publicly listed, 67% are classified as multinationals, and 52% are involved in M&A activities. In terms of sectoral composition, the largest industries represented in the sample are Manufacturing; Finance, Insurance and Real Estate (FIRE); Business Services (mostly legal); Retail and Wholesale; and infrastructures (transportation, communication, electric and gas, sanitary).

2.3 Job Descriptions

Each job description document typically contains three sections: a description of the company (activities, organization chart, history, etc); responsibilities associated with the position; and qualifications expected of candidates. For our main analysis, we use text from the responsibilities and qualifications sections. In the next section we provide some illustrative examples of the text included in these sections of the documents.

[14]The total number of searches in which the headhunter participated during the sample period for which some form of job description exists is 5,168, but 495 of these documents are not in English and 51 of these do not have a complete document available. We drop both cases.

[15]In the majority of cases these are Europe-, UK- and US-based companies looking for executives in the UK, US and Europe, respectively.

After pre-processing the text for analysis,[16] we compute the total number of words in the "responsibilities" and "qualifications" sections, which we refer to as "document length." The mean length of pre-processed documents in the sample is 440 words, with a standard deviation of 218 words. The minimum and maximum lengths are 22 and 1804. The format and length of job description documents in the sample is relatively stable over time: a scatter-plot showing the distribution of lengths (in words) of pre-processed documents by year is shown in figure A.1 in the appendix.

3 From Job Descriptions to Skills Clusters

The job search corpus provides a rich account of the characteristics that firms seek in their prospective executive hires, but the challenge is to map unstructured textual descriptions into a set of objective and interpretable job skills demanded by companies. In this section we describe the classification strategy we designed to map these documents into indices of job skills demand.

3.1 Classification Strategy

The classification strategy consists of three distinct steps.

- First, we identify a comprehensive list of skills, tasks and capabilities that are associated with Chief Officer occupations from the Occupational Information Network (O*NET) maintained by the US Department of Labor (DoL). O*NET contains data on almost 1,000 occupations, each one of which is associated with a set of standardized and occupation-specific descriptors. The O*NET entry for *Chief Executives* refers to all C-suite positions and includes a rich list of descriptors from which we selected those that relate most closely to the content of the job specifications: Skills, Work Activities, and Tasks, for a total of 68 descriptors.[17] These are represented in tables A.3-A.6 in Appendix A. We collectively refer to these occupational characteristics as "Executive skills" throughout the analysis below.

- Second, we group the numerous attributes of Chief Executive occupations included in O*NET into a smaller set of *clusters* of job skills on the basis of the linguistic distance between individual descriptors.

- Third, we detect whether the text included in these clusters is present in the job descriptions given to us by the executive search firm. Specifically, we say that a skill cluster is present in a job specification if the linguistic distance between the text of

[16] Appendix B describes in detail the data processing steps we took to prepare the data for analysis.

[17] O*NET divides Tasks into Core and Supplemental, and we consider all Core Tasks. O*NET also attaches a numeric value to the descriptors in each set according to its overall importance in the occupation, and for Skills and Work Activities we retain descriptors of broadest relevance.

the specification and the text of the skills that form the cluster is sufficiently small relative to all other clusters in the document.

The second and third steps of this classification strategy—the clustering of the O*NET descriptors and the detection of these clusters in the job descriptions—rely on measures of linguistic similarity based on *word embeddings* that we describe in detail below.

3.2 Estimating Managerial Word Embeddings

We use measures of linguistic similarities based on *word embeddings*, a popular approach in the natural language processing literature for determining the semantic relatedness among words. The broad idea is to represent each word as a vector in a low-dimensional vector space whose coordinates capture aspects of meaning. In our setting, embedding-based similarity is preferred to simpler approaches (for example, measuring distance based on shared vocabulary) since it allows us to handle situations in which texts use different words that share a similar meaning such as 'talk' and 'communicate', or 'bargain' and 'negotiate'.

Constructing word embedding models, however, requires a large amount of textual data, certainly much more than is available in our job specifications and O*NET skill descriptions. 'Off-the-shelf' models—typically estimated on large corpora that are representative of written language such as Wikipedia and Common Crawl for English—do exist, but semantic relatedness in generic English may not correspond to relatedness in the context of business and management (we provide specific examples below). For this reason, we constructed an embedding model using an auxiliary corpus formed of all articles from Harvard Business Review (HBR)—a management journal aimed at both academics and professionals in the business community—whose subject matter and language use make it more appropriate for assessing the meaning of language in our setting. HBR covers a variety of topics related to industry, leadership, work life, and technology, among other areas. We use a complete digital archive of the HBR that covers every published article since the first issue in 1922; in total there are 14,235 articles. The HBR has undergone various shifts in editorial policy and focus during its 100-year existence, which makes the content and format of the articles somewhat varied. For the purposes of the word embedding algorithm, the salient information is local co-occurrence patterns among words independently of the kind of article they appear in. An independent contribution of the paper is the publishing of this estimated embedding model for other researchers to use in their own projects that use natural language generated in business contexts.

The specific embedding algorithm we estimate is the continuous bag-of-words (CBOW) model (Mikolov et al. 2013), a standard and popular model that originated in the natural language processing literature with existing applications in economics (e.g. Atalay et al. 2020).[18]

Word embedding models begin with the idea that words can be represented as vectors

[18] Ash et al. (2020) also use a closely related algorithm.

in a vector space. To more formally describe them, some notation is useful. Let V be the number of unique vocabulary words in a corpus, and let v index the unique words. Also, let $w_{d,n} \in \{1, ..., V\}$ be the nth word in document d. The simplest vector space representation of a vocabulary has V dimensions and assigns to each unique word v the vector $\mathbf{e}_v \in \mathbb{R}^V$ where

$$e_{i,v} = \begin{cases} 1 & \text{if } i = v \\ 0 & \text{if } i \neq v. \end{cases}$$

A major limitation of this representation is that all words are by construction orthogonal to each other and so the distance between word vectors does not relate to semantic similarity. Embedding models instead construct a lower-dimensional vector space with $K \ll V$ dimensions within which to represent words. The motivating idea is that there are K relevant semantic dimensions for understanding the meaning of a word.

A key concept in the CBOW model is the context of each word $w_{d,n}$

$$\mathrm{C}(w_{d,n}) \equiv (w_{d,n-L}, \ldots, w_{d,n-1}, w_{d,n+1}, \ldots, w_{d,n+L})$$

where the window size L is a model parameter. The context is important under the assumption that a word's meaning can in part be inferred from the words that locally co-occur with it. Word embeddings can then be used to directly model these co-occurrence patterns. The CBOW model assigns to each word v an embedding vector $\rho_v \in \mathbb{R}^K$ and a context vector $\alpha_v \in \mathbb{R}^K$ that together generate the probability of observing $w_{d,n}$ given its context. The conditional probability is modeled as

$$\Pr\left[\, w_{d,n} = v \mid \mathrm{C}(w_{d,n}) \,\right] = \frac{\exp\left(\frac{1}{2L} \sum\limits_{w \in \mathrm{C}(w_{d,n})} \boldsymbol{\rho}_v^T \boldsymbol{\alpha}_w\right)}{\sum_{v'} \exp\left(\frac{1}{2L} \sum\limits_{w \in \mathrm{C}(w_{d,n})} \boldsymbol{\rho}_{v'}^T \boldsymbol{\alpha}_w\right)}.$$

The embedding and context vectors are chosen to maximize the probability of the observed data across all words in all documents.[19] We follow common defaults in the machine learning literature and set $L = 5$ and $K = 200$. The quality of an embedding model is typically evaluated in terms of its performance in downstream language tasks and, as we show, the embeddings estimated from the HBR corpus indeed appear to produce coherent and interpretable relationships among words.

The first test of the quality of the estimated embedding model we perform is to examine the words most semantically related to important concepts in management. Table A.7 shows the results of this exercise for the four words 'vision', 'team', 'leader', and 'coordination'. We compute the cosine similarity between the word embedding for each concept

[19]In practice this optimization problem is intractable to solve directly, and Mikolov et al. (2013) introduces several methods for allowing feasible computation. For estimation, we use the gensim implementation of the CBOW model in Python.

and the embeddings for every other word in the HBR corpus, then rank words accordingly. For every example, we observe that the most similar words appear naturally related to the target concept.

Table A.7 also performs the same exercise with an embedding model estimated on generic English language captured by Wikipedia articles and newswires.[20] Here one observes that the choice of HBR as a training corpus produces more targeted and specific language dependencies. While the most similar HBR terms appear to capture broadly plausible management terms, the most similar generic terms are less specific: for vision, they include many terms related to the physical process of seeing; for team, they include many sports words; for leader, the terms relate primarily to politics. This highlights the value of using a corpus that is appropriate for the context in which one seeks to uncover meaning.

The primary application of the embeddings in this paper is to compute the similarity among O*NET descriptions and job specification texts. Exploring the relationship among management concepts is a question of independent interest beyond the scope of this paper, and we make available the HBR-based model for interested researchers.

3.3 Transfer Learning

We estimate the model in one corpus (HBR) to measure semantic relatedness in other corpora (O*NET descriptors and job specifications). This is known as *transfer learning* in the machine learning literature, and allows one to leverage knowledge gained in one environment for other related ones. Because our procedure is generic and automated, it can also be used for determining whether any job-related text (e.g. an online job posting) contains skills described in external sources (e.g. O*NET skills associated with other occupations).

Clustering of O*NET skills To reduce the number of Chief Executive skills to a more manageable number, we use a k-means algorithm to group the text descriptions together. First we preprocess the descriptions in the same way as for HBR (described in appendix B). We then represent each description as a K-dimensional vector by averaging the individual word embeddings as $\frac{1}{N_d}\sum_{w \in \mathbf{w}_d} \boldsymbol{\rho}_w$ where $\mathbf{w_d}$ is the set of words in description d and N_d is the number of words in the description. Finally, we normalize the lengths of all vectors to be 1 so that variation in description length doesn't drive the results of clustering.

The key modeling choice in k-means is the number of clusters. In this instance, standard approaches to the problem (such as the elbow method) do not yield definitive results, and so we adopt a more heuristic approach. We estimate k-means for $k = 2, \ldots, 10$[21] and choose

[20] The generic corpus contains six billion total words and 400,000 unique words. The model is estimated with an alternative procedure for embedding construction called the GloVe model (Pennington et al. 2014) which is also very popular in the machine learning literature. We download the estimated model from `http://nlp.stanford.edu/data/glove.6B.zip` and use the 200-dimensional vectors in line with the choice of K in the HBR corpus.

[21] For each k, we initialize the cluster centroids at 1,000 randomly drawn points, and report as the clustering the run that results in the lowest value of the objective function at the termination of the algorithm.

the lowest value of k consistent with finding meaningful separation of clusters according to our domain expertise. This approach yields $k = 6$, and tables A.3-A.6 show the resulting assignment of descriptions into clusters. We assign the following labels to each of the clusters based on the content of the descriptions that make them up, and provide an example description for each cluster.

1. *Administrative Tasks*: basic tasks involved in running an organization.

   "Preside over or serve on Boards of Directors, management committees, or other governing boards."

2. *Financial and Material Resources*: managing the organization's physical and financial resources, operations, and infrastructure.

   "Monitoring and controlling resources and overseeing the spending of money."

3. *Human Resources*: appointing employees and ensuring they remain motivated.

   "Recruiting, interviewing, selecting, hiring, and promoting employees in an organization."

4. *Information Skills*: processing information and engaging in analytic reasoning.

   "Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts."

5. *Monitoring of Performance*: measuring and improving organizational performance.

   "Establishing long-range objectives and specifying the strategies and actions to achieve them."

6. *Social Skills*: interacting with, listening to, persuading, and empathizing with others.

   "Being aware of others' reactions and understanding why they react as they do."

The clusters we estimate are related but not identical to the short categories that O*NET itself provides. For example, the four skills that O*NET explicitly labels as Social all appear in the *Social Skills* cluster. At the same time, so does "giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times," which O*NET categorizes as a Basic skill. The Administrative Skills cluster is made up solely of 12 Core Tasks, but other Core Tasks are distributed among various other clusters.

The different clusters also capture economically relevant distinctions. *Information Skills* emphasizes cognitively demanding tasks related to information processing and problem solving. *Monitoring of Performance* also has a cognitive focus as the majority of associated skills involve aspects of firm performance related to measurement and optimization. On the other hand, *Human Resources* collects skills related to interpersonal interactions with employees to increase performance. *Social Skills*, which we define and study extensively below, also captures interpersonal interactions, but not in the context of employee motivation. Instead, it reflects a more generic ability to interact with others and understand their perspectives. Finally, *Administrative Tasks* and *Financial and Material Resources* are made up of largely operational abilities related to the day-to-day running of firms.

Mapping job specifications to skills requirements The final step in our construction is to map each job specification into the O*NET clusters. To establish the reasonableness of using similarity comparisons between embedded representations of the O*NET skills descriptions and job specifications, we break the text of the specifications into separate fragments using the structure of the documents (e.g. sentences, bullet points, paragraphs). We then pre-process each fragment and form its average embedding vector as described above for the O*NET text descriptions, and compute the cosine similarity between each observation and the embedding vector formed by concatenating the text descriptions that form each cluster. Tables A.8-A.10 display the text in job descriptions that is most similar to each cluster, and in all cases we observe that they are consistent with the broad theme represented by the cluster.

To give a sense of the content that the clusters do *not* capture, table A.11 shows the fragments that feature low similarity to all clusters. These generally refer to skills that do not relate to specific management tasks, e.g. language skills, industry experience, and educational qualifications. This provides reassurance that our procedure captures content of interest.

While working with fragments of job specifications is useful to obtain a sense of the content that one recovers from similarity comparisons, the structure of documents is somewhat heterogeneous over time. This makes parsing the text into comparable units difficult.[22] Therefore, we compute skill demand measures at the document rather than the fragment level. To do so we express each document as simple average over the individual word embeddings that make it up.

Table 1 shows the average similarity across all job specifications in the sample to the six O*NET skill clusters. Job description language overlaps most closely with *Monitoring of Performance* which suggests this is a primary component of executives' desired skill set. *Social Skills* has the lowest similarity although, as we show below, the relative importance of this cluster has been growing over time.

Table 1: Average Similarity of Job Specifications to O*NET Skill Clusters

Fin/Mat	Admin	Monitoring	Info	HR	Social
0.48	0.64	0.77	0.60	0.71	0.46

Note: This table shows the average cosine similarity between C-suite job specifications and O*NET skill description texts.

[22] For example, the text from earlier parts of the sample contain more bullet points and less regular punctuation, which makes forming individual sentences hard.

A concern with using the raw similarity computed cluster-by-cluster for empirical analysis is that all similarities positively co-move across documents. The first component of the principal components decomposition explains 30% of common variation and loads positively onto all six skill clusters. Our interpretation—borne out by inspecting the texts—is that documents vary in their level of professionalism and thoroughness and that higher degrees of both lead to systematically higher similarity scores with all clusters. Since we wish to interpret the similarity between a job description and an O*NET cluster as capturing relative demand for that skill rather than overall document structure, we adopt the following approach for classifying a skill cluster as present in a document. First, for each skill cluster, we demean its similarity across job documents. We then assign a skill cluster a '1' in a document if the demeaned similarity exceeds the median similarity of the other skill clusters within the same document, and a '0' otherwise. In this way, we identify instances in which the similarity of a document to a particular skill is higher relative to other skills within the same document. For the rest of the paper we present analysis using this constructed variable as our main measure of interest.

4 Skill Clusters

We now turn to describing the variation in the demand for different executive skills emerging from the job descriptions. We start by examining the correlation across clusters within the same document. Figure 1 plots pairwise correlations across the six clusters. The largest positive correlation is between *Social* and *HR*, followed by the one between *Financial/Material* and *Administrative*. We also see, more broadly, a pattern of negative correlations between clusters related to people (*Social* and *HR*) and those related to operations (*Financial and Material Resources* and *Administrative*). These correlations, however, are far from perfect, suggesting that there is value in considering the clusters individually, rather than using a summary index.

Second, we examine the variation in skill clusters across job titles. Figure 2 tabulates the frequency of each skill cluster for each job title. The demand for different clusters across C-suite positions reflects intuitive differences in tasks across the C-suite. *Information* is the relatively most common skill in CIO job descriptions, while *HR* is the most common skill in CHRO job descriptions.[23] These patterns in part validate our measurement algorithm since we obtain expected differences in skill composition across job titles. They also show that the content of the job descriptions is not composed of boilerplate language and that firms indeed adjust the text in line with skill demand.

CEO job titles show two findings of interest. First, CEO job titles are on average less specialized than others. The distance between the most and least common skills across non-CEO job titles is notably higher than in CEO job titles, which suggests that the CEO

[23]Note that our skill measure is a relative one. In absolute terms, the raw similarity of CIO job descriptions is *not* highest with respect to the *Information* cluster—both *Monitoring* and *HR* are higher. What figure 2 shows is that *Information* is present in CIO job texts relatively more than in other job titles.

