Title

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Journal

Strategic Management Journal, 44(13)

ISSN

0143-2095

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Publication Date

2023-12-01

DOI

10.1002/smj.3539

The Growth of Hierarchy in Organizations:

Managing Knowledge Scope

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ABSTRACT

Theory posits hierarchy as a response to coordination challenges and emphasizes organization size and the need to transfer knowledge between people as the mainspring of these challenges. However, this connection is largely based on the quantity of knowledge to be transferred rather than on the characteristics of the knowledge. Building on the knowledge-based view, we propose knowledge scope—the variety of knowledge across an organization's members—also affects coordination costs and therefore the use of hierarchy. Using an economy-wide database from Brazil, we show that firms are more likely to expand their hierarchy when knowledge scope increases. This effect varies with firms' capacities to manage knowledge; firms whose employees perform more similar tasks or have shared experience at previous employers are less likely to expand hierarchy in response to increases in knowledge scope.

Keywords: organizational structure; hierarchy; knowledge scope; knowledge-based view; new ventures

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1. INTRODUCTION

Organizations must divide labor among members and integrate their efforts to achieve shared goals (P. R. Lawrence & Lorsch, 1967; March & Simon, 1958; Mintzberg, 1979). This division of tasks often requires people to coordinate their activities with others under uncertainty about what those others are doing and how one's own decisions affect them (Puranam et al., 2012; Van De Ven et al., 1976). The severity of this problem increases with an organization's complexity and its scale of operations because acquiring the knowledge needed for coordination requires processing information via interpersonal observation and communication (Galbraith, 1973; March & Simon, 1958; Puranam, 2018). Yet, individuals' capacity for such processing is limited by time constraints, bounded rationality, and the cost of propagating accurate information through large, informal networks (Garicano & Wu, 2012; Simon, 1957; Zenger, 1994). Organizations with gaps between the demand for knowledge coordination and the capacity to manage knowledge require mechanisms to motivate effort and ensure coordination [1] (Gulati et al., 2005; P. R. Lawrence & Lorsch, 1967; Puranam, 2018).

A key mechanism for integrating individual efforts is hierarchy. Theory says that organizations can increase their capacity for information processing and coordination by empowering managers to allocate tasks, direct subordinates and hold them accountable, and resolve disputes (Puranam, 2018). Managers do this by investing in the knowledge necessary to handle unusual circumstances (Garicano, 2000), delegating to capable employees (Floyd & Wooldridge, 1997), translating information across subsets of employees (Arrow, 1974; Cremer et al., 2007), and lowering the cost of pooling knowledge to make decisions (Dobrajska et al., 2015; Garicano & Van Zandt, 2012).

[1] Taking an information-processing view of the organization, Galbraith (1974) outlines the two organization design alternatives as either reducing the need for or increasing the capacity for information processing.

Both theoretical and empirical studies have tended to emphasize organizational size as the primary antecedent of the coordination challenges that precipitate hierarchy (Blau, 1970; Colombo & Delmastro, 2008; DeSantola & Gulati, 2017; Pugh et al., 1968, 1969). This connection between size and coordination costs is based on the quantity of knowledge to be transferred rather than on its characteristics. The latter, however, may also affect coordination costs and decisions about hierarchy (Grant, 1996).

We address this gap by exploring how the scope of knowledge—the variety of knowledge used by an organization's members—affects coordination costs and thus the use of hierarchy to integrate effort. Here, we incorporate insights from the knowledge-based view of the firm, which has long recognized that not only the scale of operations but also characteristics of knowledge—and differences in organizational capability to integrate it—affect organizational design and firm performance (Grant, 1996; Kogut & Zander, 1992). Thus, the same mechanism that connects size to hierarchy expansion—increased coordination needs and the associated costs—also applies to certain characteristics of knowledge and the expansion of hierarchy to process and coordinate information within the firm.

Organizations differ not only in their knowledge coordination needs, but also in their capacity to meet them. We argue that the amount of shared experience amongst an organization's members is one determinant of common ground—shared knowledge and beliefs (Clark, 1996)—that moderates the relationship between knowledge scope and the expansion of hierarchy. Increased knowledge scope creates difficulty by reducing common ground. This, in turn, reduces predictive knowledge, such that members cannot as easily predict and adjust to others' actions (Camerer & Knez, 1996; Gulati et al., 2012; Puranam et al., 2012; Schelling, 1960). Thus, we consider how the expansion of hierarchy is affected both by integration challenges due to knowledge scope and by differences in organizational capability.

We test our predictions using employer-employee matched data on the population of firms founded in Brazil from 2003 to 2014. By following firms from inception, we can observe their entire history and capture the first hierarchy expansion while avoiding complicating organizational factors associated with larger, established firms. We use detailed information on the occupations of individual workers to measure the expansion of hierarchy, and we develop a measure of knowledge scope to characterize the knowledge of these firms. We leverage the ability to link employee's jobs across firms to quantify shared prior experience and the ability to identify the underlying tasks of employees within the focal firm to quantify task similarity, both of which are sources of common ground. We then assess common ground as a factor moderating the relationship between knowledge scope and the expansion of hierarchy.

We find that firms are more likely to expand hierarchy as knowledge scope increases, even when controlling for the well-documented effect of size (DeSantola & Gulati, 2017). Further, we show how the effect of knowledge scope on hierarchy depends on the ability of employees to coordinate via personal, informal mechanisms (Clark, 1996; March & Simon, 1958; Puranam et al., 2009). Firms whose employees share greater common ground—through overlap in their assigned tasks or shared prior experience at a previous employer—are less likely to expand their hierarchy in response to changes in knowledge scope. Thus, conditions that enhance common ground are associated with a lower likelihood of expanding hierarchy as a mechanism to coordinate knowledge.

We advance research on organizational design. First, we highlight knowledge scope as an important determinant of hierarchy expansion and show that it has effects distinct from those of firm size. While research has often emphasized size as a mainspring of coordination challenges that lead to additional hierarchy (Blau, 1970; Colombo & Delmastro, 2008; DeSantola & Gulati, 2017; Pugh et al., 1968, 1969), we explain how coordination challenges stem not only from greater dispersion of knowledge across employees (Becker & Murphy, 1992; Garicano & Wu, 2012; P. R. Lawrence & Lorsch, 1967) but also from the variety of that knowledge.

Second, we provide additional evidence to explain why organizations of similar size may adopt different structures by showing that organizations have different capacities to manage knowledge. Increased common ground in an organization increases the capacity to coordinate knowledge and is thus associated with less need for hierarchy. Together, these findings highlight knowledge scope as a driver of organizational structure.

Third, our empirical analyses contribute to a literature on the organizational structures of entrepreneurial ventures. As Puranam (2018) notes, "systematic longitudinal observations of entrepreneurial ventures and how they scale have been surprisingly rare." Furthermore, empirical research has largely focused on the technology sector (Beckman et al., 2007; Beckman & Burton, 2008; Colombo & Grilli, 2013). We instead examine millions of businesses in all industries and find that knowledge scope is an important determinant of hierarchy. Our finding that shared experience moderates the relationship between knowledge scope and hierarchy emphasizes the importance of founding conditions for subsequent role structures (Beckman & Burton, 2008; Ferguson et al., 2016). This supports the notion that organizations have, from the very start, different needs and capacities for knowledge coordination which have persistent effects on their observed structures.

2. THEORY

March and Simon (1958) suggest that organizations make adjustments in one of two modes to manage increased coordination costs: via programming or via feedback. Coordination via programming is impersonal; it includes preestablished rules and plans as well as formalized structures such as hierarchy. Coordination via feedback is more personal; it includes mutual adjustments between individuals (Thompson, 1967; Van De Ven et al., 1976). Hierarchy expansion is largely a form of adjustment via programming. However, varying capacities for coordination via feedback—that is, differences driven by variation in the shared experiences of employees—may moderate the likelihood of hierarchy expansion.

2.1. Knowledge scope

Knowledge scope is the variety of knowledge used by an organization's members. This variety is a form of diversity and can be measured as a categorical difference across an organization's members (Harrison & Klein, 2007), reflecting the fact that people have access to different subsets of an organization's knowledge. While this definition may suggest a form of specialization, increasing knowledge scope within an organization is different from increasing specialization. Specialization captures the extent to which employees focus on a narrow set of tasks distinct from those of other employees (Jain & Mitchell, 2021; Kretschmer & Puranam, 2008; Postrel, 2002). These two features of organizations—knowledge scope and specialization—are often positively correlated. At the individual level, increased division of labor is associated with increased individual specialization that, in turn, increases the costs of coordinating between individuals because it creates smaller "islands of shared knowledge" and a larger "sea of ignorance" (Postrel, 2002). However, at the organizational level, an organization that becomes increasingly specialized is one that has employees each performing fewer tasks overall and performing more tasks that are exclusively assigned to a single type of employee. In contrast, increases in knowledge scope at the organizational level reflect an underlying growth in the variety of knowledge used by the organization regardless of how many employees have narrow and non-overlapping tasks.