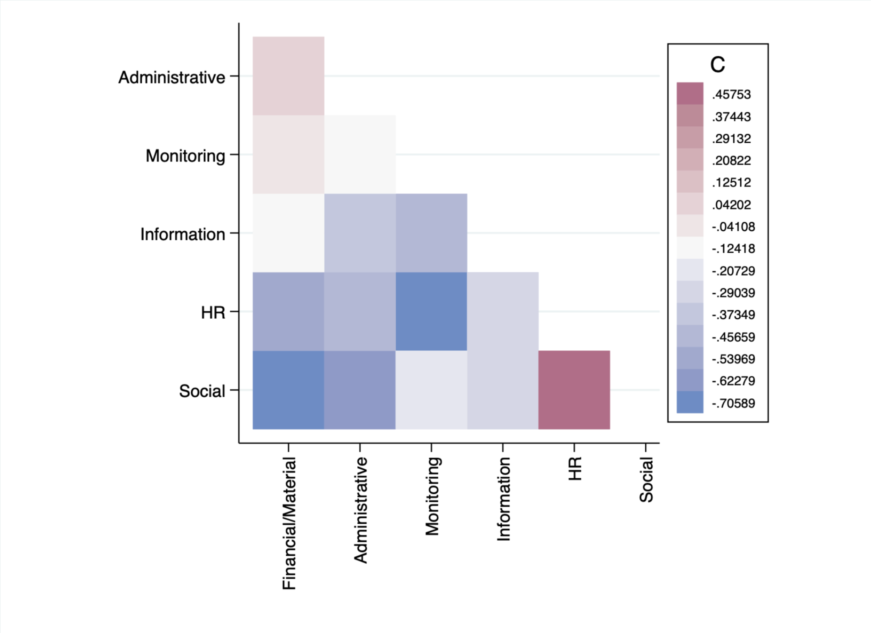


Figure 1: Pairwise Correlations of Skill Clusters within Documents

Note: The heatmap reports polychoric correlation coefficients among the skill clusters.

is expected to possess a greater variety of skills than other executives. Second, among all skills, the *Social* cluster shows the highest intensity. We will analyze the demand for social skills in more detail in the next section.

Third, we analyze variation in skills across industries and the countries in which searching firms have their corporate headquarters. To do so, we regress (using an OLS model) each skill measure on job title fixed effects, industry fixed effects (at the SIC 1 level), and region fixed effects. Figure 3 reports the point estimates of the industry and region effects along with standard errors. We do not observe substantial variation in skills across industries, with the exception of a large over-representation of *Administrative Tasks* in Health and Social Services, Membership Organizations, and Public Administration. This may be driven in part by our sample being composed of larger firms with more uniform needs across sectors. Across regions, a notable finding is that *Financial and Material Resources* is relatively more present for firms headquartered outside North America and Australia/NZ. This suggests that firms in Europe and Asia involve their most senior executives in operational tasks that are delegated to middle mangers elsewhere.

Finally, we study the evolution of skills over time by adding year-of-search effects to the previous controls for job title, country of CHQ location and industry. We report the estimated regression coefficients on the time dummies in Figure 4. During our sample period, there is a large increase in the *Social* cluster (+27% over the 2000-2017 period), while there is a decreasing trend in *Financial/Material* (-30% in 2017 relative to 2000).

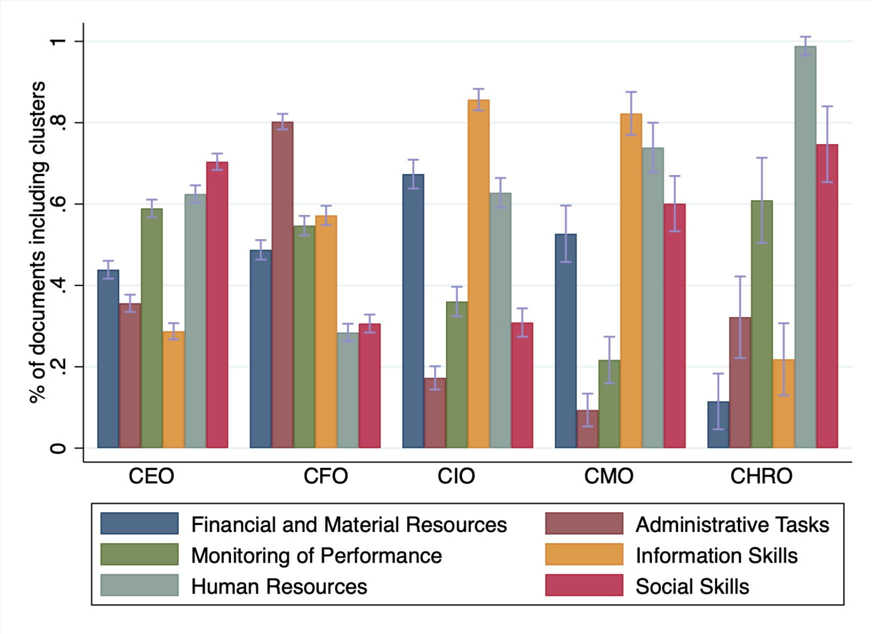


Figure 2: Skills across C-suite Job Titles

Note: The bar heights for each job title show the fraction of documents for which our algorithm identifies a skill as present.

5 The Demand for Social Skills

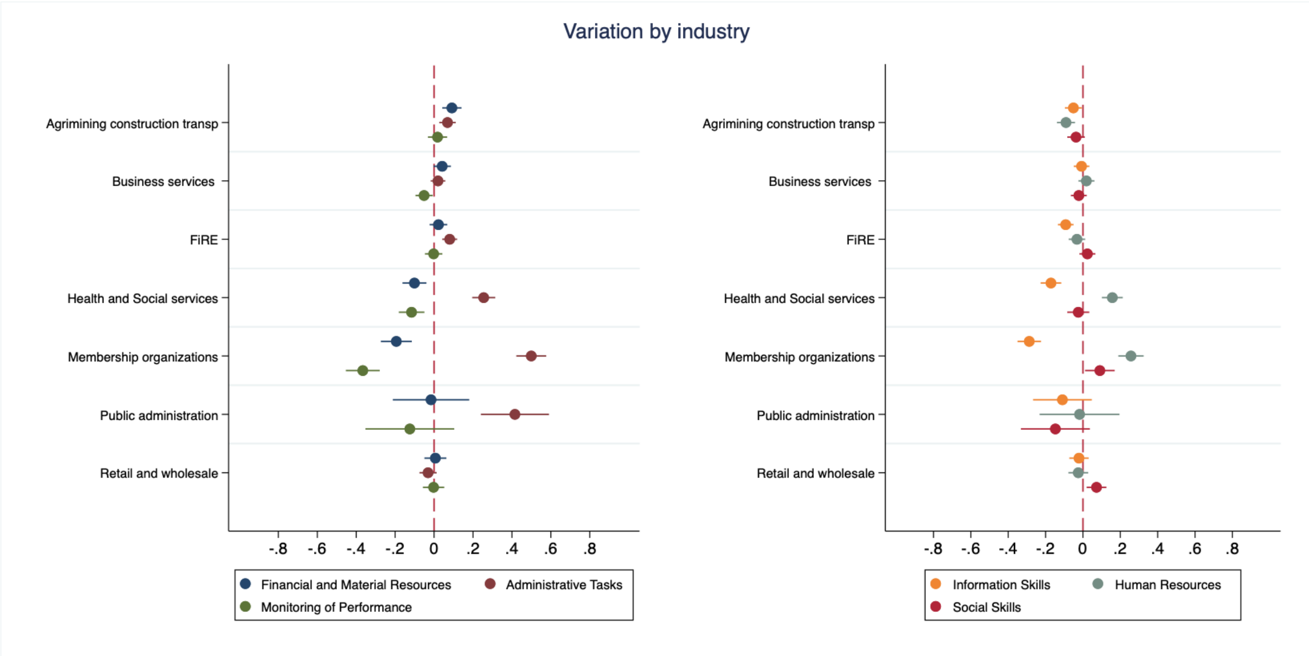
One of the novel stylized facts emerging from the classification of the job descriptions is the importance of *Social skills* in executive searches, especially in CEO job descriptions, and its large increase over time relative to all other clusters. In common with Deming (2017), we interpret the *Social* cluster as capturing the ability to read and react to others based on tacit knowledge. Social psychologists have long recognized the importance of such skills in brain development, beginning with Premack and Woodruff (1978). Korkmaz (2011) explains that

> Social cognition...embraces all the skills required to manage social communication and relationships in humans and nonhumans. It...gives rise to the awareness that others have a mind with various mental states including beliefs, intuitions, plans, emotions, information, desires, and intentions and that these may differ from one's own.

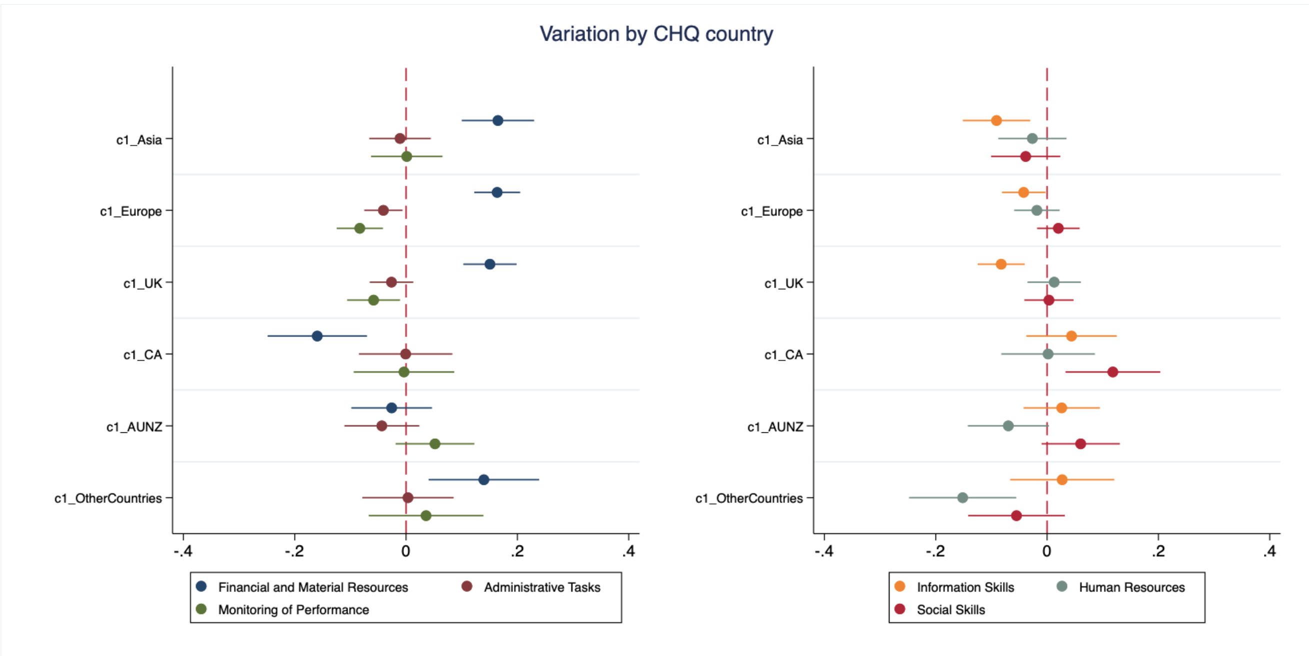
Importantly, this is quite distinct from motivational "soft skills" (which are more appropriately captured in the *Human Resources* cluster), or personal charisma.

Why do Boards explicitly include social skills in their C-suite job descriptions? A possible interpretation of the data is that the inclusion of social skills merely represents the relevance of topics related to "soft" leadership skills in managerial language. In support of this interpretation, we note that the increasing importance of Social language is also apparent in the HBR corpus, as we show in Figure 5.[24] Between 1980 and 2017, the

[24]To measure the implied skill content in HBR, we count the fraction of sentences in the HBR per year



(a) Industry Effects



(b) Region Effects

Figure 3: Executive Skills across Industry and Region of Corporate Headquarters

Note: This figure displays point estimates and 95% confidence intervals of regression coefficients from an OLS model of individual skills on region, country, and job title fixed effects. The omitted category for industry is manufacturing and the omitted category for region is USA.

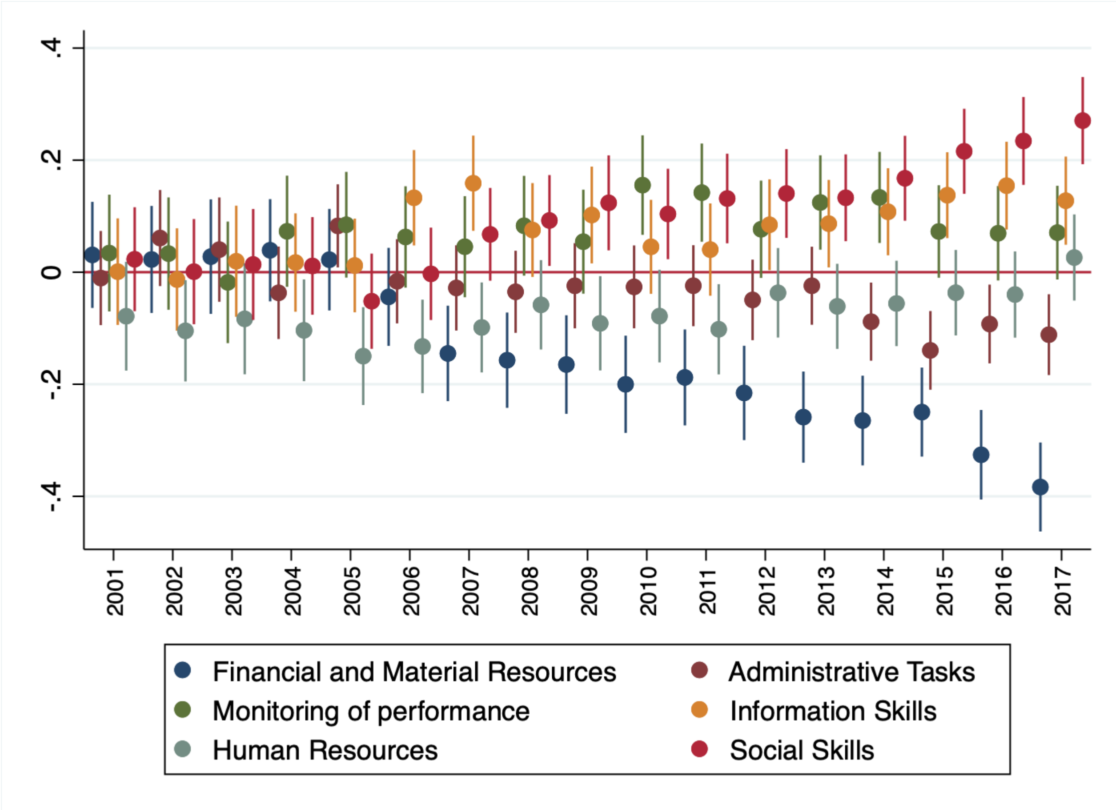


Figure 4: Executive Skills over Time

Note: This figure displays point estimates and 95% confidence intervals of regression coefficients from an OLS model of individual skills on year-of-search effects (in addition to industry, job title, and region fixed effects). The omitted category is 2000, the first year in our sample.

Social cluster doubles in size, while the operational cluster declines, albeit less intensively compared to the job descriptions.

This interpretation, however, fails to capture a salient feature of the data, which is the wide heterogeneity in the demand for executive skills (including social ones) across firms, even within countries, narrowly defined industries, and years.[25]

In what follows, we thus explore a different angle, i.e. that the demand for social skills at C-suite levels reflects actual firms' needs, and specifically in the need to reduce communication frictions in the organization. We discuss the logic of this argument and the empirical support for it below.

5.1 Modeling the Demand for Social Skills in the C-suite

A seminal paper establishing a connection between social skills and communication frictions is Deming (2017). The model studies the role of workers' social skills in a team production setting, where individuals with similar hierarchical status can trade tasks with each other

that contain the words 'leader' or 'leadership' in addition to a term from the different O*NET skill clusters.

[25] The adjusted R-squared of a simple OLS regression of each of the clusters on a set of industry, country, function and year dummies ranges between 0.063 for the cluster *Monitoring of Performance* and 0.208 for the cluster *Information*.