Because knowledge scope captures breadth in an organization's knowledge, it might be compared to firm scope. However, knowledge scope is also distinct from firm scope, which has traditionally been defined by the number of distinct businesses in which a firm is engaged. While knowledge scope is likely to increase as a firm expands its scope, firms engaged in identical businesses may nevertheless have different levels of knowledge scope. For example, two restaurants employ multiple people as cooks and waiters, but one of the two firms employs a parking garage attendant as well. These firms operate in the same business—the restaurant industry—but one has increased knowledge scope.[2] Furthermore, while firm scope is a property of an entire firm, large and complex firms may be composed of several, smaller organizations (Puranam et al., 2013). In some instances, each department, unit, or project team may be considered an organization. As such, there may be multiple organizations of varying knowledge scope within a single firm and an expansion of knowledge scope in one unit may not expand a firm's overall knowledge scope.[3]

There is precedent for measuring the breadth of an organization's knowledge as a determinant of organizational attributes and outcomes that is distinct from size, specialization, and firm scope. Katila and Ahuja (2002) study a dimension of search called "search scope" that describes how widely an organization explores new knowledge; increased scope adds variations to the knowledge base and affects new product introductions (firm scope). Similarly, Toh (2014) uses the average number of independent claims per patent in a given R&D location to measure its scope of technologies, arguing that scope reductions increase inventor specialization and vice versa.

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[2] For more details on this example as related to specialization and firm scope, see online appendix B.
[3] We thank our reviewer for highlighting this critical distinction between changes in knowledge scope and associated changes in firm scope.

Expanding knowledge scope boosts coordination costs by making knowledge integration harder (Grant, 1996; Puranam, 2018). These costs stem from employee-level limits to the ability to aggregate and process more knowledge simultaneously (Becker & Murphy, 1992; Garicano & Wu, 2012; P. R. Lawrence & Lorsch, 1967). Further, employees often use particular vocabulary or codes which can facilitate understanding among those who have similar knowledge while making it harder for them to communicate with others (Arrow, 1974; Cremer et al., 2007; Garicano & Van Zandt, 2012). More generally, there are limits to the knowledge that can be communicated between employees at reasonable cost—or even at all—for example, tacit knowledge (Polanyi, 1966). Limits to both the ability to process knowledge and the ability to communicate it mean that greater knowledge scope increases the likelihood that coordination costs will overwhelm the capacity of informal coordination mechanisms.

Hierarchy has significant support as a means for decreasing the costs of knowledge coordination among individuals. First, it allows a manager to act as an integrator focused on direction and dispute resolution for subordinates (Puranam, 2018). Second, it can perform a translation function, coordinating information flow across subsets of employees (Cremer et al., 2007). Third, it can lower the costs of pooling knowledge to make decisions (Garicano & Van Zandt, 2012).

Hierarchy has also been conceptualized as a way to manage increased complexity at the task—rather than employee—level (Zhou, 2013). Here too, it acts as a tool for resolving conflicts and reducing coordination costs (Marshak & Radner, 1972; Tushman & Nadler, 1978). Yet, in these instances, hierarchy often acts in tandem with divisionalization and is dependent on the task system's complexity and decomposability (Baldwin & Clark, 2000; Ethiraj & Levinthal, 2004a, 2004b). While some organizations certainly operate more-complex task systems—with many parts interacting in non-simple ways—there are limits to decomposability and task decomposition for managing complexity (Puranam, 2018).

In summary, increased knowledge scope increases coordination costs. Theory suggests that hierarchy can be a tool for managing organizations of both greater size and greater knowledge scope. Empirical evidence, however, has largely focused on size and has not distinguished the effect of size from that of knowledge scope. We therefore measure both size and knowledge scope, and we focus on knowledge scope while controlling for the well-understood effects of size:

> **Hypothesis (H1).** *Organizations whose employees collectively have greater knowledge scope are more likely to expand their hierarchy.*

2.2. Ability to coordinate knowledge

Organizations of similar size and knowledge scope may nevertheless have different capacities for knowledge coordination because employees—the repositories of organizational knowledge—are boundedly rational. Any single employee cannot process all the organization's knowledge. Rather, employees divide the organization's labor and integrate their efforts via coordination. This is known as coordination via feedback and is dependent on employees' relationships with each other (March & Simon, 1958). Thus, organizations may differ in their efficacy in part because their workforces have different capacities to coordinate as individuals.

These individual capacities for coordination are greater when employees have more in common. Puranam, Singh, and Chaudhuri (2009) suggest that this kind of informal coordination—among individuals in the absence of a formal design intervention (like hierarchy)—occurs when there is sufficient common ground, a concept introduced by Clark (1996), who defined it as "the sum of [two people's] mutual, common or joint knowledge, beliefs and suppositions" (p. 93). While Puranam et al. (2009) consider employees of acquirer and target organizations, the concept might well apply to individuals within an organization. This concept of knowledge that is known and known-to-be-known is closely related to the economic concept of common knowledge (Becker & Murphy, 1992), to transactive memory (Liang et al., 1995; Moreland & Myaskovsky, 2000; Wegner, 1987), to shared mental models (Klimoski & Mohammed, 1994), and to focal points (Schelling, 1960). In each of these concepts, shared experience results in knowledge accumulation that is useful for coordination in an organization (Faraj & Sproull, 2000; Lewis et al., 2005). We examine two means by which employees can have greater common ground: shared experience in current tasks and in prior jobs.

2.2.1. Task similarity

Employees assigned the same task will likely generate mutual understandings about how to do it, even if they aren't performing it together (March & Simon, 1958). These mutual understandings, or "truces," establish work patterns that informally coordinate collective effort (Nelson & Winter, 1982; Weber & Camerer, 2003). Even employees with different occupations can perform some similar tasks. Further, if there are many occupations composed of similar tasks, then the underlying knowledge is more likely to be common across individuals. Such commonality should facilitate coordination of the organization's work.

Within an organization the division of labor is not necessarily equal to the division of knowledge. Instead, many occupations are not so highly specialized as to have employees with exclusive sets of knowledge. Rather, occupations often overlap in tasks, allowing employees to share more underlying knowledge about how work is done. We expect employees in such organizations to be better at coordinating with one another informally to integrate the organization's knowledge (Becker & Murphy, 1992; Hart & Moore, 2005; Postrel, 2002).

We therefore predict that organizations of similar knowledge scope that are composed of occupations with greater task overlap will have a greater ability to coordinate and thus a lower likelihood of hierarchy expansion.

> **Hypothesis (H2).** *The positive effect of increased knowledge scope on hierarchy expansion decreases for organizations whose employees have greater task overlap.*

2.2.2. Shared prior experience

Teams of employees differ in their experience working with each other and these differences are likely to matter. Employees who have worked together have some common ground—shared knowledge of the first and higher orders—that helps them coordinate (Clark, 1996; Schelling, 1960; Srikanth & Puranam, 2014) by creating a shared language (Kogut, 2000; Kogut & Zander, 1996) and a capacity for knowledge aggregation (Grant, 1996). Puranam, Raveendran, and Knudsen (2012) suggest that working together over time can create predictive knowledge: to some extent, one knows what coworkers are going to do. Gulati and Puranam (2009: 422) offer a similar mechanism when describing the informal organization as "the emergent pattern of social interactions within organizations." These connections between individuals lower coordination frictions. Further, predictive knowledge may grow over time through interactions and shared context.

Thus, coordination costs may be lower between employees who have previously worked together. Galbraith (1974) would call this ability to coordinate an increase in the capacity to process information due to improved lateral relations. By knowing who knows what and who knows how to do what (Edmondson et al., 2003), employees are more likely to divide work effectively, to aggregate appropriate information from each other, and to trust this aggregated information (M. Lawrence, 2018; Reagans et al., 2005).

Employees with shared experience should thus be better able to coordinate a given knowledge scope, with less immediate need for hierarchy to facilitate the necessary aggregation, processing, and transmission of information. We therefore hypothesize:

Hypothesis (H3). *The positive effect of increased knowledge scope on hierarchy expansion decreases for organizations whose employees have more shared prior experience.*

3. DATA

To test our proposed theory relating knowledge scope to hierarchy expansion, we study a context in which we can follow a set of firms from their birth. This allows us to observe all changes to the organizational structure without having to be concerned with historical structures or nuances generated by firm history. By observing entire firms, we need not be concerned with alternative structural forms for knowledge coordination or with unmeasured interdependencies between divisions or teams—factors which would be significant in larger organizations.

We construct our dataset from the *Relação Anual de Informações Sociais* (RAIS), an annual survey of the entire Brazilian formal sector. All employers, regardless of size and industry, must complete this survey, which includes wage, occupation, and demographic information for everyone on the payroll. We select the population of firms in RAIS founded between 2003 and 2014. The result is an employer-employee matched dataset at the employee-job-firm-quarter level in which new firms and their workers can be followed over time. Entities in RAIS are organized by establishment—a single geographic location; a single firm can own multiple establishments. To construct our sample, we use each employer's tax identifier to aggregate establishments belonging to the same firm,[4] which ensures we do not treat new establishments of existing firms (for example, new retail outlets) as entirely new businesses.

A "new" firm is a private-sector employer reporting RAIS data for the first time at any establishment.[5] Because the survey is mandatory even for firms with a single employee, the first

[4] We use the first eight digits of the *Cadastro Nacional da Pessoa Jurídica*. Some employers in RAIS are identified by other types of tax identifier (for example, domestic employers use a *Cadastro Especifico do INSS*); we exclude them from our study.
[5] We use the term "firm" rather than the broader "organization" for those sections of the paper in which we discuss the data used specifically for this analysis. Our theorizing at the organization level applies to this specific analysis in which we have identified and tracked firms from birth.

year that a firm has employees will also be the first year it appears in our dataset. Because our focus is on hierarchy—which doesn't exist without employees—we do not find it problematic that our data excludes businesses without employees. Furthermore, this sample restriction is a common practice for survey studies of firm organization (Baron et al., 1996; Burton & Beckman, 2007).

Using criteria developed in prior research (Muendler et al., 2012; Sarada & Tocoian, 2019), we exclude firms that are branches of the government, firms with state ownership, cooperatives, business groups, firms that appear to contain another firm's transferred employees, and branches of foreign firms. Following Muendler, Rauch, and Tocoian (2012), we identify these firms using the form of incorporation reported in RAIS. By excluding them, we focus on independent firms—corporations and sole proprietorships—that rely on their own knowledge. In robustness checks, we further limit our analysis to limited liability corporations and find similar results.

We identify managers using Brazil's occupational code system (*Classificação Brasileira de Ocupações*), which contains over 2,500 jobs, allowing us to code each worker's position in the corporate hierarchy. Our approach resembles that of Caliendo et al. (2015), who use French data and occupational codes to assign employees to distinct layers—groups of workers with similar knowledge and job responsibilities. Like most occupational code systems, Brazil's system enumerates jobs and organizes them into families of related occupations. The families are further organized into increasingly general categories.

Figure 1 illustrates this hierarchy for a sample of occupations to illustrate the organization of occupations and level of detail typical of RAIS occupation codes. Using these occupation codes, job titles, and job descriptions, we manually identify two types of managerial employee: executives (e.g., chief executive officer, chief financial officer) and managers (e.g., sales manager, human resources manager, warehouse foreman).

[INSERT FIGURE 1 ABOUT HERE]

We identify founders as the people employed on the firm's first day and base all our subsequent founder measures on them. This form of measurement is consistent with the prior literature (Honore & Ganco, 2016; Shane & Stuart, 2002).

3.1. Dependent variable

Our main dependent variable, *Hierarchy expansion*, is a binary variable capturing the addition of a management layer, defined as hiring at least one employee from the manager level defined above. We exclude from our measure any executive- or manager-level employee employed on the first day ("founder-managers") because our goal is to understand the *addition* of layers of hierarchy in firms and not the propensity of founders to label themselves as managers. Additionally, we assume all firms to have at least one top manager from birth (such as an owner-founder). We further explain this approach in online appendix A and consider several alternative ways of coding the dependent variable, all of which produce results like those reported in the main text.

3.2. Explanatory variables

3.2.1. Knowledge scope measure

In the previous sections, we argue that the sum of the organization's knowledge is not perfectly characterized using the method by which it has been traditionally measured—firm size as the count of employees. Measuring an organization's knowledge scope is then a key operational issue in testing our hypotheses. In the arguments below we suggest that an organization's number of distinct occupations captures knowledge scope in a way that is meaningfully different from the count of employees.

Our measure of *Distinct occupations* maintains a connection to the established tradition viewing individuals as the ultimate repositories of knowledge (Graaff, 1957; Nelson & Winter, 1982; Penrose, 1959). Knowing that individuals act as repositories of knowledge but also that not all workers have the same knowledge nor explicitly non-overlapping knowledge, we aim to measure knowledge scope in a way that captures the breadth of the organization's knowledge. To do so, we leverage insights from firm diversification research that uses occupation data to compare knowledge bases across firms.[6] In building on the view that diversification occurs in directions where firms can best apply their underutilized resources (Teece, 1982), Fajoun (1994) proposed that firm diversification was likely to occur within resource-related industries that possess similarity in their combinations of human expertise. Then, to approximate the similarity of the knowledge base between industries, Farjoun (1994) used Occupational Employment Survey data in the United States to compare industries based on the similarity of the occupational profiles. Chang (1996) expands upon this work to predict entry and exit of firms from businesses based on the similarity and dissimilarity of human resource profiles—measured by the occupations—of industries as compared to the focal firm. Further, there has been a similar focus on occupations as a way to classify bundles of skills and abilities that constitute the human capital endowments in labor economics (e.g., Autor & Handel, 2013). Together, these literatures suggest that considering the occupations present in an industry or even a single organization is a way to infer characteristics of the knowledge present in that organization.

Building from these uses of occupational data to measure characteristics of knowledge, we propose and use *Distinct occupations*—a count of the unique occupations in an organization—to measure the knowledge scope of an organization.

Since we are the first to use the count of occupations as a measure of knowledge scope, we

[6] The term knowledge base is used to describe both the breadth and depth of knowledge in firms and therefore considers both the horizontal breadth (which we call knowledge scope) and the vertical depth of knowledge at any given occupation (which we only incorporate when measuring the task similarity across employees).

validate the measure in several ways. First, in online appendix B, we show the occupational composition of several example firms just prior to their hierarchy expansion decision. These examples demonstrate how occupation data provide information about knowledge scope that is distinct from specialization and firm scope. Second, we coarsen our occupational data from the 6-digit to the 4-digit level and plot the expansion of 4-digit codes versus 6-digit codes as a function of employment size (Figure 2). This comparison between the expansion of 4-digit and 6-digit occupations is useful because occupations are organized hierarchically, with related job titles sharing the same four digits. An increase in 6-digit occupations without a corresponding increase in 4-digit occupations would indicate a tendency for firms to extend their occupational composition within narrow fields of expertise. In contrast, an increase in the number of distinct 4-digit occupations would indicate a tendency to draw on different domains of knowledge and expertise. Figure 2 shows that firms hire across different occupational domains before increasing the count of employees and number of distinct jobs within each 4-digit segment. This pattern of breadth followed by depth provides some evidence to refute concerns about any occupational expansion representing an increase in specialization for the firm. Instead, firms on average first expand their breadth of competencies across occupations requiring distinct knowledge before deepening their competencies in particular areas. Third, we recognize the need to distinguish the effects of increasing knowledge scope from the effects of firm size, since these are highly correlated. Therefore, in Section 5.2.1, we show that firms expanding hierarchy in response to greater knowledge scope—as captured by *Distinct occupations*—hire managers with broader prior work experience which is likely to be beneficial in organizations of greater knowledge scope. We further show that larger firms—as captured by *Employee size*—do not have the same taste for managers with broad experience; instead, they prefer managers with experience in larger organizations.

[INSERT FIGURE 2 ABOUT HERE]

3.2.2. Coordination of knowledge measures

To capture differences in firms' abilities to coordinate knowledge, we create two measures for aspects of shared experience. First, we create a measure of the underlying shared experience generated by the similarity of employees' occupations, using occupation-level data on job tasks from O*NET. The O*NET data describe occupations present in the US economy—using hundreds of standardized measures for the required knowledge, skills, and abilities (O*NET Resource Center, 2021)—and are frequently used in academic research (Felten et al., 2021). To match occupations between Brazil and O*NET, we use a crosswalk developed by Nogueira Maciente (2019) that links every job in RAIS to its O*NET equivalent.

We calculate *Task similarity*—the extent to which two occupations require similar tasks—as the cosine similarity of their tasks.[7] *Task similarity* equals 1 when the two occupations have identical tasks and 0 when they have no common tasks. Tasks for a barista, for example, include "clean tools, equipment, facilities, or work areas," "prepare foods and beverages," and "monitor equipment operation," while tasks for a waiter are similar but exclude "monitor equipment operation" and include "prepare schedules for services or facilities." We calculate a firm-level measure of *Task similarity* as the mean task similarity across all possible pairs of employees. For example, a firm with one salesperson and two computer programmers has three possible pairs of employees; task similarity is high for the pair of programmers and low for the two salesperson-programmer pairs.