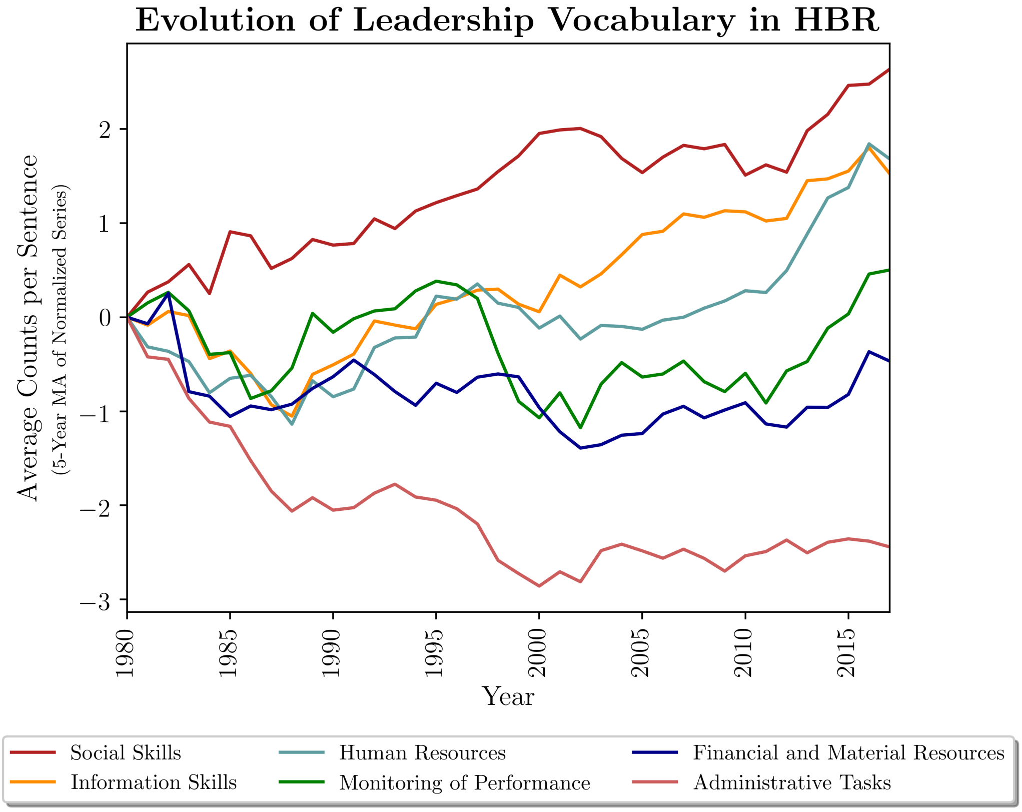


Figure 5: Executive Skills over Time

Note: To generate the HBR time series, we use the following procedure. First, we identify every sentence that contains the word 'leader' or 'leadership'. We then score these sentences as a 1 in a particular skill cluster if they contain any of the words from the related O*NET descriptions (stripped of generic stopwords). Then, for each year we obtain the fraction of flagged sentences as a proportion of all sentences. The time series plots are the five-year moving averages of these fractions normalized to their 1980 value.

to exploit their comparative advantage. In this context, individuals equipped with better social skills can perform these trades in a shorter time, and can thus specialize and work more efficiently with others. This is especially valuable when tasks are more unpredictable, and/or when there is a greater intensity of tasks whose solution is not readily available *ex-ante* (i.e., when there is a greater need for ex-post coordination among workers).

Our setting differs from Deming (2017) in one important respect, however. While co-production with other hierarchical peers is surely part of what C-suite managers do, their job typically consists of other coordination or advisory activities that require interactions with lower-ranked employees.[26] To tailor our analysis to C-suite settings, we thus need to depart from the Deming (2017) model to allow for team communication flows that are primarily *vertical*, i.e. involve individuals with different hierarchical status and specifically workers and managers. We do so through a model examining the role of social skills within a simple setup in which, as in Garicano (2000), production hinges on interactions between workers and a manager to solve problems.

5.1.1 Model setup

A firm is made up of the *workforce* and the *C-suite*. It faces a distribution of problems $F(\theta)$ on the unit interval where $\theta \in [0,1]$ is a particular problem and f is the problem density. Central to the analysis is the idea that production depends in part on vertical communication. We denote by $y(\theta)$ the incremental value of such communication. In other words, $y(\theta)$ captures the additional output that is generated when the C-suite and the workforce interact in the context of addressing problem θ. We assume that $y(0) = 0$ and $y'(\theta) > 0$, which captures the idea that problems are ordered according to increasing difficulty and that the gains from vertical communication are increasing in difficulty.

Given the setup, output is maximized when the C-suite and workforce interact for every problem the firm faces.[27] The maximum value of communication is therefore

$$y^E = \int_0^1 y(\theta) f(\theta) d\theta. \tag{1}$$

In practice, communication frictions can limit organizations from achieving this. In Garicano (2000) communication frictions arise due to managerial time constraints combined with a technological cost of communicating between levels of the organizational hierarchy. In our setting, we maintain a C-suite time constraint but instead conceive of communication costs as arising from the (lack of) social skills of managers. The key assumption is that executives with good social skills are able to spend less time communicating with workers to understand the problems that must be solved. This idea is explored by Deming (2017)

[26] Using detailed time diaries on a sample of 1,114 CEOs, Bandiera et al. (2020) show that executives spend on average 70% of their time in interactive activities such as meetings and calls, of which only a fraction involves exclusively other C-suite managers.

[27] One could more realistically add a mass of problems for which there were no gain to communication, but this would not affect the main conclusions of the analysis.

in the context of collaborative production in the labor force, but rarely in the context of hierarchical manager-worker interactions.[28] The time cost of communicating a unit mass of problems is c and the total time available for the C-suite to engage in communication is T. The efficient output level y^E is therefore only attainable when $1 \leq \frac{T}{c}$, where 1 is the demand for managerial time (i.e. the unit mass of problems for which communication is valuable) and $\frac{T}{c}$ is the effective supply of time. For the remainder of the analysis, we focus on a situation in which this condition fails so that the C-suite lacks the social skills to fully realize the gains from interaction.

Maximizing output under a binding managerial time constraint requires the firm to choose how to allocate managerial time. We model this by introducing a communication rule Θ^C with the interpretation that workers interact with managers whenever $\theta \in \Theta^C$. In words, the firm decides which problems benefit from vertical communication and which do not. The formal problem is

$$\max_{\Theta^C} \int_{\theta \in \Theta^C} y(\theta) f(\theta) d\theta \quad \text{such that} \quad \int_{\theta \in \Theta^C} f(\theta) d\theta = \frac{T}{c}. \tag{2}$$

Given that the value of communication is increasing in θ, the optimal communication rule allocates problems to the C-suite whenever they surpass a threshold θ^* that is chosen to satisfy the resource constraint:

$$1 - F(\theta^*) = \frac{T}{c}. \tag{3}$$

The choice of θ^* determines the demand for managerial time, and is chosen so that demand (left-hand side) equals supply (right-hand side). This in turn generates second-best output

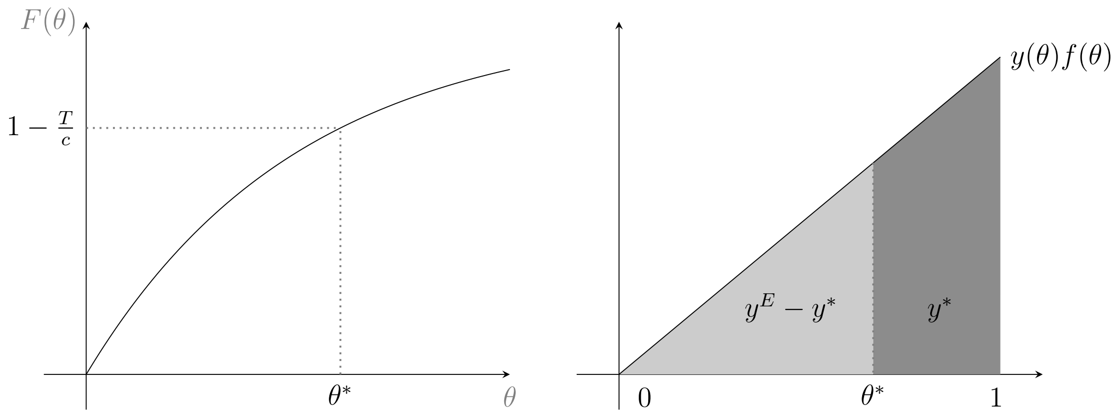
$$y^* = \int_{\theta^*}^{1} y(\theta) f(\theta) d\theta. \tag{4}$$

Figure 6 presents a graphical representation of the outcome. The left panel presents the distribution of problems, where θ^* is chosen in line with (3) to satisfy $F(\theta^*) = 1 - \frac{T}{c}$. The right panel presents the resulting loss in output relative to the efficiency benchmark y^E. Because problems in $(0, \theta^*)$ receive no managerial input when such input is valuable, output falls accordingly.

5.1.2 Social Skills and Firm Characteristics

In the baseline setup, reducing c is valuable because it reduces θ^* and allows the C-suite to engage with a broader range of problems where its input is valuable. We now study how the marginal gain of decreasing c depends on firm characteristics to generate predictions that we can take to the data. We consider two specific situations: how the demand for

[28] One exception is McCann et al. (2015), in which agents differ in cognitive and communication skills and endogenously sort into worker and managerial positions. Agents with higher communication skills become managers because their communication skills allow them to better help workers, although the model does not feature management by exception.



(a) Equilibrium Communication Cutoff

(b) Output with Frictions (Dark Shade) and Loss Relative to No Frictions (Light Shade)

Figure 6: Outcome of Model with Communication Frictions

social skills depends on the volume of problems that firms face, and on the value of vertical communication between managers and workers.

Volume of Problems. We extend the baseline model to incorporate the volume of problems the C-suite faces by introducing N separate classes of problem, each with the same distribution $F(\theta)$ as above.[29] One interpretation of N is that it represents the number of employees in the firm, where problems arise at the individual level and require bilateral interaction. Another is that N represents different types of problems that arise in the course of production. For example, a car manufacturer might need to acquire inputs, assemble them into a car, and then market the cars to buyers. The more distinct tasks that production requires, the greater the volume of problems the C-suite faces. Finally, N could capture the number of divisions in a firm, under the assumption that vertical communication with the C-suite is intermediated by division managers. We explore different empirical counterparts for N to account for these distinct possibilities.

The maximization problem accounting for problem volume is

$$\max_{\Theta^C} N \int\limits_{\theta \in \Theta^C} y(\theta) f(\theta) d\theta \quad \text{such that} \quad N \int\limits_{\theta \in \Theta^C} f(\theta) d\theta = \frac{T}{c}. \tag{5}$$

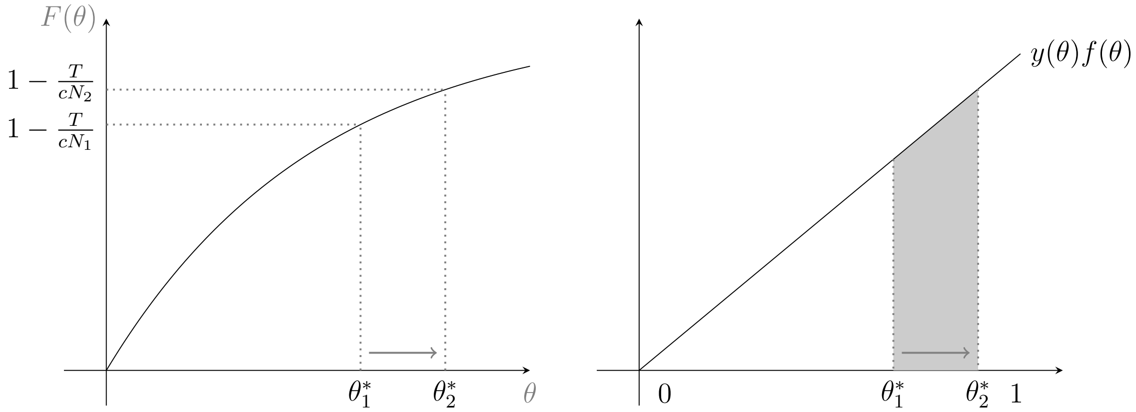
which produces an optimal communication rule given by

$$N[1 - F(\theta^*)] = \frac{T}{c}. \tag{6}$$

As the mass of problems grows, additional demands are placed on the C-suite which reduces the amount of time available for communication about any one class of problem (see left panel of figure 7). Moreover, this shifts the marginal problem that the C-suite can solve to

[29]Problem classes could in principle have different distributions, but this would not affect the main predictions.

the right (right panel). Importantly, the marginal gain to relaxing time constraints is now higher because the marginal problem that benefits from vertical communication is more valuable.



(a) Evolution in Communication Cutoff **(b)** Impact on Output

Figure 7: Effect of Increase in Problem Volume on Communication and Output

Note: This figure shows the impact of increasing the volume of problems from N_1 to N_2. To satisfy the resource constraint on C-suite time, the marginal problem within any class shifts to the right (left panel). This in turn further reduces total output by an amount equal to the light shaded region (right panel).

We formalize these observations in the following result.

Proposition 1 $\frac{\partial^2 y^*}{\partial c \partial N} < 0$. *That is, output falls more quickly when communication costs rise when problem volume increases.*

Proof. By differentiating (6) we obtain:

$$\frac{d\theta^*}{dc} = \frac{T}{f(\theta^*)c^2 N} \quad \textit{and} \quad \frac{d\theta^*}{dN} = \frac{T}{f(\theta^*)cN^2}.$$

Furthermore,

$$\frac{\partial y^*}{\partial N} = \int_{\theta^*}^{1} y(\theta)f(\theta)d\theta - Ny(\theta^*)f(\theta^*)\frac{d\theta^*}{dN} = \int_{\theta^*}^{1} y(\theta)f(\theta)d\theta - \frac{Ty(\theta^*)}{cN}.$$

Now observe that

$$\begin{aligned}\frac{\partial^2 y^*}{\partial N \partial c} &= -y(\theta^*)f(\theta^*)\frac{d\theta^*}{dc} + \frac{Ty(\theta^*)}{c^2 N} - \frac{Ty'(\theta^*)}{cN}\frac{d\theta^*}{dc} \\ &= -\frac{Ty(\theta^*)}{c^2 N} + \frac{Ty(\theta^*)}{c^2 N} - \frac{Ty'(\theta^*)}{cN}\frac{d\theta^*}{dc} \\ &= -\frac{Ty'(\theta^*)}{cN}\frac{d\theta^*}{dc} < 0.\end{aligned}$$

■

The conclusion is that firms that face a higher volume of problems suffer greater output losses from poor executive social skills, and also benefit more on the margin from improving social skills of the C-suite.

Information Intensity of Worker Skills. A straightforward prediction of the model is that increasing the value of vertical communication increases the value of social skills. To see this, consider Figure 8, which illustrates a situation where the value of C-suite communication rises from $y_1(\theta)$ to $y_2(\theta)$. The total loss from communication frictions rises because the problems below the cutoff θ^* would benefit more from vertical communication. More relevant for social skill demand on the margin is that the loss incurred on the marginal problem θ^* rises by $y_2(\theta^*) - y_1(\theta^*)$. This in turn raises the value of easing the time constraint on the margin, which we summarize as:

Proposition 2 *Suppose that the value of C-suite communication changes from $y_1(\theta)$ to $y_2(\theta)$ in such a way that $y_2(\theta^*) > y_1(\theta^*)$. Then $\frac{\partial y^*}{\partial c}$ is larger in absolute value under y_2 than under y_1.*

Proof. From 3 we obtain $\frac{d\theta^*}{dc} = \frac{T}{f(\theta^*)c^2}$. The equilibrium value of communication is $y^* = \int_{\theta^*}^{1} y(\theta)f(\theta)d\theta$ so that

$$\frac{\partial y^*}{\partial c} = -y(\theta^*)f(\theta^*)\frac{d\theta^*}{dc} = \frac{-y(\theta^*)T}{c^2}.$$

The result follows directly by evaluating this expression under y_1 and y_2. ■

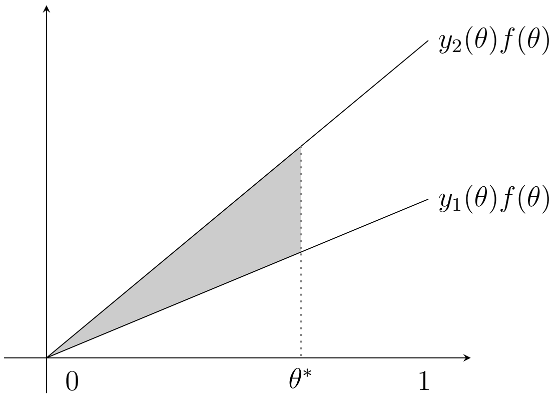


Figure 8: Effect of Increasing Value of Vertical Communication

Note: This figure shows the impact of increasing the value of vertical communication from $y_1(\theta)$ to $y_2(\theta)$. This increases the loss from communication frictions by an amount equal to the light shaded region.

To give this result an empirical grounding, we focus on a particular channel that the management literature has long emphasized increases the value of vertical communication: the extent to which workforce skills are oriented towards information processing activities. The argument is that the shift towards information-intensive work requires executives to exert additional effort in communication in order to coordinate employees and achieve organizational alignment:

> [With computerization] more effort is needed to establish the necessary minimum of communications so that we understand each other and know each other's needs, goals, perceptions and ways of doing things. Information does not supply this. Only direct contact, whether by voice or by written word, can

> communicate... The more we automate information-handling, the more we will have to create opportunities for effective communication (Drucker 2007, *The Effective Executive*, original edition 1967).

To this argument, our model adds the additional insight that firms should seek out executives who are better communicators when communication needs become more salient. This channel is quite distinct from work in organizational economics that shows how IT adoption facilitates the collection, analysis and communication of information that, in turn, complements executive decision-making (e.g. Garicano 2000, Guadalupe et al. 2013, Bloom et al. 2014). The argument of Drucker (2007) is that the changing nature of worker skills, not the adoption of new technology in the form of physical capital *per se*, is key for driving a change in what constitutes effective management. This motivates us to test the relationship between executive social skills and direct measures of workforce skills.

Summary The model illustrates a mechanism through which firm characteristics may affect the demand for social skills in the C-suite. In particular, the value of managerial social skills is greater when the organization faces a greater volume of problems, or when vertical communication becomes more valuable. This is because better social skills allow for more communication per unit of time, and thus relax the managerial time constraint. These are the main predictions that we take to the data.[30]

5.2 Empirical results on social skill demand

5.2.1 Empirical model

To explore the empirical support for the predictions of the model, we estimate a regression model of the form:

$$Social_{ft} = \alpha + \beta X_{ft} + \psi_o + \theta_i + \phi_{chq} + \phi_{sl} + \delta_t + \varepsilon_{jt} \tag{7}$$

Where $Social_{ft}$ is a dummy to denote the relative importance of the *Social* cluster in the job description for firm f at time t, X_{ft} are firm characteristics that proxy for the volume of problems in production and the value of C-suite communication (all described below in more detail), ψ_o are C-title fixed effects, θ_i are industry fixed effects (measured at the SIC 2 level), ϕ_{chq} are fixed effects for the continent in which the firm originating the search is located, ϕ_{sl} are fixed effects for the continent in which the search is launched from, δ_t are year of search dummies. We cluster the standard errors by firm. The key prediction is that the β parameter is positive.

[30] While the model provides a framework for understanding potential channels for the demand for social skills, it may indirectly relate to demand for other skills too. For example, if certain skills are complementary to social skills, one would expect their demand to rise along with social. On the other hand, executives may be horizontally differentiated, so that emphasizing social skills in a job description may be associated with a fall in emphasis in other skills.

5.2.2 Social Skills and the Volume and Scope of Problems

Our first proxy for the volume of problems is firm size, expressed in terms of total employee count.[31] In addition, we use measures of firm activities and organizational complexity as additional proxies of the scope of problems requiring C-suite input: whether the firm is a multinational and whether it is diversified across industries, to capture problems involving decisions across countries or sectors; whether the firm was involved in M&A activities prior to the search, to capture problems related to post-merger integration or divestiture activities; and whether the firm is publicly listed, to measure the need to solve problems involving external constituencies, such as investors and regulators.

Table 2 shows the cross-sectional relationship between social skills and these proxies. All regressions include controls for industry, continent of CHQ location and continent of search, job title and year of search fixed effects. Errors are clustered at the firm level across all regressions.

Table 2: Social Cluster and Firm Characteristics

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Social Skill Cluster					
Log(Employment)	0.014***	0.012***	0.015***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MNE		0.047***			
		(0.017)			
Diversified			-0.004		
			(0.017)		
M&A activity				0.030*	
				(0.016)	
Public					0.030*
					(0.018)
Observations	4,618	4,618	4,618	4,618	4,618
Adjusted R-squared	0.196	0.198	0.196	0.197	0.197

Notes: * p<0.1, ** p<0.05, *** p<0.01. All columns are estimated by OLS. Standard errors are clustered at the firm level, in parentheses under the coefficient. The dependent variable across all columns is a dummy denoting an above-the-median similarity with the *Social* O*NET cluster (where the median is computed using the raw similarity of all clusters in the job description). *MNE*=1 if the firm has operations in more than one country; *Diversified*=1 if the firm has operations in more than one 4 digit SIC sector; *M&A* activity=1 if the firm is involved in M&A activity (as a buyer, target or seller); *Public*=1 if the firm is publicly listed. All independent variables are measured using data in the three years prior to the executive search. All columns control for country of CHQ location, country of search, industry (SIC 2 level), year of search, type of C-suite position advertised.

We start by looking at the relationship between the *Social* cluster and firm size in column (1), and find that larger firms are significantly more likely to include social skills in their job

[31] All firm variables used in this section are measured in the three years prior to the executive search.

description.[32] The magnitude of the coefficient implies that a standard deviation change in log employment is associated with a 3.5 percentage point increase in the probability of including the social cluster. In columns (2)-(5) we examine the relationship between the *Social* cluster and the other firm characteristics described above, controlling for firm size. In sum, we find a strong and significant relationship with MNE status, and weaker or insignificant relationships with the other variables. The magnitude of the coefficients implies that MNE status is associated with an increase in the probability that the job description includes references to social skills of 4.7 percentage points, significant at the 1% level. The coefficient on both the M&A and the Public status dummy imply a 3 percentage point change, but the coefficient is significant at the 10% level, and the coefficient on the diversification dummy is close to zero and insignificant (coefficient -0.004. standard error 0.017).

5.2.3 Executive Social Skills and Worker Information Technology Skills

As explained above, an important potential factor in raising the need for effective executive communication is the information intensity of skills in the workforce. Our measure of this relies on detailed information on the type of skills demanded by firms, which we infer from the vacancies posted by the firm in the years adjacent to the search.[33] We draw this information from Burning Glass Technologies data, which collects detailed vacancies for millions of organizations in the U.S. starting from 2007.[34] We are able to match Burning Glass data only for a subset of organizations in our sample (703 U.S.-based searches, and within this sample 8 are repeated searches by the same firm), though this small matched sample includes a large number of job postings (over 5,000,000). We exploit information on the detailed skills associated with each vacancy using the 27 skill clusters generated by Burning Glass,[35] shown in Table B.13. We start by using the share of postings requiring skills that are classified in the "Information Technology" and "Analysis" skill categories, which groups a variety of basic IT skills ranging from "Microsoft Excel" to advanced software skills (e.g. "Natural Language Processing"), as well as other broader cognitive skills related to information tasks (e.g. "Data Analysis"). The average value of the IT skills variable is 0.12 (standard deviation 0.08). To take into account latent patterns of correlation with other skills within the constraints of our limited sample, we also use summary factors emerging from a principal component decomposition. This generates six factors with eigenvalue greater than one, as shown in Table B.14. Among these factors, the most relevant

[32] We obtain similar results when we use log sales as a proxy for firm size, which is available for a subset of 1916 observations. The coefficient on log sales is 0.012, standard error 0.005.

[33] To maximize the number of companies matched with the our sample, we use information on vacancies posted within both the three years prior and following the executive search year (results are qualitatively similar but include a much smaller sample using only the three years prior to the search).

[34] Burning Glass data have been extensively used in prior research to document job market trends and skill demand across firms and MSAs within the U.S. (Deming and Kahn 2018, Hershbein and Kahn 2018). To our knowledge, this is the first time that they are combined with data on skill demands at C-suite-level positions. We thank Bledi Taska for giving us access to the Burning Glass for this project.

[35] Each vacancy can include reference to multiple skill categories.

for our purposes is Factor 1, which loads positively on the Information Technology and Analysis skills but also, interestingly, on skills such as "Design", "Marketing", "Media and Writing" and "Business" capturing managerial, creative and communicative tasks, in line with the idea that information skills are associated with different bundles of complementary cognitive tasks. To make sure that the skills measures are not sensitive to the Burning Glass classification, we also use as an alternative classification the skill taxonomy developed by Deming and Kahn (2018), focusing specifically on software skills (See Table B.15).[36] Using this approach, the IT Skill variable is higher on average, and still heterogeneous across firms (mean 0.26, standard deviation 0.23). Also in this case, the demand for technological skills covaries with other skills related to communication ("Writing") and interactive tasks ("Social") (see B.17 for details). In the analysis, we examine the relationship between the basic technology variables, as well as the factors, using both classification schemes.

Table 3 presents the results. In column (1), we examine the relationship between social skills and the technology adoption variable derived from Burning Glass, in a regression including controls for the log of total number of job vacancies posted by the firm (which serves as a proxy for firm size in these regressions, since the variable is highly correlated with employment), the same set of controls used in the earlier regressions (with the main difference that industry controls are now at the 1 digit SIC level given the smaller sample) and additional controls related to the Burning Glass data (specifically, total number of occupations advertised, the share of job ads with levels of education and years of experience required). The IT variable is positively and significantly correlated with the *Social* cluster (coefficient 0.680, standard error 0.241): a standard deviation change in the share of job vacancies listing IT skills is associated with a 5.2 percentage points increase in the Social cluster. In column (2) we show that the two variables continue to be significantly correlated even when we include controls for other characteristics of the posted vacancies (the average level of education and experience requested, and the total number of occupations advertised). In column (3) we replace the IT shares variables with the principal component factors described above, and find that the factor loading on the IT variables continues to be positively and significantly correlated with the *Social* skills cluster.[37] Columns (4) and (5) repeat the analysis using the IT variables and factors derived from the Deming and Khan (2018) classification, showing similar results: a standard deviation change in the software variable is associated with a 6.3 percentage point increase in the *Social* cluster, and the

[36]We extended the classification of Deming and Kahn (2018) to include skills that had not been present in the original taxonomy, and to make sure that we could capture the heterogeneity present in the IT skills information. For example, "Cloud storage", appears in our data but was not included in the original classification, and we classified it into the "Software" category. We also reclassified some of the IT skills that were originally classified into the "Character" group (e.g. "Basic Computer Knowledge" and "Microsoft Office") in a dedicated "Basic Software" category, where we include other non-specialist software skills. We present the details of the data construction in Appendix.

[37]This column includes as additional controls also all the other five factors with eigenvalues greater than one. None of the other factors are significantly associated with the Social skills cluster. We find qualitatively and quantitatively similar results when we control for a full battery of occupation fixed effects, results available upon request.

Table 3: Social Cluster, IT Adoption and Cognitive Skills

	(1)	(2)	(3)	(5)	(6)
Dependent Variable: Social Skill Cluster					
Log(Total Vacancies)	0.042***	0.056***	0.061***	0.053***	0.056***
	(0.012)	(0.018)	(0.018)	(0.018)	(0.018)
IT Skills	0.680***	0.758***			
(Skill Shares, Burning Glass)	(0.241)	(0.270)			
IT & Cognitive Skills			0.093***		
(Factor, Burning Glass)			(0.023)		
IT Skills				0.285***	
(Skill Shares, Deming and Khan)				(0.098)	
IT & Cognitive Skills					0.061***
(Factor, Deming and Khan)					(0.018)
Observations	703	703	703	703	703
Adjusted R-squared	0.222	0.227	0.239	0.228	0.230

Notes: * p<0.1, ** p<0.05, *** p<0.01. All columns are estimated by OLS. Standard errors are clustered at the firm level, in parentheses under the coefficient. The dependent variable across all columns is a dummy denoting an above-the-median similarity with the *Social* O*NET cluster (where the median is computed using the raw similarity of all clusters in the job description). *IT Skills* measures the average share of job vacancies including reference to the Burning Glass skill categories *Information Technology* or *Analysis*. *IT & Cognitive Skills* is the first principal factor derived from the set of 27 skills categories (factor loadings are presented in Table B.14). The last two rows refer to skill shares and factor built using the alternative Deming and Kahn (2018) classification. All independent variables are measured using data in the three years prior to and following the executive search. All columns control for country of CHQ location, country of search, industry (SIC 1 level), year of search, type of C-suite position advertised, total number of occupations advertised, the share of job ads with levels of education and years of experience required.

summary IT factor continues to be positively and significantly correlated with it.

5.2.4 Other clusters

We next examine whether the patterns observed in the data are present for other clusters beyond *Social*. This analysis is shown in Table 4 (in this table each coefficient corresponds to a different regression). In summary, the positive correlation with firm size, MNE status and M&A activity is specific to the *Social* cluster. In fact, if anything, the MNE and M&A dummies are *negatively* correlated with some of the other clusters. For example, employment is negatively and significantly correlated with the *Material and Financial Resources* cluster, and the MNE and the M&A dummies with *HR* and *Administrative* clusters. This suggests that the increase in social language is capturing a broader patter of substitution in the job description of C-suite managers, and specifically a shift away from the mentioning of more operational and easier-to-delegate tasks, and toward more coordination activities. The other interesting aspect of this analysis is the absence of correlation (or negative correlation) of the proxies with the *HR* cluster,[38] which is primarily focused on the ability to improve individuals' motivation, in contrast with the *Social* cluster, which is primarily focused the ability to interact with other through listening, persuasion and empathy. This suggests that it is important to distinguish between different types of capabilities that are typically lumped into a unique "soft skills" category.

We also observe that our measures of worker information technology skills positively correlate with the executive *Information* skill cluster, consistent with the notion that these skills complement cognitively intensive activities at the C-suite level. This finding—as well as the negative and significant correlation between the workers' information skills variables and the demand for operational and administrative skills in C-suite job descriptions—is in line with the patterns of task complementarity and substitution examined in the earlier literature (Autor and Dorn 2013, Deming and Kahn 2018). Differently from the earlier literature, however, these patterns occur across, rather than within, occupations and hierarchical levels.

[38]The only variable for which we find a positive correlation between the *HR* cluster if whether the firm is publicly listed

Table 4: Skill Clusters and Firm Characteristics

Dependent Variable:	(1) Social (Baseline)	(2) Management of Financial and Material Resources	(3) Administrative Tasks	(4) Monitoring of Performance	(5) Information Skills	(6) Personnel Management
Log(Employment)	0.014***	-0.008**	-0.005	0.006	-0.002	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MNE	0.047***	0.003	-0.054***	0.023	0.021	-0.040**
	(0.017)	(0.017)	(0.015)	(0.017)	(0.017)	(0.017)
Diversified	-0.004	0.009	-0.011	0.016	0.005	-0.015
	(0.017)	(0.018)	(0.015)	(0.018)	(0.017)	(0.018)
M&A Activity	0.030*	-0.003	-0.060***	0.030*	0.009	-0.062***
	(0.016)	(0.016)	(0.013)	(0.016)	(0.014)	(0.013)
Public	0.030*	-0.038**	0.007	-0.062***	0.022	0.040**
	(0.018)	(0.018)	(0.016)	(0.019)	(0.018)	(0.019)
IT Skills	0.758***	0.177	-0.669***	-0.894***	0.663**	-0.036
(Shares, Burning Glass)	(0.270)	(0.262)	(0.247)	(0.279)	(0.260)	(0.278)
IT & Cognitive Skills	0.093***	-0.043**	-0.050**	-0.075***	0.060***	0.014
(Factor, Burning Glass)	(0.023)	(0.022)	(0.021)	(0.024)	(0.021)	(0.023)
IT Skills	0.285***	0.074	-0.259***	-0.163	0.168*	-0.105
(Shares, Deming & Khan)	(0.098)	(0.096)	(0.086)	(0.103)	(0.099)	(0.100)
IT & Cognitive Skills	0.061***	-0.035*	-0.035**	-0.027	0.026	0.011
(Factor, Deming & Khan	(0.018)	(0.018)	(0.016)	(0.020)	(0.019)	(0.020)

Notes: * p<0.1, ** p<0.05, *** p<0.01. Each coefficient in this table corresponds to a different regression. All columns except are estimated by OLS. Standard errors are clustered at the firm level, in parentheses under the coefficient. *MNE*=1 if the firm has operations in more than one country; *Diversified*=1 if the firm has operations in more than one 4 digit SIC sector; *M&A* activity=1 if the firm is involved in M&A activity (as a buyer, target or seller); *Public*=1 if the firm is publicly listed. *IT Skills* measures the average share of job vacancies including reference to the Burning Glass skill categories *Information Technology* or *Analysis*. *IT & Cognitive Skills* is the first principal factor derived from the set of 27 skills categories (factor loadings are presented in Table B.14). The last two rows refer to skill shares and factor built using the alternative Deming and Kahn (2018) classification. MNE, Diversified, M&A and Public are measured using data in the three years prior to the executive search. All the IT skills variables are measured using data in the three years prior to and following the executive search. All columns control for country of CHQ location, country of search, industry (SIC 2 level), year of search, type of C-suite position advertised.

5.2.5 Robustness

Finally, we explore the robustness of the baseline empirical results above. These are contained in Table 5, with column (1) reporting the baseline results of Tables 2 and 3 (in this table each coefficient corresponds to a different regression). To begin, column (2) uses a probit rather than linear probability model and the results are nearly identical.