To examine the second aspect of shared experience, we identify the extent to which a firm's employees have worked together in prior jobs. We identify all instances in which its employees

[7] We measure tasks at the level of "intermediate work activities" in O*NET. There are 332 unique tasks.

previously worked for another firm in the same establishment, occupation, and year. We can thus draw a networked structure for each firm in each quarter based on these prior connections. While working in the same establishment and occupation does not guarantee that employees knew each other directly, this is often a reasonable assumption given that the average establishment in Brazil during our sample period has only 12.6 employees and even the 95th percentile is only 30 employees.[8]

Shared prior experience is the size of the largest, multi-employee connected component of employees in the shared experience network divided by team size. In our context, this connected component is the largest set of employees who can be linked by shared work experience at one or more firms. For example, if a firm has four employees—A, B, C, and D—and if A and B previously had the same occupation at the same establishment but no others share such connections, *Shared prior experience* would equal one-half (two out of four). Alternatively, if A had the same occupation at the same establishment as B and, in a different year, B had the same occupation at the same establishment as C, *Shared prior experience* would equal three-fourths because there is a path of shared experience linking A to B and B to C, making the largest connected component three (out of four) employees. This scenario is shown in Figure 3.

[INSERT FIGURE 3 ABOUT HERE]

While number of employees is not our variable of interest, it is important to distinguish size from knowledge scope. We therefore define *Ln Employees* as the natural log of the count of nonmanagerial employees. This measure has been used as a proxy for knowledge generally (DeSantola & Gulati, 2017).

3.3. Controls and fixed effects

[8] These statistics include all establishments, not just newly founded firms, and are thus representative of the population of establishments that employees may have worked at before joining the newly founded firms in our sample.

We include several control variables in our analyses. First, our survival model includes *Age*—the number of quarters since the firm first completed RAIS—for which we estimate a coefficient on likelihood of hierarchy expansion. That coefficient indicates the extent to which the likelihood of hierarchy expansion is increasing or decreasing with the firm's age. We also include *Age squared*¸ to account for potential nonlinearity of the age effect.

Second, we control for several potentially relevant founding team characteristics. To distinguish between firms with small and large founding teams, we use *Ln founding team size*, the natural log of the size of the founding team, which is constant across years. We use the natural log to account for the long tail on the number of founders and because graphical analysis suggests a log-linear relationship between team size and hierarchy expansion. We also account for founders' prior experience, which affects the firm's relevant knowledge stock and entrant capabilities (Alexy et al., 2021; Carroll et al., 1996; Helfat & Lieberman, 2002; Klepper & Simons, 2000). A major advantage of our employer-employee matched dataset is the ability to identify each person's employment history back to 1992. We use this history to calculate the total months of experience of each founding team member; *Founder experience* is the team average of these values, in years. We also include founder human capital by measuring *Founder education*. More education may raise the opportunity cost of time for founders and/or make them aware of more valuable practices (Bennett et al., 2017; Bloom et al., 2012; Bloom & Van Reenen, 2007; Colombo & Grilli, 2013). Specifically, we calculate the proportion of the founding team with at least a high school diploma. We use high school since relatively few employees in Brazil have college degrees.

We control for founders' wages at their previous employer. Higher-paid employees are less likely to leave, in part because the opportunity cost of leaving to found a startup is higher (Campbell et al., 2012). Highly paid employees who leave to start their own firm are therefore likely to have better startup ideas and/or higher ability. Founder ability and the quality of the startup idea—unobservable to us—could be correlated with our variable of interest and related to the expansion of hierarchy. We therefore use the employer-employee matched nature of our data to calculate the average wage of all founders at their previous employers. We then categorize all new firms each year into prior-wage quintiles and include an indicator for each quintile in our models. Some founders, such as those coming right out of school, cannot be traced to a prior employer. We treat their firms as a separate category in our models so that our final model has six indicators: one for founders with no prior employment history (the omitted group) and five for the quintiles of the distribution of founders' prior wages.

We include three fixed effects in our models: *quarter*, *industry*, and *micro-region*. The *quarter* fixed effect controls for changes over time—in either the expansion of hierarchy or the propensity to use managerial occupation codes when reporting RAIS data—that are unrelated to our variable of interest. Our results are thus not driven by time-specific factors that affect all firms, such as macro-economic conditions. The *industry* fixed effect accounts both for differences in industries' propensities to use the available managerial occupation codes and for any time-invariant industry feature related to hierarchy expansion. For example, some industries have better-educated workers and may therefore have a larger pool from which to draw talent. Alternatively, some industries are more competitive, which may affect the propensity to hire. Finally, we include a *micro-region* fixed effect. Brazil's 557 micro-regions are government-defined geographic areas with populations that can conveniently be served by a commercial enterprise or social service. Including a *micro-region* effect controls for time-invariant differences attributable to geography, such as differences in population, infrastructure, and natural resources.

3.4. Characterizing the data

The data we describe comes from more than 3 million firms and more than 40 million firm-quarter observations in Brazil. We examine hierarchy expansion in all Brazilian firms started in our 12-year observation period. Only 15 percent of firms ever add a managerial layer to their hierarchy, which we attribute to both lack of survival and lack of growth.[9] In line with prior work (Åstebro et al., 2014; Romanelli, 1989), we find that about half of firms created between 2003 and 2009 survive five years, but the median (mean) survivor has only 3 (6.4) employees in its fifth year, versus 2 (4) after its first year. Even after 10 years, the median (mean) firm has only 4 (7.6) employees.

Table 1(a) summarizes the characteristics of the firms in our study across all years while Table 1(b) summarizes the characteristics in their founding quarter. The average age of a firm in our sample across firm-quarter observations is 3.1 years and the average firm employs 5 people. Looking only at the founding quarter, we find that the average number of founders is 1.9, with 31 percent of firms having multiple founders. The average experience of founding teams is 3.8 years and, on average, about 60 percent of founders have at least a high school education.

[INSERT TABLE 1 ABOUT HERE]

The distribution for *Founder prior wage*—founders' average hourly wages at their previous jobs (in Brazilian reais)—shows a wide range; those in the 90th percentile earned over three times more than those in the 10th. So large a standard deviation warrants explanation. There are a few extreme outliers in the wage distribution, some of which are almost surely reporting errors in RAIS. Fortunately, we find the values in our data to be realistic for even the 99.5th percentile of the distribution. Additionally, our models control for founders' prior wages using a categorical variable for each quintile of the distribution instead of a continuous value; our results

[9] This statistic is not conditional on survival. Conditional on survival, about 25 percent of firms have expanded their hierarchy by their fifth year and about 35 percent have done so by their tenth year.

are therefore not overly influenced by extreme and potentially erroneous outliers.

Statistics for *Distinct occupations*, which captures knowledge scope, show that firms have an average of two to three unique jobs for the quarters in our dataset prior to expanding their hierarchy. While this may seem low, most are very small firms that never expand their hierarchy. At the 90th percentile, there are five occupations prior to the expansion of hierarchy.

Table 2 shows correlation coefficients for the variables in our main models. The high correlation between *Ln employees* and *Distinct occupations*, 0.74, is expected given the definitions of our variables. With no VIF above 3.2, a condition number of 13.8, and a sample of millions of firms, we are not concerned about multicollinearity (Belsley, 1991; Belsley et al., 1980).

[INSERT TABLE 2 ABOUT HERE]

4. METHODOLOGY

We model the time until a firm hires a manager using a discrete time survival model (Cox 1972). Specifically, we consider the odds that firm i hires a manager at time t_a:

$$\frac{\lambda(t_a|x_{ia})}{1-\lambda(t_a|x_{ia})} = \frac{\lambda_0(t_a)}{1-\lambda_0(t_a)} e^{\beta' x_{ia}+\alpha_t+\gamma_j+\theta_k},$$

where x_{ia} is a vector of covariates for firm i at age a and $\lambda_0(t_a)$ is a baseline hazard, also in quarter t, which we model for all specifications as a quadratic in firm age. Q*uarter*, *industry*, and *micro-region* fixed effects are captured by α_t, γ_j, and θ_k, respectively. Our specification implies:

$$y_{ia} = \text{logit}[\lambda(t_a|x_{ia})] = \delta_a + \beta' x_{ia} + \alpha_t + \gamma_j + \theta_k$$

$$\delta_a = \text{logit}[\lambda_0(t_a)].$$

We estimate the parameters of the model via logistic regression on a firm-quarter panel in which the dependent variable, y_{ia}, is an indicator equal to 1 if firm *i* hired its first manager at age a. Each firm has observations for each quarter up to either the quarter in which a manager was hired, the firm ceases to have employees, or the final quarter of the sample (Q4 of 2014). When estimating the model, we lag our independent variables by one quarter to ensure that hiring a manager does not itself affect values of the right-hand–side variables (such as employee count and number of distinct occupations). We restrict our sample to firms with multiple nonmanagerial employees because our interest is hierarchy and several variables of interest, such as task similarity, require more than one employee observation. This restriction eliminates about a third of firm-quarters such that our final analysis includes 1,971,615 firms founded from 2003 to 2014.