One concern is that the inclusion of references to social skills may simply reflect differences in the effort that Boards put in drafting job descriptions, rather than actual firm needs. For example, Boards of larger and more complex firms may simply spend more time writing the job descriptions, and hence refer to more skills in the documents. While the data construction controls for these basic differences in document structure—recall that the dependent variable in our analysis takes value one if the similarity of the social cluster is higher relative to other clusters in the same document—we also examine whether our main results hold after including a variable for document length in column (3). We find little difference with the baseline.

Another concern is that search consultants may influence Boards to include language that may help them cross-sell additional consulting services, regardless of specific firm needs. For example, consultants may suggest including references to specific skills for which they are able to provide additional screening or development services. To the extent that this incentive varies across organizations—for example, if cross-selling incentives are higher in larger firms—and that they focus specifically on social skills, this would bias our estimates. To address this issue, we exploit the subsample of firms for which we have multiple searches over time. We use this sample to examine whether references to social skills are always added—which would be consistent with job descriptions merely reflecting additions to the "menu" of services offered by search consultants—or also removed—which would be more in line with the notion that language is instead tailored to firms' specific needs. More importantly, this sample allows us to study the relationship between *changes* in coordination needs and in the language used in the executive search documents, thus controlling for time invariant firm characteristics that may be salient to search consultants (e.g. differences in firm size in levels).[39]

The within-firm analysis is based on 530 unique firms and 1,273 searches.[40] Changes in job descriptions include both the addition of references to the *Social* cluster (in 26% of the cases) and deletion (18% of cases). This is important, as it shows that firms both add and remove references to *Social* skills. We also see heterogeneity in the employment changes: 19% of the sample records a decline in employment over time (average change of -14%), and 23% an increase (average change of 17%). Column (4) of Table 5 shows the

[39]Clearly, if the omitted variable is time varying—for example, if cross-selling incentives focused specifically on social skills are higher in *growing* firms—this would still bias our estimates.

[40]We consider only multiple searches that are conducted in different years. Since some firms appear in the sample in more than two years of data, we include only the first and last job description included in the corpus. If a company runs multiple searches within a single year (which happens for 165 searches), we build an average of the cluster measures across all searches within a given year.

within-firm correlation between the *Social* cluster and log firm employment, the only firm level proxy where we observe meaningful variation over time.[41] This shows that the *Social* cluster and firm size are strongly correlated even in this demanding specification. In fact, the coefficient on employment is even larger than in the cross sectional results: a standard deviation change in employment is associated with an increase in the *Social* cluster by 20 percentage points.[42]

Finally, Boards may draft job descriptions with a specific candidate in mind, rather than trying to find the best available match for the job. A specific concern is that referencing social skills in the job descriptions may help tilt the selection process towards internal candidates, as it refers to skills (e.g. persuasion, motivation, listening, etc.) that are easier to assess "on the job." If Boards of firms characterized by more complex production needs are more likely to prefer internal candidates,[43] this would generate a spurious association with the *Social* cluster. To allay this concern, we measure whether the search led to the hire of an internal candidate (that is, a person that was formally employed by the firm prior to the search). We were able to retrieve information on hiring outcomes for 1,093 US- and UK-based searches (out of a total of 3,305 in the sample), using both external public sources and manual searches conducted by a team of Research Assistants.[44] We use this information to examine whether there is a systematic relationship between social skills and internal hires, and whether the relationship between social skills and firm characteristics is sensitive to controlling for internal hiring outcomes. The results are as follows. First, the hiring of an internal candidate is not associated with the probability that the job description included a reference to social skills. Second, as shown in columns (5) and (6), controlling for internal hires does not alter the magnitude and significance of the results.[45]

[41] Firms may advertise for different C-suite positions within and across different years. To account for these differences, the fixed effects specification also includes a dummy to denote which C-suite positions were used to build the averages. These variables are built exactly as in earlier tables, using information on the three years preceding the search.

[42] We find no evidence of a correlation with employment in the within-firm regressions for the other clusters, results available upon request.

[43] Cziraki and Jenter (2020) show that the share of internal CEO hires has been steadily increasing over the past two decades.

[44] We started this exercise drawing information on executive appointments from Boardex data. After noticing some inconsistencies, especially for private firms, we decided to rely more intensively on manual searches. Eventually, we decided to focus on US and UK searches since these were the countries more compatible with the language skills of our RAs, and more likely to include hiring announcements in the news. Our ability to retrieve data on hires varies dramatically over time. We were able to find data on hires for only 22% of the sample of searches taking place between 2000 and 2009, and 43% of the sample for searches between 2010 and 2017. See Appendix B for details on the data construction.

[45] In these columns We use a coarser set of industry (SIC 1) and time (4 year intervals) controls given the smaller sample size.

Table 5: Robustness Checks

Dependent Variable: Social Cluster	(1) Baseline	(2) Probit	(3) Control for document length	(4) Within firm	(5) Internal sample	(6) Internal sample, control for internal
Log(Employment)	0.014***	0.001**	0.014***	0.080***	0.014**	0.016**
	(0.003)	(0.001)	(0.003)	(0.029)	(0.006)	(0.006)
MNE	0.047***	0.147***	0.048***		0.058*	0.061*
	(0.017)	(0.050)	(0.017)		(0.033)	(0.033)
Diversified	0.030*	0.091*	0.031*		0.008	0.009
	(0.016)	(0.054)	(0.018)		(0.034)	(0.034)
MA Activity	-0.004	-0.011	-0.004		0.007	0.011
	(0.017)	(0.051)	(0.017)		(0.036)	(0.036)
Public	0.030*	0.088*	0.030*		-0.012	-0.010
	(0.018)	(0.047)	(0.016)		(0.031)	(0.031)
IT Skills	0.680***	2.550***	0.763***			
(Shares, Burning Glass)	(0.241)	(0.875)	(0.271)			
IT & Cognitive Skills	0.093***	0.310***	0.094***			
(Factor, Burning Glass)	(0.023)	(0.074)	(0.023)			
IT Skills	0.285***	0.949***	0.288***			
(Shares, Deming & Khan)	(0.098)	(0.320)	(0.098)			
IT & Cognitive Skills	0.061***	0.210***	0.061***			
(Factor, Deming & Khan	(0.018)	(0.060)	(0.018)			

Notes: See next page.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. All columns except column (2) are estimated by OLS. Column (2) is estimated by Probit. Standard errors are clustered at the firm level, in parentheses under the coefficient. The dependent variable across all columns is a dummy denoting an above-the-median similarity with the *Social* O*NET cluster (where the median is computed using the raw similarity of all clusters in the job description). *MNE*=1 if the firm has operations in more than one country; *Diversified*=1 if the firm has operations in more than one 4 digit SIC sector; *M&A* activity=1 if the firm is involved in M&A activity (as a buyer, target or seller); *Public*=1 if the firm is publicly listed. *IT Skills* measures the average share of job vacancies including reference to the Burning Glass skill categories *Information Technology* or *Analysis*. *IT & Cognitive Skills* is the first principal factor derived from the set of 27 skills categories (factor loadings are presented in Table B.14). The last two rows refer to skill shares and factor built using the alternative Deming and Kahn (2018) classification. MNE, Diversified, M&A and Public are measured using data in the three years prior to the executive search. All the IT skills variables are measured using data in the three years prior to and following the executive search. All columns control for country of CHQ location, country of search, industry (SIC 2 level), year of search, type of C-suite position advertised. Column (3) includes a control for log document length. Column (4) includes firm fixed effects on the sample of 1,006 searches and 503 firms with repeated searches. Column (5) presents the estimation of the model presented in Table 2 for the sample of searches where we could verify the provenance of the incoming CEO. Column (6) presents the results of the regression including a dummy for the appointment of an internal CEO (i.e., a CEO that was previously employed in the firm)

5.2.6 Summary of empirical results

In summary, the demand for social skills in executive positions is systematically associated with specific firm characteristics, namely firm size, geographic diversification, and involvement in M&A activities. The results related to firm size are significant in cross sectional and longitudinal regressions. We also find that the demand for social skills is greater in firms with greater demand for workers' information skills. These results by and large hold only for the *Social* cluster, except for the fact that a greater demand for workers' information skills is positively correlated also with the *Information* cluster. Overall, these results are consistent with the notion that the demand for social skills in executive searches reflects specific firm needs, and in particular the need to coordinate more, and more complex, activities within firms.

6 Conclusion

We draw on a rich dataset of job specifications for executive searches across thousands of firms, and document substantial variation in language that describes the skill content of top managerial positions. This provides the first measurement of demand for executive skills in the literature.

The data show that the demand for executive skills comprises a range of operational, cognitive, and interpersonal skills. The demand for specific skills, however, is highly heterogeneous across firms: far from adhering to similar boilerplate language, firms instead spend considerable effort in specifying the skills and capabilities they look for in potential candidates, even within the same country, industry, and year of search. The data also show that the demand for executive skills has evolved over time. In particular, firms have become increasingly more likely to demand *Social* skills—i.e. the capability to interact, persuade and more generally relate to others—relative to more traditional operational and administrative capabilities (e.g., monitoring the allocation of financial resources).

Guided by a simple model of management by exception in the spirit of Garicano (2000), we show that social skills vary with proxies for the importance of C-suite communication within firms and that such skills are becoming more important over time, in line with broader trends in the labor market.

More generally, our results show that the managerial labor market is similar to generic labor markets insofar as different firms heterogeneously value different skills, although this perspective is typically not emphasized in discussion of top-level executives. An important feature of the executive labor market, however, is its thinness, as relatively few participants exist on both sides of the market. This makes satisfying skill demand arguably harder than in typical labor markets, and brings to the forefront important issues surrounding the matching process of firms and managers. Open questions include whether the supply of executive skills meets demand; whether firms can adequately screen potential candidates, especially as non-verifiable soft skills become more important; how quickly firms can identify and remove executives whose skill set is not appropriate; and whether training can adequately equip managers with "soft" skills deemed important by organizations. We believe that this paper provides an important step in providing an evidence base to begin exploring these crucial issues.

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A Appendix Tables and Figures For Online Publication

A.1 Sample Description (Section 2)

Table A.1: Sample Descriptives

(a) Job titles

Job Title	Frequency	Percent
CEO	1,977	42.77
CFO	1,678	36.3
CHRO	677	14.65
CIO	87	1.88
CMO	203	4.39
Total	4,622	100

(b) CHQ continent of search

CHQ location	Frequency	Percent
Asia	245	5.3
Oceania	199	4.31
Canada	115	2.47
USA	2,642	57.17
Europe	805	17.42
UK	526	11.38
Other countries	246	1.95
Total	4,622	100

(c) Year of search

Year	Frequency	Percent
2000	210	4.54
2001	156	3.38
2002	169	3.66
2003	133	2.88
2004	185	4
2005	219	4.74
2006	246	5.32
2007	255	5.52
2008	269	5.82
2009	229	4.95
2010	258	5.58
2011	278	6.01
2012	283	6.12
2013	339	7.33
2014	364	7.88
2015	375	8.11
2016	335	7.25
2017	319	6.9
Total	4,622	100

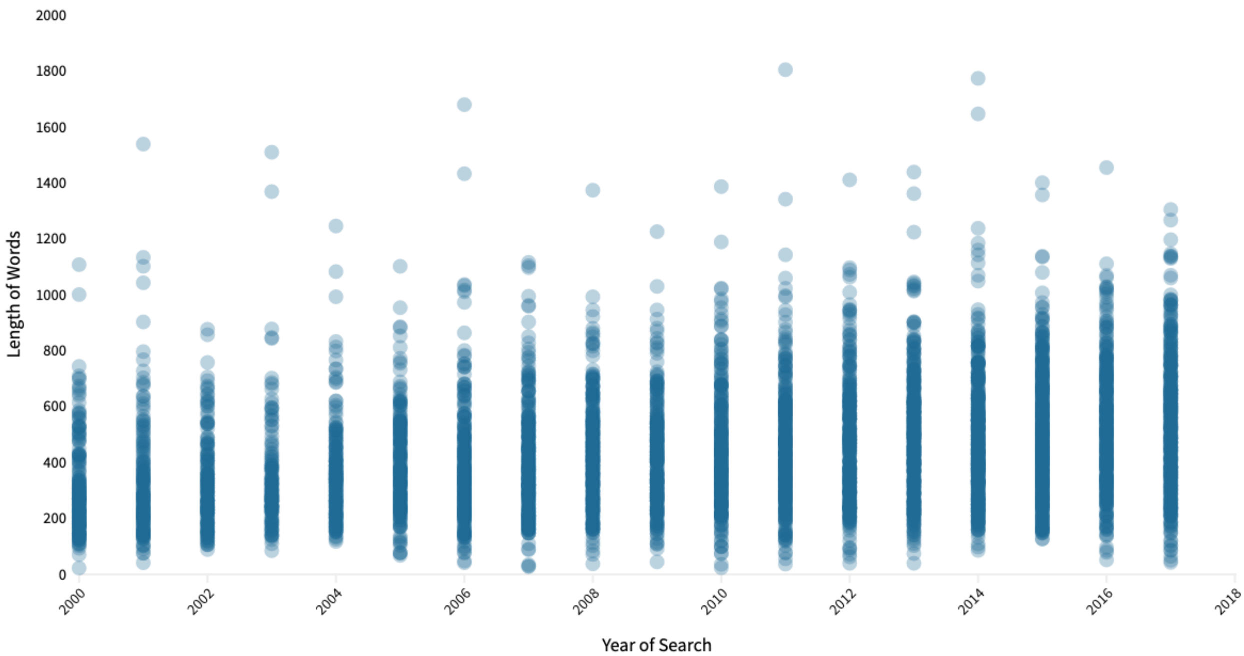
This table documents the composition of the corpus of job description texts by job title, location of the firm initiating the search, and the year the position is advertised.

Table A.2: Firm characteristics

(a) Job titles

Variable	Mean	Median	Standard Deviation	Observations
Employment	15205.75	1483.125	55009.66	3786
MNE	0.67	1		4515
M&A activity	0.52	1		4622
Diversified	0.26	0		4515
Public	0.26	0		4622

This table documents the characteristics of the firms included in the sample, measured in the the three years prior to the search.



This figures shows scatter plots of job search document lengths (in words) by year.

Figure A.1: Distribution of Document Lengths by Year

A.2 Classification Approach (Section 3)

	Description	Short Description	Category	Subcategory
Information Skills	Talking to others to convey information effectively.	Speaking	Skill	Basic
	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.	Critical reasoning	Skill	Basic
	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.	Complex problem solving	Skill	Complex Problem Solving
	Understanding written sentences and paragraphs in work-related documents.	Reading comprehension	Skill	Basic
	Understanding the implications of new information for both current and future problem-solving and decision-making.	Active learning	Skill	Basic
	Deliver speeches, write articles, or present information at meetings or conventions to promote services, exchange ideas, or accomplish objectives.		Task	Core
	Analyzing information and evaluating results to choose the best solution and solve problems.	Making decisions and solving problems	Work Activities	Mental Processes
	Observing, receiving, and otherwise obtaining information from all relevant sources.	Getting information	Work Activities	Information Input
	Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.	Analyzing data or information	Work Activities	Mental Processes
	Using relevant information and individual judgment to determine whether events or processes comply with laws, regulations, or standards.	Evaluating information to determine compliance with standards	Work Activities	Mental Processes
	Identifying information by categorizing, estimating, recognizing differences or similarities, and detecting changes in circumstances or events.	Identifying objects, actions and events	Work Activities	Information Input
	Using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information.	Interacting with computer systems	Work Activities	Work Output
	Translating or explaining what information means and how it can be used.	Interpreting the meaning of information for others	Work Activities	Interacting With Others
	Compiling, coding, categorizing, calculating, tabulating, auditing, or verifying information or data.	Processing information	Work Activities	Mental Processes
	Monitoring and reviewing information from materials, events, or the environment, to detect or assess problems.	Monitor, processes, materials or surroundings	Work Activities	Information Input
	Determining how money will be spent to get the work done, and accounting for these expenditures.	Management of financial resources	Skill	Resource Management
	Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.	Management of material resources	Skill	Resource Management
	Administer programs for selection of sites, construction of buildings, or provision of equipment or supplies.		Task	Core
	Monitoring and controlling resources and overseeing the spending of money.	Monitoring and controlling resources	Work Activities	Interacting With Others

Table A.3: "Information Skills" Cluster for O*NET Executive Skills

O*NET Executive Skills that are grouped together using a k-means algorithm with six clusters applied to the texts in the *Description* field. We choose the label "Information Skills" to describe this cluster. The *Short Description*, *Category*, and *Subcategory* fields are also provided by O*NET to further classify the individual descriptions. *Short Description* is not available for the O*NET Task Category.