Although our dataset includes the population of firms founded in Brazil during our time frame, there are several challenges to causal inference. The primary issues are endogeneity caused by simultaneity or omitted-variable bias. The concern with simultaneity is that the decision or plan to hire a manager affects decisions about team composition. For example, the decision to hire a manager may influence the expansion into distinct occupations. Solving this problem would require a model with a valid instrument or a joint model for manager and occupation expansion. Though our analysis falls short of these two solutions, we address these concerns with several robustness tests in Section 5.2 and by lagging the independent variables.

In our setting, the primary concern with omitted-variable bias is that unobserved factors may influence hierarchy expansion. If the omitted variable is not correlated with an independent variable, then our coefficient estimates will be attenuated; we will *underestimate* the importance of the variable of interest (Mood, 2010). Underestimation is better than overestimation, but if the omitted variable is also correlated with an independent variable, then we have the more familiar problem from ordinary least squares regression: an omitted variable that increases the probability of hiring a manager and is positively correlated with our independent variables could lead us to overestimate our effects of interest. This is the main justification for the *quarter*, *industry*, and *micro-region* fixed effects. Our estimates are not affected by omitted variables within industry or region that are stable over time or by time-varying omitted variables that affect all firms.

Finally, we do not think endogeneity caused by measurement error is a serious problem for our analyses because our main data source is government records used to administer social programs. Both workers and firms have strong incentives to provide accurate information and the government data we use is likely to be more accurate than sources typically used for research on this topic (such as retrospective surveys).

5. RESULTS AND DISCUSSION

Table 3 shows coefficient estimates for the survival model testing our three hypotheses. *Age* is curvilinearly related to the likelihood of hiring a manager in all specifications. Firms are most likely to hire managers soon after founding; the probability decreases each quarter, albeit at a decreasing rate. Unsurprisingly, larger firms are more likely to hire managers—the coefficient on *Ln employees* is positive in all specifications. Larger or more experienced founding teams are less likely to expand hierarchy,[10] while those with a higher average education level are more likely. These patterns are broadly consistent with Colombo and Grilli's (2013) findings that high-tech ventures are more likely to hire middle managers when (a) founding teams are smaller, (b) founders have less managerial experience, and (c) the founders are more educated.

Also, in Table 3, our controls for founders' prior wages show, as expected, that those who earned more at prior jobs are more likely to expand hierarchy. The most highly paid founders (fifth quintile) are more likely to hire a manager than those in the fourth quintile, who are more likely than those in the third quintile, and so on. This is consistent with the notion that founders who were highly paid in previous roles have business ideas more likely to result in survival and scaling.

[10] This is only true after controlling for founders' prior wages. Without this control, the coefficient on prior experience is positive. Our controls for founders' education, total experience, and prior wages all capture aspects of human capital. Taken together, the coefficients on these variables suggest that more knowledgeable or capable founders are more likely to adopt hierarchy.

[INSERT TABLE 3 ABOUT HERE]

In Specifications (2) and (5)–(8) of Table 3, we distinguish knowledge scope from firm size and other controls. We find that firms with more occupations, indicative of greater knowledge scope, are more likely to hire a manager. Because we control for firm size, this finding suggests that the variety of knowledge among a given number of employees matters for decisions about when to expand hierarchy. Figure 4 illustrates the distinct effects of size and knowledge scope. For an equal number of employees, firms with a greater number of distinct occupations are more likely to expand hierarchy, which supports H1.

[INSERT FIGURE 4 ABOUT HERE]

Firms differ in their employees' ability to coordinate knowledge, which affects the timing of hierarchy expansion. We hypothesize and test two such relationships, based on shared current experience (H2) and shared prior experience (H3). Results in Table 3 support the view that shared experience affects decisions of whether and when to hire additional managers. In Specifications (3)–(5), we introduce *Task similarity* and *Shared prior experience*, which both lower the likelihood of hiring a manager. To test Hypotheses 2–3 about the interaction of these variables with knowledge scope, we interact them with *Distinct occupations* in Specifications (6)–(8). Examining the interaction of *Task similarity* with *Distinct occupations* in Specification (6), we find that the effect of more occupations on hierarchy expansion decreases with greater *Task similarity*. Figure 5(a) plots the predicted effect for the 10th versus 90th percentile of *Task similarity*. The combined effects of *Distinct occupations* and *Task similarity* illustrate that the quarterly probability of hiring a manager is increasing in number of occupations, but more rapidly for firms with lower task similarity; this supports H2. Similarly, in Specification (7), we find that the effect of more occupations on hierarchy expansion decreases for firms with greater *Shared prior experience*. The combined effect of *Shared prior experience* and *Distinct occupations* is more difficult to interpret due to the changed sign on the coefficient for *Shared prior experience* once the interaction term with *Distinct occupations* is included. Figure 5(b) plots the predicted effects for the 10th versus 90th percentile of *Shared prior experience* when *Distinct occupations* ranges from 1 to 8. The moderating effect of *Shared prior experience* on the probability of hiring a manager is strengthened as the number of distinct occupations—that is, knowledge scope—increases; this, too, supports H3.

[INSERT FIGURE 5 ABOUT HERE]

Shared experiences—current and prior—have larger effects on hierarchy expansion as knowledge scope increases. However, the magnitude of the effects between the 10th and 90th percentiles of *Task similarity* and *Shared prior experience* are quite low when a firm has only one occupation, further supporting our hypotheses that the capacity to manage knowledge is put to increasing use as knowledge scope increases. We include both interactions in Specification (8) and find effects sizes similar to those when examining the interactions separately.

5.1. Interpreting the likelihood of hierarchy expansion

Although the signs of the estimates in Table 3 are easily interpreted, assessing the magnitude of the effects implied by the survival model requires estimating the likelihood of hiring a manager for different levels of the independent variables. Table 4 shows the average predictive margins based on Specification (8) of Table 3. The values in this table can be interpreted as the percentage of firms—for a given variable, such as *Age*—that would hire a manager *each quarter* if all firms were moved to the specified percentile of that variable's distribution (for example, the empirical age distribution). The difference between the 90th and 10th percentiles (right-most column) suggests the magnitude of the variable's effect on the likelihood of hiring a manager.

[INSERT TABLE 4 ABOUT HERE]

Shifting from the 10th to the 90th percentile of *Age* decreases the quarterly probability of hiring a manager by 2.5 percentage points. If a firm has not adopted hierarchy early, it becomes significantly less likely to do so—all else equal—as it ages. Moving from the 10th percentile of *Ln employees* (2 employees) to the 90th (8 employees) increases the quarterly likelihood of adopting hierarchy by 2 percentage points each quarter. While that magnitude may seem small, at an annual level it is a 7.87-percentage-point increase in the likelihood of expanding hierarchy—a near doubling of the hazard at the 10th percentile of the firm size distribution.

All other effects are smaller but meaningful. Focusing on our variables of interest, teams in the 90th percentile of *Distinct occupations* are 0.42 percentage points (~25%) more likely than those in the 10th percentile to hire a manager in each quarter. Overall, firms with employees distributed across more occupations are more likely to adopt hierarchy. Firms whose employees have *Task similarity* in the 90th percentile are 0.33 percentage points (~16%) less likely than those in the 10th percentile to hire a manager in each quarter. Similarly, firms whose employees have *Shared prior experience* in the 90th percentile are 0.21 percentage points (~11%) less likely than those in the 10th percentile to hire a manager in each quarter. Overall, these effects are meaningful and suggest that increased knowledge scope is associated with increased likelihood of hierarchy expansion but also that increased shared experience—present or past—moderates that likelihood by improving knowledge coordination among employees.

5.2. Supplementary analysis and robustness checks

5.2.1. Knowledge scope as a separable driver of hierarchy expansion

The main mechanism we propose for hierarchy expansion is increased knowledge scope of the organization. However, knowledge scope is closely tied—both theoretically and empirically—to the size of an organization. The key distinction between knowledge scope and size in hierarchy expansion is that coordination costs are based not only on the quantity of knowledge to be transferred but also the characteristics of that knowledge.

We use this theoretical distinction to guide additional empirical tests, which further support the claim that knowledge scope (as opposed to just size) is associated with hierarchy expansion in the data. Specifically, our argument that the effects of knowledge scope and size on hierarchy are distinct suggests that organizations experiencing coordination problems concomitant with knowledge scope may hire distinct types of managers from those experiencing problems related to scaling and size. Firms driven to hire managers due to increases in size may seek managers with past work experience in larger organizations. Firms driven to hire managers due to increases in knowledge scope, however, may want managers with a wider breadth of previous work experience. If the effects of size and knowledge scope are indeed distinct as we claim, we would not expect knowledge scope to be predictive of hiring managers with large-firm experience, only those with breadth of experience, after controlling for size.

For the sample of firms that hire managers, we exploit the employer-employee linked nature of our data to identify all the managers' prior jobs. We define prior large-firm experience as the largest firm, in number of employees, the manager previously worked in and define prior occupations as the number of distinct, non-managerial occupations held by the manager.[11] We then use attributes of our focal firms to predict these attributes of the hired managers. Because both attributes (prior firm size and prior occupations) are positive counts, we estimate a Poisson model. We include greater detail on the modelling choices and data in online appendix D.

[11] Some managers have no identifiable prior roles, either because they are assuming their first job or their first job in Brazil's formal sector. We treat these observations as zeros (because there are no prior occupations or prior firm sizes), but our results are robust to excluding these observations and examining only managers with observable prior jobs.

Table 5 presents estimates of the Poisson model, with Specifications (1)–(2) showing models without control variables and Specifications (3)–(4) models with the control variables from Table 3. Coefficients on the variables of interest—log employees and log distinct occupations—can be interpreted as elasticities reflecting the percentage change in expected value of the dependent variables given a percentage change in the explanatory variables (Winkelmann, 2008). The estimates in Specifications (1) and (3) show that size is predictive of hiring managers with prior experience in larger organizations while knowledge scope (unique occupations) is not. Estimates in Specifications (2) and (4), however, show that knowledge scope is, as expected, predictive of hiring managers with a wider breadth of occupational experience. Moreover, size has smaller effects on hiring managers with a wider breadth of occupational experience than on hiring managers with large firm experience.

[INSERT TABLE 5 ABOUT HERE]

In summary, these results provide additional support our finding that there is a distinction in hierarchy expansion because of increased knowledge scope and because of increased size alone. The type of manager who is hired to coordinate the challenges arising from larger size is different from the type of manager hired to coordinate the challenges arising from broader knowledge scope.

5.2.2. Variable construction

Because no single way of coding our variables of interest is without its drawbacks, we confirm the consistency of our results using alternative ways to code hierarchy expansion, knowledge scope, and our proposed measures for the capacity to manage knowledge.

First, we note that there are other ways to code hierarchy expansion, the main question being how and when to code founders as expansions of management. Online appendix A further explains our dependent variable and presents alternative ways of coding hierarchy. Our findings are consistent across alternative methods.

Second, as explained in Section 3.2.1, we coarsen our occupation data to the 4-digit level to provide further support for our occupation data as measuring knowledge scope. Figure 2 shows that firms in our data tend to hire employees to expand across "families" of occupations before expanding the types of occupations within families. However, an alternative way to provide support for our proposed relationship between knowledge scope and hierarchy expansion is to define knowledge scope using occupational families (4-digit occupation codes). In online appendix B (Table B2)**Error! Reference source not found.**, we present average predictive margins for our variables of interest using the alternative definition of knowledge scope and find consistent results.

Third, we test alternative measures to build the evidence for our proposed coordination mechanism. In our main specifications, we have used what we believe are the best approximations to those current and shared prior experiences that may boost the capacity to manage knowledge; for additional support, we calculate these same proposed variables using alternative measures. Our alternative measure of *Task similarity* is based on task data from Brazil's Ministry of Labor rather than the O*NET data used for our main measure. Our alternative measure of *Shared prior experience* is the maximum number of employees in the firm who have worked together at a previous establishment and performed the same occupation there in the same year divided by the team size. We expand upon these measures and show both average predictive margins and coefficient estimates using them in online appendix C along with additional measures of coordination. Across all specifications using these alternative and additional measures, we find support for our proposed mechanism that shared experience expands employees' capacities for coordination and is associated with later hierarchy expansion.

5.2.3. Ruling out alternative explanations and models

Finally, because accounting for the knowledge scope of even a subset of firms over time, much less an entire economy, is a difficult undertaking, we consider the robustness of our proposed specifications against alternative explanations and model choices.[12]

In proposing that knowledge scope is a separable determinant of organizational structure, we are sensitive to alternative explanations which may drive our result. We rule out the two most likely alternative mechanisms motivating organizational structure heterogeneity. The first is that firms differ from the outset in their abilities and/or the quality of their ideas, which drives the choice of occupations for initial employees. To address this, our main specifications control for prior wages, providing evidence that founders with higher prior wages are more likely to adopt hierarchy. Our results hold even when controlling for this alternative.

We also recognize that founding teams may differ in aspiration or in their establishment of "founding blueprints" (Alexy et al., 2021; Baron et al., 1996, 1999; Dahl & Klepper, 2015), which could affect occupational and organizational design. We address this concern, at least in part, by examining a subsample of our data likely to have more similar aspirations. Roughly half the firms in our main analyses are sole proprietorships, which may have different ambitions or knowledge than incorporated limited liability corporations. Table 6 shows average predictive margins from our main survival model (Specification (8) of Table 3) after limiting the sample to limited liability corporations; the predictive margins resemble our main results across our variables of interest—*Distinct occupations*, *Task similarity*, and *Shared prior experience*.

[INSERT TABLE 6 ABOUT HERE]

Our results are also robust to changes in our sample and specification (see remainder of estimates in Table 6). Companies born large may be more likely to be the result of divestitures or

[12] In online appendix E, we show that our results are robust to subsamples of the population: manufacturing industries only and knowledge intensive industries only.

other circumstances; such firms are not truly startups, which is why prior work has excluded them (Sarada & Tocoian, 2019). We omit firms with more than 100 initial employees at birth, then firms with more than 10, and find similar results for both samples. Another concern is that firms in Brazil could have operated in the informal economy before appearing in RAIS. Excluding companies that are large from birth alleviates this concern.

Our final alternative specification limits the definition of managers to workers hired externally rather than promoted. The employer-employee matched nature of the dataset allows us to see whether a manager previously held a different job at the firm. One might be concerned that growing firms begin to label early employees "managers" even if their responsibilities have not changed; for example, to justify pay differences based on tenure (Chan et al., 2014; Zenger, 1992), to increase the status of the earliest employees (Rider & Tan, 2015), or to seek legitimacy in the eyes of funders or other stakeholders (Zimmerman & Zeitz, 2002). This analysis can also partially address concerns about simultaneity and reverse causality. People present from the firm's early days are both the most plausible internal candidates and more likely to be already known to the founders as the founding team is taking shape. It seems unlikely, however, that future managers hired externally would affect initial team composition. This final set of predictive margin calculations for each of our variables (labeled "external manager only" in Table 6) shows that our results are similar if we define a manager as being externally hired.

6. CONCLUSION

We theorize and find evidence for the proposition that (a) knowledge scope creates coordination challenges that impair integration and (b) organizations are more likely to expand their hierarchy as knowledge scope increases. We suggest that increased knowledge scope decreases common ground among members, reducing their predictive knowledge (Camerer & Knez, 1996; Gulati et al., 2012; Puranam et al., 2012; Schelling, 1960). Since predictive knowledge is critical for coordination, organizations with greater knowledge scope are more likely to expand hierarchy. This effect of knowledge scope is distinct from the effect of increased size, which has been extensively theorized and documented (Blau, 1970; Colombo & Delmastro, 2008; DeSantola & Gulati, 2017; Pugh et al., 1968, 1969). The dual role of knowledge scope and organizational size underscores a premise of the knowledge-based view that not only the amount but also the nature of the knowledge to be coordinated affects organizational design (Grant, 1996).

We emphasize how organizations differ in their capacity to manage knowledge. Organizations of similar size and knowledge scope will therefore differ in their propensity to rely on hierarchy. Thus, we find that a greater degree of common ground—from shared prior experience and/or high task overlap—moderates the positive relationship between knowledge scope and the propensity to expand hierarchy. This result suggests that increased common ground increases an organization's capacity to manage knowledge and contributes to our understanding of knowledge management as a driver of organizational structure.

While there are many advantages to our dataset and setting for studying hierarchy expansion, we acknowledge its limitations. First, our empirical test uses only smaller firms, half of which are less than three years old, so we cannot generalize our empirical results to larger organizations with complicating organizational factors such as multiple divisions or subsidiary relationships. We believe knowledge scope creates similar coordination challenges in larger organizations but that these organizations have opportunities to use other adaptations, such as delegation (Dobrajska et al., 2015), to facilitate coordination. Future research would be beneficial to empirically distinguish hierarchy expansions from other adaptations in these organization types. Second, we do not have measures of specialization and firm scope as compared to knowledge scope. Our most compelling evidence distinguishing our results from specialization is the pattern of firms expanding across families of occupations before hiring more related occupations within families. For firm scope, our focus on young and smaller organizations makes it less likely that our results are driven by expansions of firm scope into new industries; only 0.3 percent of firm-years in our sample belong to multi-industry firms and only 0.5 percent of firms in the sample are *ever* multi-industry (in any year). Third, we acknowledge the imperfection of our methods for considering alternative mechanisms for our results. Ideally, we would randomly allocate varying knowledge scope to firms with ideas and employees of equal quality. This being impossible, we believe that finding consistent results across several subsamples, with additional controls, and across alternative specifications supports our proposed relationship between knowledge scope and the need for coordination.