Table A.4: "Human Resources" Cluster for O*NET Executive Skills

	Description	Short Description	Category	Subcategory
Human Resources	Motivating, developing, and directing people as they work, identifying the best people for the job.	Management of personnel resources	Skill	Resource Management Skills
	Communicating effectively in writing as appropriate for the needs of the audience.	Writing	Skill	Basic
	Managing one's own time and the time of others.	Time management	Skill	Resource Management Skills
	Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person.	Communicating with supervisors, peers or subordinates	Work Activities	Interacting With Others
	Communicating with people outside the organization, representing the organization to customers, the public, government, and other external sources. This information can be exchanged in person, in writing, or by telephone or e-mail.	Communicating woth people outisde the organization	Work Activities	Interacting With Others
	Encouraging and building mutual trust, respect, and cooperation among team members.	Developing anf building teams	Work Activities	Interacting With Others
	Developing constructive and cooperative working relationships with others, and maintaining them over time.	Establishing and maintaining interpersonal relationships	Work Activities	Interacting With Others
	Keeping up-to-date technically and applying new knowledge to your job.	Updating and using relevant knowledge	Work Activities	Mental Processes
	Getting members of a group to work together to accomplish tasks.	Co-ordinating the work and activties of others	Work Activities	Interacting With Others
	Identifying the developmental needs of others and coaching, mentoring, or otherwise helping others to improve their knowledge or skills.	Coaching and developing others	Work Activities	Interacting With Others
	Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions.	Thinking creatively	Work Activities	Mental Processes
	Recruiting, interviewing, selecting, hiring, and promoting employees in an organization.	Staffing organizational units	Work Activities	Interacting With Others
	Providing guidance and expert advice to management or other groups on technical, systems-, or process-related topics.	Communicationg with supervisors, peers, or subordinates	Work Activities	Interacting With Others
	Scheduling events, programs, and activities, as well as the work of others.	Scheduling work and activities	Work Activities	Mental Processes
	Identifying the educational needs of others, developing formal educational or training programs or classes, and teaching or instructing others.	Training and teaching others	Work Activities	Interacting With Others

O*NET Executive Skills that are grouped together using a k-means algorithm with six clusters applied to the texts in the *Description* field. We choose the label "Human Resources" to describe this cluster. The *Short Description*, *Category*, and *Subcategory* fields are also provided by O*NET to further classify the individual descriptions. *Short Description* is not available for the O*NET Task Category.

Table A.5: "Monitoring of Performance" and "Financial and Material Resources" Clusters for O*NET Executive Skills

	Description	Short Description	Category	Subcategory
Monitoring of Performance	Considering the relative costs and benefits of potential actions to choose the most appropriate one.	Judgment and decision making	Skill	Systems Skills
	Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action.	Monitoring	Skill	Basic
	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.	Systems analysis	Skill	Systems Skills
	Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system.	Systems evaluation	Skill	Systems Skills
	Direct or coordinate an organization's financial or budget activities to fund operations, maximize investments, or increase efficiency.		Task	Core
	Analyze operations to evaluate performance of a company or its staff in meeting objectives or to determine areas of potential cost reduction, program improvement, or policy change.		Task	Core
	Direct, plan, or implement policies, objectives, or activities of organizations or businesses to ensure continuing operations, to maximize returns on investments, or to increase productivity.		Task	Core
	Implement corrective action plans to solve organizational or departmental problems.		Task	Core
	Coordinate the development or implementation of budgetary control systems, recordkeeping systems, or other administrative control processes.		Task	Core
	Providing guidance and direction to subordinates, including setting performance standards and monitoring performance.	Guiding, directing, and motivating subordinates	Work Activities	Interacting With Others
	Establishing long-range objectives and specifying the strategies and actions to achieve them.	Developing objectives and strategies	Work Activities	Mental Processes
	Developing specific goals and plans to prioritize, organize, and accomplish your work.	Organizing, planning and prioritizing work	Work Activities	Mental Processes
Financial and Material Resources	Determining how money will be spent to get the work done, and accounting for these expenditures.	Management of financial resources	Skill	Resource Management Skills
	Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.	Management of material resources	Skill	Resource Management Skills
	Administer programs for selection of sites, construction of buildings, or provision of equipment or supplies.		Task	Core
	Monitoring and controlling resources and overseeing the spending of money.	Monitoring and controlling resources	Work Activities	Interacting With Others
	Estimating sizes, distances, and quantities; or determining time, costs, resources, or materials needed to perform a work activity.	Estimating the quantifiable charactersitics of products, events or information	Work Activities	Information Input
	Performing day-to-day administrative tasks such as maintaining information files and processing paperwork.	Performing administrative activities	Work Activities	Interacting With Others

O*NET Executive Skills that are grouped together using a k-means algorithm with six clusters applied to the texts in the *Description* field. We choose the labels "Monitoring of Performance" and "Financial and Material Resources" to describe these clusters. The *Short Description*, *Category*, and *Subcategory* fields are also provided by O*NET to further classify the individual descriptions. *Short Description* is not available for the O*NET Task Category.

Table A.6: "Administrative Tasks" and "Social Skills" Clusters for O*NET Executive Skills

	Description	Short Description	Category	Subcategory
Administrative Tasks	Appoint department heads or managers and assign or delegate responsibilities to them.		Task	Core
	Prepare budgets for approval, including those for funding or implementation of programs.		Task	Core
	Confer with board members, organization officials, or staff members to discuss issues, coordinate activities, or resolve problems.		Task	Core
	Direct human resources activities, including the approval of human resource plans or activities, the selection of directors or other high-level staff, or establishment or organization of major departments.		Task	Core
	Establish departmental responsibilities and coordinate functions among departments and sites.		Task	Core
	Preside over or serve on boards of directors, management committees, or other governing boards.		Task	Core
	Negotiate or approve contracts or agreements with suppliers, distributors, federal or state agencies, or other organizational entities.		Task	Core
	Review reports submitted by staff members to recommend approval or to suggest changes.		Task	Core
	Interpret and explain policies, rules, regulations, or laws to organizations, government or corporate officials, or individuals.		Task	Core
	Prepare or present reports concerning activities, expenses, budgets, government statutes or rulings, or other items affecting businesses or program services.		Task	Core
	Review and analyze legislation, laws, or public policy and recommend changes to promote or support interests of the general population or special groups.		Task	Core
	Direct or conduct studies or research on issues affecting areas of responsibility.		Task	Core
Social Skills	Being aware of others' reactions and understanding why they react as they do.	Social perceptiveness	Skill	Social
	Adjusting actions in relation to others' actions.	Coordination	Skill	Social
	Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.	Active listening	Skill	Basic
	Persuading others to change their minds or behavior.	Persuasion	Skill	Social
	Bringing others together and trying to reconcile differences.	Negotiation	Skill	Social
	Assessing the value, importance, or quality of things or people.	Judging the qualities of things, services, or people	Work Activities	Mental Processes
	Handling complaints, settling disputes, and resolving grievances and conflicts, or otherwise negotiating with others.	Resolving conflicts and negotiating with others	Work Activities	Interacting With Others
	Convincing others to buy merchandise/goods or to otherwise change their minds or actions.	Selling or influencing others	Work Activities	Interacting With Others

O*NET Executive Skills that are grouped together using a k-means algorithm with six clusters applied to the texts in the *Description* field. We choose the labels "Administrative Tasks" and "Social Skills" to describe these clusters. The *Short Description*, *Category*, and *Subcategory* fields are also provided by O*NET to further classify the individual descriptions. *Short Description* is not available for the O*NET Task Category.

Table A.7: Most Similar Terms in Harvard Business Review and Generic English Text.

vision		**team**		**leader**		**coordination**	
HBR	Generic	HBR	Generic	HBR	Generic	HBR	Generic
visions	visions	teams	teams	leadership	leaders	integration	cooperation
mission	mind	project_team	squad	leaders	leadership	collaboration	coordinating
strategic_vision	view	management_team	players	manager	party	cooperation	coordinate
goals	perspective	executive_team	football	person	opposition	coordinating	co-ordination
strategy	objective	group	coach	strong_leader	led	standardization	strengthen
core_values	sense	staff	league	chief_executive	rebel	communication	facilitate
strategic_direction	experience	organization	championship	boss	leading	coordinated	enhance
aspirations	eyes	top_team	player	line_manager	movement	coordinate	hand-eye
aspiration	image	team_leader	teammates	team_player	communist	information_flow	strengthening
objectives	dream	team_leaders	basketball	leadership_style	socialist	specialization	governmental
goal	eye	project	coached	senior_manager	faction	information_sharing	coordinated
passion	focus	committee	season	assertive	democratic	supervision	consultation
culture	our	executive_committee	coaches	negotiator	politician	centralization	mechanism
leadership	clarity	project_manager	played	achiever	former	execution	mechanisms
philosophy	understanding	working_group	soccer	follower	cleric	procurement	improve
ideals	achieve	top_management	club	politician	government	centralized	co-operation
commitment	visual	manager	coaching	outsider	prime	control	communication
ambition	dreams	crew	hockey	administrator	meanwhile	alignment	supervision
understanding	visionary	personnel_department	games	executive	who	information_exchange	monitoring
value_system	truly	subteams	game	middle_manager	behind	interdependence	assistance

For each term in bold, we report the twenty most similar terms in embedding spaces estimated with the Harvard Business Review and generic English text (Wikipedia and Gigaword), respectively. Similarity is computed using the cosine similarity between word embeddings. The estimated embedding model for generic text is available from `http://nlp.stanford.edu/data/glove.6B.zip`.

Table A.8: Text Segments from CEO Job Specifications Most Similar to O*NET Clusters

Information Skills		Human Resources	
Text	**Sim**	**Text**	**Sim**
Understands the complexities of running a successful software and services business including the management and application of data and data flows and subsequent productization of data into information.	0.819	The successful candidate should have the ability to interact and work effectively with personnel at all levels of the organization as well as with members of management in client companies and should bring a practical approach to management both in obtaining information from company personnel and making presentations to a board of directors.	0.858
S/he is analytical and objective in evaluating information and solving business problems.	0.818	The person stepping into this role will have demonstrated their ability to manage people effectively including assessing the skills and developmental needs of subordinates and providing appropriate coaching and guidance to maximize these peoples efforts and contribution to the company.	0.841
Uses data analysis and judgment to solve problems.	0.817	Demonstrates a track record of hiring, retaining, and nurturing a high quality staff team and of motivating diverse groups of people to work together to achieve a common mission or goal.	0.839
Strong analytical and process mindset able to manage the application of data and data flows and subsequent productization of data into information.	0.814	Proven people management skills with the ability to focus and guide others in accomplishing work objectives using methods and a flexible interpersonal style to help build a cohesive team.	0.831
As [COMPANY NAME] is a highly information data driven enterprise, the president will investigate and align the application of new technologies with the business in order to streamline and improve information gathering and storage techniques.	0.808	Because of the breadth of this individual's activities, we seek a person who has outstanding communication skills and can develop ideas that are translatable throughout the enterprise.	0.828
S/he can gather, organize, and systematically analyze complex operational information metrics and analysis in order to gauge progress and refine the plan and the strategy.	0.804	Staff and Culture Development: hire and develop people who possess the technical skills and interpersonal skills to be constructive and cooperative members of a management team.	0.827
It will be the CEO's responsibility to develop systems, reports, and procedures that ensure timely access to accurate relevant and actionable information on key financial performance indicators.	0.797	The person stepping into this role must have demonstrated the ability to assess the skills and developmental needs of subordinates and provide appropriate coaching and guidance.	0.826
You will need to demonstrate that you organize and integrate data, ideas, and/or concepts into a usable system that can be applied to solving problems.	0.791	In addition to the needed general management and leadership skills, candidates must have the self confidence, business maturity, and communication skills to work effectively with the chairman, board of directors, support functions at [COMPANY NAME], and a variety of external constituents.	0.817
He or she will have background in using data and insight to inform the business, optimize operational decisions, and guide strategy.	0.790	Good team player able to integrate support from [COMPANY NAME] to optimize results; ability to attract, motivate, and retain highly talented team of [SECTOR] experts.	0.815
Makes sound, timely decisions based on analysis of available information, intuition, customer feedback, and supporting data.	0.786	The job requires extraordinary people skills enabling one to work with government officials, ceos, staff, board members and others at all levels.	0.812

We rank text segments from CEO job specifications according to their cosine similarity with the concatenated text of executive skill descriptions from the Information Skills and Human Resources clusters. The table represents the most similar text segments along with their cosine similarity.

Table A.9: Text Segments from CEO Job Specifications Most Similar to O*NET Clusters

Monitoring of Performance		Financial and Material Resources	
Text	**Sim**	**Text**	**Sim**
Analyzes operations to evaluate performance of divisions and staff for meeting objectives and to determine areas of potential cost reduction process improvement, program improvement, and policy change	0.899	In addition the CEO will oversee company operations to insure production efficiency, quality service, and cost effective management of resources	0.755
Establish, lead, and decide objectives, strategies, plans, policies, and programs as they affect [COMPANY NAME] in the areas of human capital management, enhancing organization capabilities and performance, and leading transformation and post-merger project executions.	0.898	Oversee company operations to ensure production efficiency, quality service, and cost effective management of resources	0.744
The CEO will monitor and manage the operational results of the company's businesses, functions, and respective organization units to assure results against plans and take appropriate remedial actions as and when necessary.	0.893	Manage the day-to-day operations on the sites and deliver the major facility investment programme to ensure the required operational capability and manufacturing output is achieved and that value for money is secured for the customer	0.732
Participate in global game-planning sessions to match high potential talent with global opportunities; perform annual operational people planning review; and lead resulting action plan to ensure continuous improvement of leadership.	0.893	The CEO will both individually and through their direct reports provide strategic and/or administrative direction and management in all functions including finance, accounting, business development, information technology, compliance, facility management, human resources, investments, lending, marketing operations, retail services, risk management, security, and data.	0.732
Ensure that all staff activities, internal structure, and policies are aligned with strategic plan and that performance outcomes are evaluated in terms of objectives set forth in the plan.	0.878	The successful delivery of material growth capital expenditure projects and efficiently operating capital intensive assets; the setting and delivering of budgets and business plans.	0.73
Work closely with the board to meet, set strategic financial and growth targets, lead a culture that drives continuous business improvement in all measures of company performance with particular emphasis on process capability, operational performance, new product development, and high customer satisfaction.	0.875	The CEO oversees company operations, credit, legal, human resources, and risk functions to ensure efficiency, quality service, and cost effective management of resources	0.729
Setting and achieving revenue and profit growth targets; monitoring financial performance through appropriate attention to critical performance metrics; creation of a high performance work environment; development and maintenance of a high-performing senior leadership team; building a high-performance executive team while meeting the needs of the organization and the demands of the marketplace.	0.867	Facilities evaluation: the CEO must evaluate the facilities and equipment	0.729
Finalization and timely submission of the annual business plan to the board for approval, which includes PVNBP, ROCE, NBC, EEV, operating profit, and embedded value objectives; evaluate, develop, and implement business, product, and distribution strategies that aim at meeting these plans.	0.867	Oversee company operations to ensure production efficiency, quality service, and cost effective management of resources	0.728
In collaboration with the Board of Trustees, run the strategy process on the active ownership role to ensure [COMPANY NAME] performs in accordance with agreed long-term targets including growth, profitability, value creation, and project portfolio; monitor the development of [COMPANY NAME] and report to Board of Trustees on any deviations and suggested corrective actions.	0.866	In addition, the company will continue to work with strategic sourcing and procurement, and there will be further improvements in the supply chain, i.e. reducing stock and production facilities.	0.726

We rank text segments from CEO job specifications according to their cosine similarity with the concatenated text of executive skill descriptions from the Monitoring of Performance and Financial and Material Resources clusters. The table represents the most similar text segments along with their cosine similarity.

Table A.10: Text Segments from CEO Job Specifications Most Similar to O*NET Clusters

Administrative Tasks		Social Skills	
Text	**Sim**	**Text**	**Sim**
Efficiently administer [COMPANY NAME] in accordance with the approved budget, available personnel and other resources determined by the Board.	0.838	You have effectively influenced the thoughts and actions of others, winning them over to a particular position, viewpoint, or course of action and negotiating skillfully in tough situations; settling differences with minimum noise; and winning concessions without damaging relationships	0.798
Coordinate the activities of the numerous departments and committees of the corporation including budgets, spending, and respective goals and objectives.	0.83	This person has to be sincerely interested in people, respect and value the opinions of others, communicate well, and interact effectively with all stakeholders at all levels	0.76
S/he will plan, direct, and control all [COMPANY NAME] activities in accordance with [COMPANY NAME]'s plans, policies, directives, and activities as established by the Board of Directors.	0.826	This individual will need to express views candidly, while making the effort to understand the views of others.	0.754
Working with the Board of Directors and Board Executive Committee, develop policy positions on legislation proposed, regulations and other governmental and public policy activities that affect reliability in the [REGION].	0.817	This person has to be sincerely interested in people, respect and value the opinions of others, communicate well, and interact effectively with all stakeholders.	0.753
S/he will work closely with the Board and officers on the development and implementation of the [COMPANY]'s strategic vision, as well as have oversight for the development of policies and programs to advocate on behalf of the membership in a variety of settings.	0.815	[COMPANY NAME] values: communicating openly, honestly, and transparently; welcoming challenge; learning from mistakes; listening; treating people fairly; being inclusive; building connections; collaborating across boundaries; caring about individuals and their progress; showing respect; being supportive and responsive to ensure that everyone who works for [COMPANY NAME] lives by these values.	0.75
Upon approval by the Board of Directors, ensure staff has the necessary information, resources, working procedures, and guidelines to implement policies and plans.	0.815	In terms of personality the ideal candidate has an attitude of making things happen, is proactive and hands on and can make decisions quickly	0.741
Confers with Chief Officers to deliberate business objectives; develop organizational policies; coordinate functions and operations between offices departments units; and to establish responsibilities and procedures for achieving objectives.	0.815	Straightforward and accustomed to negotiating with an ability to create win-win situations by listening and understanding others' motives and views.	0.736
Implement and develop policy-related activities in line with the Board of Directors' priorities; maximise [COMPANY NAME]'s influence in European affairs. Ensure that the policies and procedures laid down in the statutes and internal rules are respected.	0.814	Inspires others and understands what motivates different people; understands what motivates others and relates to them on that basis; helps people feel they are a part of something significant; empowers and delegates so that all can contribute to the cause; can convey enthusiasm that rallies the troops and ignites a spark in others.	0.735
S/he will represent [INDUSTRY] regulation at the most senior level, forming effective relationships with [INDUSTRY] firms, [INDUSTRY] executives and Board members, other regulatory bodies, provincial and Federal departments, and elected officials and relevant international bodies.	0.811	Communicating reasons for change and ensuring that others understand them.	0.731
S/he will work closely with the Board of Directors and the various committees on the development and implementation of [COMPANY NAMES]'s strategic vision and the policies and programs to advance the interests of the industry.	0.809	The individual should be a decisive leader who is willing to listen to various opinions on issues, but in the end is capable of making quick and clear decisions	0.73

We rank text segments from CEO job specifications according to their cosine similarity with the concatenated text of executive skill descriptions from the Administrative Tasks and Social Skills clusters. The table represents the most similar text segments along with their cosine similarity.

Table A.11: Selection of Sentences with Low Similarity to all Clusters

Certifications and/or a graduate degree, e.g. CPA, MBA, CFA, are preferred
Fluency in a language other than English is considered a plus
He or she will also represent the company in the equity and bond investor markets and the restaurant industry
First-class academic background
Experience leading a successful IPO is desired
The ideal candidate has preferably gained experience in a blue chip company acting globally
He or she will likely be a sitting CFO of a public life sciences, biotechnology, or specialty pharmaceutical company
Has taken something that began with an idea and moved it to a thriving enterprise
Postgraduate financial study (MBA, CPA, or equivalent), fluency in English, and familiarity with western business culture
He should have had experience in leading big multifunctional teams
Experience and credibility with Wall Street is a plus, as is international experience
Fluent English and one or more continental European languages could be an advantage, particularly Southern European languages such as Italian, Spanish, French, or Portuguese
Experience in multimedia and internet business
The ideal candidate will be a strong CFO with pan-European experience in a background of ideally telecommunications or hi-tech business which has undergone rapid growth
An entrepreneurial and civic-minded leader, the CEO will exude a sincere passion for STEM education
The successful candidate will be an accomplished financial executive with unquestionable integrity, a positive reputation, and demonstrated success serving as a CFO of a private-equity-backed or publicly-listed company

The table displays a selection of sentences all of which are in the bottom quintile of the similarity distribution for all six O*NET clusters.

B Data Construction

B.1 Text preprocessing

All text data in the paper (Harvard Business Review; O*NET descriptions; executive job search specification) is preprocessed following the same steps.

The first step is to find and replace multi-word expressions with a single token. We construct one set of expressions by tabulating all bigrams, trigrams, and 4-grams in the HBR; retaining those with a Wikipedia entry; and manually pruning the resulting list to remove generic expressions. This procedure generates 2,148 expressions. We construct another set by first searching the corpus for named entities using the named entity recognizer provided in the StanfordNLP package, and then retaining named entity phrases that occur more than ten times overall in the HBR corpus. This generates an additional 4,653 expressions.

After replacing multi-word expressions, we lowercase all text; tokenize;[46] remove tokens not comprised entirely of alphabetic characters; remove stopwords;[47] and words that appear fewer than three times in the HBR corpus.[48]

For the estimation of the embeddings model, we treat individual HBR sentences as the unit of analysis. In the HBR, we have 1,835,972 sentences that together form 19,649,620 word tokens. Overall there are 70,760 unique tokens in the HBR corpus.

Our corpus of job descriptions after pre-processing contains 22,59,887 total words and 18,792 unique words.

B.2 Burning Glass data

After implementing a fuzzy match procedure to pair company names from our job search corpus to company names in Burning Glass, we obtain 1,463 matches in total, which represents nearly half of the firms in our executive search dataset. We then apply two filters. First, we only keep job posts which are within the seven-year window of the CEO search year (three years before and after). Second, we further restricted our sample to ensure a minimum number of 11 job posts in each year of the window around the search. In this way, we obtain 695 firms in the final sample. We summarize the number of firms and job postings over years of executive search (2004 - 2017) in Table B.12.

Our first IT skills measure comes directly from Burning Glass. Table B.13 shows the groupings of raw skills from the job ads that Burning Glass uses for classification. For each firm, we thereby obtain 27 firm-level variables that measure the share of total postings in

[46] Tokenization is the process whereby a character string is broken into individual units of meaning. In most cases these units are synonomous with English words, but also include the multi-word expressions identified above. We will simply refer to tokens more generically as 'words' for simplicity.

[47] Stopwords are frequently occurring words like 'a', 'the', 'for', etc., that do not contribute to the understanding of a text's relevant content. We take our stopword list from `http://snowball.tartarus.org/algorithms/english/stop.txt`.

[48] Since we estimate an embeddings model on the HBR to represent all of our text data, we need to ensure we only retain words that appear a sufficient number of times to have meaningful semantics.

the window around the search that contain a skill from any of these groupings. Table B.14 presents the factors from a principal components decomposition of these skill categories across firms. We use the projection of job ads onto the first factor as a measure of IT-intensive skills.

Our second IT skills measure extends the skill categories of Deming and Kahn (2018) to account for the appearance of new skills in the Burning Glass data in the last several years. We additionally include categories for "energy", "industry-specific", "basic software" and "manufacturing" not present in the original Deming and Kahn (2018) classification. Table B.17 presents the factors from a principal components decomposition of these alternative skill categories across firms. We use the projection of job ads onto the third factor as a measure of IT-intensive skills.

Finally, we control for the share of job ads with levels of education and years of experience required in some specifications. For education controls, we calculated the share of job ads that do not specify a degree requirement, require a high school degree, and those that require a degree above high school; for experience controls, we have the share of job ads that do not specify any experience requirement, require zero year of experience, less than one year of experience, one to six years of experience, and more than six years of experience. We also constructed average years of experience required using the *Minimum Experience* column defined in Burning Glass open text fields (we did not include job ads with missing minimum years of requirement when calculating the average). All measures are defined at the firm-year level.

Table B.12: Summary Statistics of Vacancies by Year of Executive Searches

Year of Search	Number of Firms	Mean	SD	Min	q10	q90	Max	Total
2004	21	708	1,124	11	33	2,016	4,382	14,859
2005	29	1,610	3,689	20	34	4,853	18,100	46,696
2006	18	653	1,018	15	24	1,693	3,487	11,752
2007	35	998	1,736	11	44	2,338	7,432	59,881
2008	48	682	1,964	12	27	1,365	12,599	75,001
2009	42	1,556	3,738	11	20	6,483	24,411	182,015
2010	45	498	979	11	20	1,102	6,462	78,218
2011	59	3,295	13,419	11	22	5,319	13,7089	70,1897
2012	72	460	764	11	17	1,515	5,913	135,247
2013	68	1,010	2,177	11	18	2,816	16,832	313,004
2014	62	2,095	6,082	11	20	3,222	49,496	659,950
2015	76	1,460	6,440	11	22	2,482	99,351	588,318
2016	63	4,154	15,901	11	20	5,981	149,287	1,341,869
2017	65	2,454	8,361	11	22	5,249	87,856	792,595

Table B.13: Description of Burning Glass Skill Clusters and Skills

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Skill Clusters	Skills
Administration	Telephone Skills, Dictation, Memoranda Preparation, Office Machines, Office Management, Administrative Support, General Administrative and Clerical Tasks, Scheduling
Agriculture, Horticulture, and the Outdoors	Agricultural Research, Landscaping and Yard Care, Agronomy and Farming
Analysis	Natural Language Processing (NLP), Mathematics, Mathematical Software, Ad Hoc Analysis and Reporting, Mathematical Modeling, Validation, Machine Learning, Data Mining, Data Science, Business Intelligence Software, Statistics, Data Visualization, Statistical Software, Data Techniques, Business Intelligence, Data Analysis
Architecture and Construction	Road and Bridge Construction, Construction Labor, Green Architecture, Conduits, Architectural Design, Masonry, Insulation, Construction Painting, Roofing, Construction Inspection, Drywall, Electrical Construction, General Architecture, Carpentry, Construction Management, Estimating
Administration	Telephone Skills, Dictation, Memoranda Preparation, Office Machines, Office Management, Administrative Support, General Administrative and Clerical Tasks, Scheduling
Business	risk management, Internal Controls, Benefits Analysis, Knowledge Management, Category Management, Optimization, Property Management, Technical Assistance, Real Estate and Rental, Event Planning and Management, Due Diligence, Pricing Analysis, Business Consulting, Business Communications, Order Management, Operations Management, Key Performance Indicators, Contract Management, Business Solutions, Product Management, Performance Management, Process Improvement, Quality Assurance and Control, Risk Management, Business Management, People Management, Business Strategy, Business Process and Analysis, Project Management
Customer and Client Support	Payment Processing and Collection, Claims Processing, Cash Register Operation, Advanced Customer Service, Basic Customer Service
Design	Digital Design, Art and Illustration, Creative Design, Animation and Game Design, Industrial Design, Graphic and Visual Design, Presentation Design, User Interface and User Experience (UI/UX) Design, Graphic and Visual Design Software
Economics, Policy, and Social Studies	Social Studies, Urban Planning, Economic Development, Policy Analysis, Economics
Education and Training	Test Administration, Interpretations and Translations, Coaching and Athletic Training, Instruction, Archiving, Childhood Education and Development, Higher Education, Library and Cataloging, Child Development, Education Administration, Learning Management Systems, Exercise Training, Peer Review, Instructional and Curriculum Design, Program Management, Teaching, Training Programs
Energy and Utilities	Water Energy, Gas Drilling, Power Plant, Hydraulic Fracturing, Oil Refining, Oil Wells, Petroleum Science, Wind Energy, Oil Drilling, Oil Reservoirs, Water Supply, Nuclear Energy, Oil Well Intervention, Natural Gas, Clean Energy, Power Generation, Solar Energy, Energy Solutions, Electrical Power, Energy Management, Energy Efficiency
Engineering	Engineering Activities, Aerospace Engineering, Roads and Drainage, Optical Engineering, Geotechnical Engineering, Surveying, Radio Frequency Equipment, Automotive Technologies, Imaging, Chemical Engineering, Hardware Description Languages (HDL), Civil and Architectural Engineering, Radio Frequency (RF), Signal Processing, Electronic Hardware, Circuitry, Robotics, Engineering Software, Automation Engineering, Industrial Engineering, Engineering Management, Simulation, Process Engineering, Mechanical Engineering, Engineering Practices, Drafting and Engineering Design, Electrical and Computer Engineering
Environment	Forestry, Ecology, Ethanol, Emissions Management, Environmental Geology, Air Quality, Resource Management and Restoration, Conservation, Waste Management, Environmental Work, Environmental Regulations, Water Testing and Treatment, Hazardous Waste Management
Finance	Financial Aid Counseling, Commodities, Specialized Accounting, Lending Assessment, Banking Services, Costing, Accounts Payable and Receivable, Financial Accounting, Cost Accounting, Financial Regulations, Commercial Lending, Accounting and Finance Software, Mergers and Acquisitions, Corporate Accounting, Tax, General Lending, Financial Trading, Underwriting, Cash Management, Mortgage Lending, Financial Advisement, Financial Management, Investment Management, Financial Reporting, Auditing, Financial Analysis, Billing and Invoicing, General Accounting, Budget Management
Health Care	Injury Treatment, Nuclear Medicine, Orthopedics, Geriatrics, Mental Health Diseases and Disorders, Gastroenterology, Ear, Nose, and Throat, Dermatology, Speech Language Pathology, Medical Documentation and Abstraction, Pulmonology, Obstetrics and Gynecology (OBGYN), Neurology, Alternative Therapy, Clinical Data Management, Anesthesiology, Endocrinology, Eye Care, Mental Health Therapies, Nutrition and Diet, First Aid, Pediatrics, Social Work, Physical Therapy, Animal Health and Veterinary Medicine, Health Information Management and Security, Rehab Therapy, Rehabilitation, Clinical Informatics, Medical Research, Allergies, Hematology, Cardiology, Medical Procedure and Regulation, Patient Reception, Dental Care, Pathology, Clinical Research, Blood Collection, Routine Examination Tests and Procedures, Pharmacy, Mental and Behavioral Health Specialties, Surgery, Infectious Diseases, Radiology, Urology, Oncology, Mobility Assistance, Patient Physical Measurements, Public Health and Disease Prevention, General Medical Tests and Procedures, Medical Records, Patient Education and Support, Health Care Procedure and Regulation, Nephrology, Basic Living Activities Support, Medical Billing and Coding, General Medicine, Emergency and Intensive Care, Medical Support, Advanced Patient Care, Physical Abilities, Basic Patient Care

Skill Clusters	Skills
Human Resources	Deductions, Human Resource Management Systems, Payroll, Compensation and Benefits, Recruitment, Employee Relations, Human Resource Management and Planning, Talent Management, Employee Training, Occupational Health and Safety
Industry Knowledge	Electrical Engineering Industry Knowledge, Supply Chain and Logistics Industry Knowledge, Insurance Industry Knowledge, Apparel Industry Knowledge, Telecommunications Industry Knowledge, Allied Health Care Industry Knowledge, Civil Engineering Industry Knowledge, Automotive Industry Knowledge, Employment Services Industry Knowledge, Local Government Industry Knowledge, Industrial Engineering Industry Knowledge, Biologics Industry Knowledge, Financial Services Industry Knowledge
Information Technology	JavaScript and Jquery, IT Hardware, Augumented Reality / Virtual Reality (AR / VR), cybersecurity, Mobile development, Enterprise Messaging, Wiki, Application Development, cloud solutions, Document Management Systems, Internet Security, database administration, Enterprise Content Management (ECM), Health Checks, Geographic Information System (GIS) Software, Android Development, Web Content, Anti-Malware Software, Cloud Storage, Network Security, Application Programming Interface (API), iOS Stack, Application Security, Artificial Intelligence, Mobile Development, SAP, Help Desk Support, Microsoft SQL Extensions, Other Programming Languages, Computer Hardware, PHP Web, Integrated Development Environments (IDEs), Internet of Things (IoT), Data Storage, Distributed Computing, Cloud Computing, IT Automation, Web Design, Productivity Software, Network File System (NFS), Advanced Microsoft Excel, NoSQL Databases, Networking Hardware, Mainframe Technologies, Software Development Tools, Version Control, Middleware, Software Development Methodologies, Extensible Languages, Basic Computer Knowledge, Web Servers, Information Security, Project Management Software, Extraction, Transformation, and Loading (ETL), Microsoft Windows, Scripting, Data Warehousing, Big Data, Network Protocols, C and C++, Test Automation, Virtual Machines (VM), Microsoft Development Tools, Software Quality Assurance, IT Management, Systems Administration, JavaScript and jQuery, Network Configuration, Cloud Solutions, Programming Principles, General Networking, Scripting Languages, Web Development, Cybersecurity, Telecommunications, Data Management, Management Information System (MIS), Oracle, Java, Database Administration, Operating Systems, SQL Databases and Programming, Enterprise Resource Planning (ERP), Technical Support, Software Development Principles, System Design and Implementation, Microsoft Office and Productivity Tools
Legal	Forensics, Labor Compliance, Federal Acquisition, Legal Research, Law Enforcement and Criminal Justice, Intellectual Property, Litigation, Regulation and Law Compliance
Maintenance, Repair, and Installation	electrical and mechanical labor, Hazard Identification, Tailoring and Sewing, Bike Repair, Heavy Equipment, Appliance Repair and Maintenance, Equipment Operation, Painting, Power Tools, Schematic Diagrams, Electrical and Mechanical Labor, Basic Electrical Systems, Hand Tools, HVAC, Vehicle Repair and Maintenance, Plumbing, Equipment Repair and Maintenance
Manufacturing and Production	Micro Manufacturing, Metal Fabrication, Materials Process, Manufacturing Design, Brazing and Soldering, Computer-Aided Manufacturing, Materials Science, Computer-aided manufacturing, Welding, Machine Tools, Manufacturing Standards, Product Inspection, Manufacturing Processes, Machinery, Lean Manufacturing, Product Development
Marketing and Public Relations	Grant Applications, Concept Development, Fundraising, Investor Relations, Promotional Materials, Corporate Communications, Media Strategy and Planning, Online Advertising, Promotions and Campaigns, Web Analytics, Advertising, Marketing Software, Public Relations, Brand Management, Online Marketing, Marketing Strategy, Packaging and Labeling, Social Media, General Marketing, Marketing Management, Market Analysis, Customer Relationship Management (CRM)
Media and Writing	Audio Production, Music, Multimedia, Media Production, Journalism, Visual Design Production, Content Development and Management, Writing
Personal Care and Services	Animal Care, Child Care, Personal Care, Housekeeping, Food and Beverage Service
Public Safety and National Security	Transportation Security, Physical Security, Emergency Services, Intelligence Collection and Analysis, Fire Inspection, Government Clearance and Security Standards, Surveillance, Loss Prevention
Religion	Ministry
Sales	Trade Shows, Online Sales, Technical Demonstrations, Business-to-Business (B2B) Sales, Telemarketing, Sales Analysis, Technical Sales, Insurance Sales, Salesmanship, E-Commerce, Outside Sales, Solution Sales Engineering, Account Management, Specialized Sales, Inside Sales, Prospecting and Qualification, Sales Management, Business Development, Company Product and Service Knowledge, Merchandising, Retail Sales, General Sales Practices, General Sales
Science and Research	Earth and Space Science, Neuroscience, Molecular Biology, Biopharmaceutical Manufacturing, Surveys, Cellular Biology, Chemical Analysis, Drug Development, Biology, Genetics, Physics, Chemistry, Laboratory Research, Research Methodology
Supply Chain and Logistics	Transportation Operation and Management, TSA Regulation, Air Transport, Transportation Operations Management, Operations Analysis, Supply Chain Planning, Warehouse Management, Facility Management and Maintenance, Logistics, General Shipping and Receiving, Inventory Maintenance, Supplier Relationship Management, Transportation Operations, Supply Chain Management, Retail Store Operations, Store Management, Inventory Management, Procurement, Material Handling