As we illustrate, employer-employee matched data that include occupational information offer several opportunities for large-sample empirical research on organizational design. While we emphasize how internal organizational attributes affect design, future research using employer-employee matched data to measure hierarchy might fruitfully examine how the relationships we document vary with features of the external environment, such as competition and the availability of information technology. Research would also benefit from new algorithms for and insights on measurement: for example, how best to measure an organization's hierarchy (or other aspects of its design), given detailed data on employees' occupations, wages, and work history.

Practically, our results underscore the importance of considering multiple dimensions of organizational scaling (DeSantola and Gulati 2017). As they grow, organizations must coordinate not only more employees, but also more knowledge domains. Our findings suggest that task allocation and hiring practices (such as relying on referrals) can—along with hierarchy—help organizations manage knowledge and achieve their goals.

REFERENCES

Alexy, O., Poetz, K., Puranam, P., & Reitzig, M. (2021). Adaptation or persistence? Emergence and revision of organization designs in new ventures. *Organization Science*, *32*(6), 1439–1472. https://doi.org/10.1287/orsc.2021.1431

Arrow, K. (1974). *The Limits of Organization*. Norton.

Åstebro, T., Herz, H., Nanda, R., & Weber, R. A. (2014). Seeking the Roots of Entrepreneurship: Insights from Behavioral Economics. *Journal of Economic Perspectives*, *28*(3), 49–69.

Autor, D. H., & Handel, M. J. (2013). Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics*, *31*(2), S59–S96. https://doi.org/10.1086/669332

Baldwin, C. Y., & Clark, K. B. (2000). *Design Rules: The power of modularity*. MIT Press.

Baron, J. N., Burton, M. D., & Hannan, M. T. (1996). The road taken: Origins and evolution of employment systems in emerging companies. *Industrial and Corporate Change*, *5*(2), 239–275.

Baron, J. N., Burton, M. D., & Hannan, M. T. (1999). Engineering Bureaucracy: The Genesis of Formal Policies, Positions, and Structures in High-Technology Firms. *Journal of Law, Economics, & Organization*, *15*(1), 1–41.

Becker, G. S., & Murphy, K. M. (1992). The Division of Labor, Coordination Costs, and Knowledge. *The Quarterly Journal of Economics*, *107*(4), 1137–1160.

Beckman, C. M., & Burton, M. D. (2008). Founding the Future: Path Dependence in the Evolution of Top Management Teams from Founding to IPO. *Organization Science*, *19*(1), 3–24.

Beckman, C. M., Burton, M. D., & O'Reilly, C. (2007). Early teams: The impact of team demography on VC financing and going public. *Journal of Business Venturing*, *22*(2), 147–173.

Belsley, D. (1991). *Conditioning Diagnostics, Collinearity and Weak Data in Regression*. John Wiley & Sons.

Belsley, D., Kuh, E., & Welsch, R. (1980). *Regression Diagnostics: Iden- tifying Influential Data and Sources of Collinearity*. John Wiley & Sons.

Bennett, V. M., Lawrence, M., & Sadun, R. (2017). Are Founder CEOs Good Managers? In J. Haltiwanger, E. Hurst, J. Miranda, & A. Schoar (Eds.), *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*. University of Chicago Press.

Blau, P. M. (1970). A Formal Theory of Differentiation in Organizations. *American Sociological Review*, *35*(2), 201–218.

Bloom, N., Sadun, R., & Van Reenen, J. (2012). The Organization of Firms Across Countries. *The Quarterly Journal of Economics*, *127*(4), 1663–1705.

Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics*, *CXXII*(4), 1351–1408.

Burton, M. D., & Beckman, C. M. (2007). Leaving a Legacy: Position Imprints and Successor Turnover in Young Firms. *American Sociological Review*, *72*(2), 239–266.

Caliendo, L., Monte, F., & Rossi-Hansberg, E. (2015). The Anatomy of French Production Hierarchies. *Journal of Political Economy*, *123*(4), 809–852.

Camerer, C., & Knez, M. (1996). Coordination, organizational boundaries and fads in business practices. *Industrial and Corporate Change*, *5*(1), 89–112.

Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. (2012). Who Leaves, Where To, and Why Worry? Employee Mobility, Entrepreneurship and Effects on Source Firm Performance. *Strategic Management Journal*, *33*, 65–87.

Carroll, G. R., Bigelow, L. S., Seidel, M.-D. L., & Tsai, L. B. (1996). The fates of De Novo and De Alio producers in the American Automobile Industry 1885-1981. *Strategic Management Journal*, *17*, 117–137.

Chan, T. Y., Li, J., & Pierce, L. (2014). Compensation and peer effects in competing sales teams. *Management Science*, *60*(8), 1965–1984.

Chang, S. J. (1996). An Evolutionary Perspective on Diversification and Corporate Restructuring: Entry, Exit, and Economic Performance During 1981–89. *Strategic Management Journal*, *17*(8), 587–611.

Clark, H. H. (1996). *Using Language*. Cambridge University Press.

Colombo, M. G., & Delmastro, M. (2008). *The economics of organizational design: Theoretical Insights and Empirical Evidence*. Palgrave MacMillan.

Colombo, M. G., & Grilli, L. (2013). The Creation of a Middle-Management Level by Entrepreneurial Ventures: Testing Economic Theories of Organizational Design. *Journal of Economics and Management Strategy*, *22*(2), 390–422.

Cremer, J., Garicano, L., & Prat, A. (2007). Language and the Theory of the Firm. *The Quarterly Journal of Economics*, *February*, 373–408.

Dahl, M. S., & Klepper, S. (2015). Whom do new firms hire? *Industrial and Corporate Change*, *24*(4), 819–836.

DeSantola, A., & Gulati, R. (2017). Scaling: Organizing and Growth in Entrepreneurial Ventures. *Academy of Management Annals*.

Dobrajska, M., Billinger, S., & Karim, S. (2015). Delegation within Hierarchies: How Information Processing and Knowledge Characteristics Influence the Allocation of Formal and Real Decision Authority. *Organization Science*, *26*(3), 687–704.

Edmondson, A. C., Winslow, A. B., Bohmer, R. M. J., & Pisano, G. P. (2003). Learning How and Learning What: Effects of Tacit and Codified Knowlenge on Performance Improvement Following technology Adoption. *Decision Sciences*, *34*(2), 197–224.

Ethiraj, S. K., & Levinthal, D. (2004a). Bounded Rationality and the Search for Organizational Architecture: An Evolutionary Perspective on the Design of Organizations and Their Evolvability. *Administrative Science Quarterly*, *49*(3), 404–437.

Ethiraj, S. K., & Levinthal, D. (2004b). Modularity and Innovation in Complex Systems. *Management Science*, *50*(2), 159–173.

Faraj, S., & Sproull, L. (2000). Coordinating Expertise in Software Development Teams. *Management Science*, *46*(12), 1554–1568.

Farjoun, M. (1994). Beyond Industry Boundaries: Human Expertise, Diversification and Resource-Related Industry Groups. *Organization Science*, *5*(2), 185–199.

Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, *April*, 1–23.

Ferguson, A. J., Cohen, L. E., Burton, M. D., & Beckman, C. M. (2016). Misfit and milestones: Structural Elaboration and Capability Reinforcement in the Evolution of Entrepreneurial Top Management Teams. *Academy of Management Journal*, *59*(4), 1430–1450.

Floyd, S. W., & Wooldridge, B. (1997). Middle Management's Strategic Influence and Organizational Performance. *Journal of Management Studies*, *34*(3), 465–485.

Galbraith, J. R. (1973). *Designing Complex Organizations*. Addison-Wesley Longman Publishing Co., Inc.

Galbraith, J. R. (1974). Organization Design: An Information Processing View. *Interfaces*, *4*(3), 28–36.

Garicano, L. (2000). Hierarchies and the Organization of Knowledge in Production. *Journal of Political Economy*, *108*(51), 874–904.

Garicano, L., & Van Zandt, T. (2012). Hierarchies and the division of labor. In R. Gibbons & J. Roberts (Eds.), *The Handbook of Organizational Economics* (pp. 604–654). Princeton University Press.

Garicano, L., & Wu, Y. (2012). Knowledge, communication, and organizational capabilities. *Organization Science*, *23*(5), 1382–1397.

Graaff, J. de V. (1957). *Theoretical Welfare Economics*. Cambridge University Press.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*(Winter Special Issue), 109–122.