Note: The Burning Glass data associates each online posting with (potentially multiple) skills based on the free text of the job ad. This table shows the categorization that Burning Glass uses to organize the skills into broader groups. We use the share of online posts in a seven-year window around a search that contains any of the skills in the "Analysis" and "Information Technology" categories as a measure of information-intensive skills in the workforce.

Table B.14: Burning Glass Skills–Factors

Skill	**Factor1**	Factor2	Factor3	Factor4	Factor5	Factor6	Uniqueness
Administration	-0.46	-0.09	-0.17	0.32	0.47	-0.11	0.42
Customer Service	-0.44	-0.48	0.24	0.03	-0.21	-0.19	0.44
Supply Chain	-0.43	-0.01	0.41	-0.20	-0.14	0.16	0.56
Maintenance	-0.39	0.42	0.37	-0.05	0.26	-0.16	0.44
Human Resources	-0.38	0.18	0.24	0.24	0.22	0.20	0.62
Health Care	-0.30	0.00	-0.76	-0.13	0.11	-0.06	0.30
Sales	-0.20	-0.65	0.36	-0.27	-0.17	0.14	0.29
Education	-0.12	-0.09	-0.37	0.03	0.39	-0.21	0.64
Manufacturing	-0.11	0.62	0.29	-0.18	0.16	0.29	0.38
Science and Research	-0.01	0.31	-0.44	-0.25	-0.25	0.53	0.31
Finance	-0.01	0.05	0.06	0.80	-0.15	0.07	0.32
Engineering	0.06	0.63	0.30	-0.24	0.13	-0.23	0.39
Business	0.25	0.22	0.12	0.72	-0.23	0.08	0.29
Media and Writing	0.41	-0.21	0.02	0.07	0.56	0.22	0.42
Marketing and Public Relations	0.45	-0.44	0.23	0.01	0.31	0.37	0.31
Analysis	0.54	0.20	-0.20	-0.02	-0.18	0.14	0.58
Design	0.67	-0.11	0.20	-0.12	0.30	-0.03	0.39
Information Technology	0.72	0.08	0.11	-0.10	-0.16	-0.50	0.19

Note: The table shows the factor loadings on the first six principal component factors derived from the matched Burning Glass Data using the BG skill classification (only factors with eigenvalue greater than one are shown). We use **Factor 1** as a proxy for information-intensive skills in the firm.

Table B.15: Description of Job Skills

Job Skills	Skills
Cognitive	Agricultural Research, Ad Hoc Analysis and Reporting, Business Intelligence, Data Analysis, Mathematics, Statistics, Validation, Architectural Design, General Architecture, Green Architecture, Benefits Analysis, Business Process and Analysis, Business Solutions, Business Strategy, Key Performance Indicators, Operations Management, Pricing Analysis, risk management, Risk Management, Animation and Game Design, Art and Illustration, Creative Design, Digital Design, Graphic and Visual Design, Graphic and Visual Design Software, Industrial Design, Presentation Design, Economic Development, Economics, Policy Analysis, Social Studies, Urban Planning, Aerospace Engineering, Automation Engineering, Automotive Technologies, Chemical Engineering, Circuitry, Civil and Architectural Engineering, Drafting and Engineering Design, Electronic Hardware, Engineering Activities, Engineering Management, Engineering Practices, Geotechnical Engineering, Hardware Description Languages (HDL), Imaging, Industrial Engineering, Mechanical Engineering, Optical Engineering, Process Engineering, Radio Frequency (RF), Radio Frequency Equipment, Roads and Drainage, Robotics, Signal Processing, Simulation, Surveying, Cardiology, Clinical Informatics, Clinical Research, Dermatology, Endocrinology, Gastroenterology, Hematology, Infectious Diseases, Medical Research, Nephrology, Neurology, Nuclear Medicine, Nutrition and Diet, Obstetrics and Gynecology (OBGYN), Oncology, Pathology, Public Health and Disease Prevention, Pulmonology, Radiology, Urology, cloud solutions, Cloud Solutions, Federal Acquisition, Forensics, Intellectual Property, Labor Compliance, Law Enforcement and Criminal Justice, Legal Research, Litigation, Regulation and Law Compliance, General Marketing, Market Analysis, Marketing Strategy, Media Strategy and Planning, Intelligence Collection and Analysis, Biology, Biopharmaceutical Manufacturing, Cellular Biology, Chemical Analysis, Chemistry, Drug Development, Earth and Space Science, Genetics, Laboratory Research, Molecular Biology, Neuroscience, Physics, Research Methodology, Surveys, Air Transport, Facility Management and Maintenance, Logistics, Operations Analysis, Procurement, Retail Store Operations, Store Management, Supplier Relationship Management, Supply Chain Management, Supply Chain Planning, Transportation Operation and Management, Transportation Operations, Transportation Operations Management
Social	Business Communications, Business Consulting, Social Work, Advertising, Concept Development, Corporate Communications, Grant Applications, Investor Relations, Online Advertising, Online Marketing, Packaging and Labeling, Public Relations, Social Media, Ministry
Character	Administrative Support, Dictation, General Administrative and Clerical Tasks, Memoranda Preparation, Office Machines, Scheduling, Telephone Skills, Agronomy and Farming, Landscaping and Yard Care, Carpentry, Conduits, Construction Inspection, Construction Labor, Construction Painting, Drywall, Electrical Construction, Estimating, Insulation, Masonry, Road and Bridge Construction, Roofing, Due Diligence, Optimization, Order Management, Quality Assurance and Control, Real Estate and Rental, Technical Assistance, Archiving, Child Development, Childhood Education and Development, Coaching and Athletic Training, Education Administration, Exercise Training, Higher Education, Instruction, Instructional and Curriculum Design, Interpretations and Translations, Learning Management Systems, Library and Cataloging, Peer Review, Program Management, Teaching, Test Administration, Training Programs, Air Quality, Conservation, Ecology, Environmental Geology, Environmental Regulations, Environmental Work, Ethanol, Forestry, Water Testing and Treatment, Health Information Management and Security, Medical Billing and Coding, Medical Documentation and Abstraction, Medical Procedure and Regulation, Medical Records, Appliance Repair and Maintenance, Basic Electrical Systems, Bike Repair, electrical and mechanical labor, Electrical and Mechanical Labor, Equipment Operation, Equipment Repair and Maintenance, Hand Tools, Hazard Identification, Heavy Equipment, HVAC, Painting, Plumbing, Power Tools, Schematic Diagrams, Tailoring and Sewing, Vehicle Repair and Maintenance, Emergency Services, Fire Inspection, Government Clearance and Security Standards, Loss Prevention, Physical Security, Surveillance, Transportation Security, General Shipping and Receiving, Inventory Maintenance, Material Handling, TSA Regulation
Writing	Underwriting, Web Content, Promotional Materials, Promotions and Campaigns, Audio Production, Content Development and Management, Journalism, Media Production, Multimedia, Music, Visual Design Production, Writing
Customer Service	Advanced Customer Service, Basic Customer Service, Cash Register Operation, Claims Processing, Payment Processing and Collection, Advanced Patient Care, Allergies, Alternative Therapy, Anesthesiology, Animal Health and Veterinary Medicine, Basic Living Activities Support, Basic Patient Care, Blood Collection, Clinical Data Management, Dental Care, Ear, Nose, and Throat, Emergency and Intensive Care, Eye Care, First Aid, General Medical Tests and Procedures, General Medicine, Geriatrics, Health Care Procedure and Regulation, Injury Treatment, Medical Support, Mental and Behavioral Health Specialties, Mental Health Diseases and Disorders, Mental Health Therapies, Mobility Assistance, Orthopedics, Patient Education and Support, Patient Physical Measurements, Patient Reception, Pediatrics, Pharmacy, Physical Abilities, Physical Therapy, Rehab Therapy, Rehabilitation, Routine Examination Tests and Procedures, Speech Language Pathology, Surgery, Animal Care, Child Care, Food and Beverage Service, Housekeeping, Personal Care, Account Management, Business Development, Business-to-Business (B2B) Sales, Company Product and Service Knowledge, E-Commerce, General Sales, General Sales Practices, Inside Sales, Insurance Sales, Merchandising, Online Sales, Outside Sales, Prospecting and Qualification, Retail Sales, Sales Analysis, Sales Management, Salesmanship, Solution Sales Engineering, Specialized Sales, Technical Demonstrations, Technical Sales, Telemarketing, Trade Shows

NOTE. – Shown in the authors categorization of open text fields in Burning Glass Technologies data.

Table B.16: Description of Job Skills (Continued)

Job Skills	Skills
Project management	Construction Management, Category Management, Contract Management, Event Planning and Management, Internal Controls, Knowledge Management, Process Improvement, Product Management, Project Management, Property Management, Energy Management, Emissions Management, Hazardous Waste Management, Resource Management and Restoration, Waste Management, Data Management, Document Management Systems, Enterprise Content Management (ECM), Enterprise Messaging, Enterprise Resource Planning (ERP), IT Management, Brand Management, Marketing Management, Inventory Management, Warehouse Management
People management	Office Management, Business Management, People Management, Performance Management, Compensation and Benefits, Deductions, Employee Relations, Employee Training, Human Resource Management and Planning, Human Resource Management Systems, Occupational Health and Safety, Payroll, Recruitment, Talent Management, Management Information System (MIS), Customer Relationship Management (CRM)
Financial	Accounting and Finance Software, Accounts Payable and Receivable, Auditing, Banking Services, Billing and Invoicing, Budget Management, Cash Management, Commercial Lending, Commodities, Corporate Accounting, Cost Accounting, Costing, Financial Accounting, Financial Advisement, Financial Aid Counseling, Financial Analysis, Financial Management, Financial Regulations, Financial Reporting, Financial Trading, General Accounting, General Lending, Investment Management, Lending Assessment, Mergers and Acquisitions, Mortgage Lending, Specialized Accounting, Tax, Fundraising
Computer (general)	Electrical and Computer Engineering
Software (specific)	Business Intelligence Software, Data Mining, Data Science, Data Techniques, Data Visualization, Machine Learning, Mathematical Modeling, Mathematical Software, Natural Language Processing (NLP), Statistical Software, User Interface and User Experience (UI/UX) Design, Engineering Software, Android Development, Anti-Malware Software, Application Development, Application Programming Interface (API), Artificial Intelligence, Augumented Reality / Virtual Reality (AR / VR), Big Data, C and C++, Cloud Computing, Cloud Storage, Data Storage, Data Warehousing, Distributed Computing, Extensible Languages, Extraction, Transformation, and Loading (ETL), General Networking, Geographic Information System (GIS) Software, Health Checks, Integrated Development Environments (IDEs), Internet of Things (IoT), iOS Stack, IT Automation, Middleware, Mobile development, Mobile Development, Network Configuration, Network File System (NFS), Network Protocols, Networking Hardware, NoSQL Databases, Operating Systems, Oracle, Other Programming Languages, PHP Web, Productivity Software, Programming Principles, Project Management Software, SAP, Scripting, Scripting Languages, Software Development Methodologies, Software Development Principles, Software Development Tools, Software Quality Assurance, SQL Databases and Programming, System Design and Implementation, Test Automation, Virtual Machines (VM), Web Design, Web Development, Web Servers, Wiki, Marketing Software, Web Analytics
——-Additional Categories Created by Authors——-	
Energy	Clean Energy, Electrical Power, Energy Efficiency, Energy Solutions, Gas Drilling, Hydraulic Fracturing, Natural Gas, Nuclear Energy, Oil Drilling, Oil Refining, Oil Reservoirs, Oil Well Intervention, Oil Wells, Petroleum Science, Power Generation, Power Plant, Solar Energy, Water Energy, Water Supply, Wind Energy
Industry-specific	Allied Health Care Industry Knowledge, Apparel Industry Knowledge, Automotive Industry Knowledge, Biologics Industry Knowledge, Civil Engineering Industry Knowledge, Electrical Engineering Industry Knowledge, Employment Services Industry Knowledge, Financial Services Industry Knowledge, Industrial Engineering Industry Knowledge, Insurance Industry Knowledge, Local Government Industry Knowledge, Supply Chain and Logistics Industry Knowledge, Telecommunications Industry Knowledge
Basic Software	Advanced Microsoft Excel, Application Security, Basic Computer Knowledge, Computer Hardware, cybersecurity, Cybersecurity, database administration, Database Administration, Help Desk Support, Information Security, Internet Security, IT Hardware, Java, JavaScript and jQuery, JavaScript and Jquery, Mainframe Technologies, Microsoft Development Tools, Microsoft Office and Productivity Tools, Microsoft SQL Extensions, Microsoft Windows, Network Security, Systems Administration, Technical Support, Telecommunications, Version Control
Manufacturing	Brazing and Soldering, Computer-aided manufacturing, Computer-Aided Manufacturing, Lean Manufacturing, Machine Tools, Machinery, Manufacturing Design, Manufacturing Processes, Manufacturing Standards, Materials Process, Materials Science, Metal Fabrication, Micro Manufacturing, Product Development, Product Inspection, Welding

NOTE. – Shown in the authors categorization of open text fields in Burning Glass Technologies data.

Note: The Burning Glass data associates each online posting with (potentially multiple) skills based on the free text of the job ad. This table shows a categorization of these skills based on Deming and Kahn (2018), extended to include four additional categories. We use the share of online posts in a seven-year window around a search that contains any of the skills in the “Computer (general)”, “Software (specific)”, and “Basic Software” categories as a measure of information-intensive skills.

Table B.17: Deming and Khan Skills–Factors

Skill	Factor1	Factor2	**Factor3**	Factor4	Uniqueness
Software	0.54	-0.33	-0.55	0.16	0.26
Writing	0.42	0.18	-0.45	-0.29	0.51
Social	0.45	0.16	-0.36	-0.31	0.54
Computer	0.13	-0.57	-0.24	0.25	0.53
Basic Software	0.78	0.05	-0.24	0.16	0.31
Project Management	0.84	-0.02	0.01	0.01	0.29
Customer	-0.11	0.67	0.03	-0.05	0.54
People Management	0.57	0.48	0.10	0.20	0.40
Financial	0.57	0.35	0.21	-0.07	0.50
Cognitive	0.73	-0.23	0.21	-0.25	0.31
Energy	0.16	-0.11	0.28	0.64	0.47
Manufacturing	0.40	-0.47	0.40	-0.02	0.45
Character	0.46	0.25	0.47	0.28	0.42
Industry Knowledge	0.20	-0.31	0.52	-0.60	0.24

Note: The table shows the factor loadings on the first four principal component factors derived the matched Burning Glass Data using the Deming and Khan skill classification (only factors with eigenvalue greater than one are shown). We interpret the inverse of **Factor 3** as the proxy for information-intensive skills in the firm.