Gulati, R., Lawrence, P. R., & Puranam, P. (2005). Adaptation in vertical relationships: Beyond incentive conflict. *Strategic Management Journal*, *26*(5), 415–440.

Gulati, R., & Puranam, P. (2009). Renewal Through Reorganization: The Value of Inconsistencies Between Formal and Informal Organization. *Organization Science*, *20*(2), 422–440.

Gulati, R., Puranam, P., & Tushman, M. (2012). Meta-organization design: Rethinking design in interorganizational and community contexts. *Strategic Management Journal*, *33*(6), 571–586.

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review*, *32*(4), 1199–1228.

Hart, O., & Moore, J. (2005). On the Design of Hierarchies: Coordination Versus Specialization. *Journal of Political Economy*, *113*(4), 675–702.

Helfat, C. E., & Lieberman, M. B. (2002). The Birth of Capabilities: Market Entry and the Importance of Pre-history. *Industrial and Corporate Change*, *11*(4), 725–760.

Honore, F., & Ganco, M. (2016). Entrepreneurial Teams' Acquisition of Talent: A two-sided Approach. *CES Working Paper*.

Jain, A., & Mitchell, W. (2021). Specialization as a double-edged sword: The relationship of scientist specialization with R&D productivity and impact following collaborator change. *Strategic Management Journal*, *June 2019*, 1–39. https://doi.org/10.1002/smj.3357

Katila, R., & Ahuja, G. (2002). Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. *Academy of Management Journal*, *45*(6), 1183–1194. https://doi.org/10.2307/3069433

Klepper, S., & Simons, K. L. (2000). Dominance by birthright: Entry of prior radio producers and competitive ramifications in the U.S. television receiver industry. *Strategic Management Journal*, *21*(10–11), 997–1016.

Klimoski, R., & Mohammed, S. (1994). Team mental model: Construct or metaphor? *Journal of Management*, *20*(2), 403–437.

Kogut, B. (2000). The Network as Knowledge: Generative Rules and the Emergence of Structure. *Strategic Management Journal*, *21*(3), 405–425.

Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science*, *3*(3), 383–397.

Kogut, B., & Zander, U. (1996). What firms do? Coordination, identify, and learning. *Organization Science*, *7*(5), 502–518.

Kretschmer, T., & Puranam, P. (2008). Integration through incentives within differentiated organizations. *Organization Science*, *19*(6), 860–875.

Lawrence, M. (2018). Taking Stock of the Ability to Change: The Effect of Prior Experience. *Organization Science*, *29*(3), 489–506.

Lawrence, P. R., & Lorsch, J. W. (1967). Differentiation and Integration in Complex Organizations. *Administrative Science Quarterly*, *12*(1), 1–47.

Lewis, K., Lange, D., & Gillis, L. (2005). Transactive Memory Systems, Learning, and Learning Transfer. *Organization Science*, *16*(6), 581–598.

Liang, D. W., Moreland, R. L., & Argote, L. (1995). Group Versus Individual Training and Group Performance: The Mediating Role of Transactive Memory. *Personality and Social Psychology Bulletin*, *21*(4), 384–393.

March, J. G., & Simon, H. (1958). *Organizations*. John Wiley & Sons.

Marshak, J., & Radner, R. (1972). *Economic Theory of Teams*. Yale Press.

Mintzberg, H. (1979). *The structuring of organizations: A synthesis of the research*. Prentice-Hall.

Mood, C. (2010). Logistic regression: Why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, *26*(1), 67–82.

Moreland, R. L., & Myaskovsky, L. (2000). Exploring the performance benefits of group training: Transactive memory or improved communication? *Organizational Behavior and Human Decision Processes*, *82*(1), 117–133.

Muendler, M.-A., Rauch, J. E., & Tocoian, O. (2012). Employee spinoffs and other entrants: Stylized facts from Brazil. *International Journal of Industrial Organization*, *30*(5), 447–458.

Nelson, R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. The Belknap Press of Harvard University Press.

Nogueira Maciente, A. (2019). Occupations and Skills in the Formal Brazilian Labor Market. *Instituto de Pesquisa Econômica Aplicada, Unpublished Working Paper*.

O*NET Resource Center. (2021). *O*NET® Database Releases Archive*. https://www.onetcenter.org/db_releases.html

Penrose, E. (1959). *The theory of the growth of the Firm* (Issue June). Basil Blackwell & Mott Ltd.

Polanyi, M. (1966). The Logic of Tacit Inference. *Philosophy*, *41*(155), 1–18.

Postrel, S. (2002). Islands of shared knowledge: Specialization and mutual understanding in problem-solving teams. *Organization Science*, *13*(3), 303–320.

Pugh, D. S., Hickson, D. J., Hinings, C. R., & Turner, C. (1968). Dimensions of Organization Structure. *Administrative Science Quarterly*, *13*(1), 65–105.

Pugh, D. S., Hickson, D. J., Hinings, C. R., & Turner, C. (1969). The Context of Organization Structures. *Administrative Science Quarterly*, *14*(1), 91–114.

Puranam, P. (2018). *The Microstructure of Organizations*. Oxford University Press.

Puranam, P., Alexy, O., & Reitzig, M. (2013). What's "new" about new forms of organizing? *Academy of Management Review Forthcoming*.

Puranam, P., Raveendran, M., & Knudsen, T. (2012). Organization design: The epistemic interdependence perspective. *Academy of Management Review*, *37*(3), 419–440.

Puranam, P., Singh, H., & Chaudhuri, S. (2009). Integrating acquired capabilities: When structural integration is (Un)necessary. *Organization Science*, *20*(2), 313–328.

Reagans, R., Argote, L., & Brooks, D. (2005). Individual Experience and Experience Working Together: Predicting Learning Rates from Knowing Who Knows What and Knowing How to Work Together. *Management Science*, *51*(6), 869–881.

Rider, C. I., & Tan, D. (2015). Labor Market Advantages of Organizational Status: A Study of Lateral Partner Hiring by Large U.S. Law Firms. *Organization Science*, *26*(2), 356–372.

Romanelli, E. (1989). Environments and Strategies of Organization Start-Up: Effects on Early Survival. *Administrative Science Quarterly*, *34*(3), 369–387.

Sarada, & Tocoian, O. (2019). Is it all about who you know? Prior work connections and entrepreneurial success. *ILR Review*, *72*(5), 1200–1224.

Schelling, T. C. (1960). *The Strategy of Conflict*. Harvard University Press.

Shane, S., & Stuart, T. (2002). Organizational Endowments and the Performance of University Start-ups. *Management Science*, *48*(1), 154–170.

Simon, H. A. (1957). *Administrative Behavior: A Study of Decision-Making Processes in A dministrative Organization*. The Free Press.

Srikanth, K., & Puranam, P. (2014). The Firm as a Coordination System: Evidence from Software Services Offshoring. *Organization Science*, *25*(4), 1253–1271.

Teece, D. J. (1982). Towards an economic theory of the multiproduct firm. *Journal of Economic Behavior and Organization*, *3*(1), 39–63. https://doi.org/10.1016/0167-2681(82)90003-8

Thompson, J. D. (1967). *Organizations in Action*. McGraw-Hill.

Toh, P. K. (2014). Chicken, or the Egg, or Both? The Interrelationship Between a Firm's Inventor Specialization and Scope of Technologies. *Strategic Management Journal*, *35*, 723–738.

Tushman, M. L., & Nadler, D. A. (1978). Information Processing as an Integrating Concept in Organizational Design. *Academy of Management Review*, *3*(3), 613–624.

Van De Ven, A. H., Delbecq, A. L., & Koenig Jr., R. (1976). Determinants of Coordination Modes within Organizations. *American Sociological Review*, *41*(2), 322–338.

Weber, R. A., & Camerer, C. F. (2003). Cultural conflict and merger failure: An experimental approach. *Management Science*, *49*(4), 400–415.

Wegner, D. M. (1987). Transactive Memory: A Contemporary Analysis of the Group Mind. *Theories of Group Behavior*, 185–208.

Winkelmann, R. (2008). *Econometric analysis of count data* (5th edition). Springer Science & Business Media.

Zenger, T. R. (1992). Why Do Employers Only Reward Extreme Performance? Examining the Relationships Among Performance, Pay, and Turnover. *Administrative Science Quarterly*, *37*(2), 198–219.

Zenger, T. R. (1994). Explaining Organizational Diseconomies of Scale in R&D: Agency Problems and the Allocation of Engineering Talent, Ideas, and Effort by Firm Size. *Management Science*, *40*(6), 708–729.

Zhou, Y. M. (2013). Designing for Complexity: Using Divisions and Hierarchy to Manage Complex Tasks. *Organization Science*, *24*(2), 339–355.

Zimmerman, M., & Zeitz, G. (2002). Beyond Survival: Achieving New Venture Growth by Building Legitimacy. *Academy of Management Review*, *27*(3), 414–431.

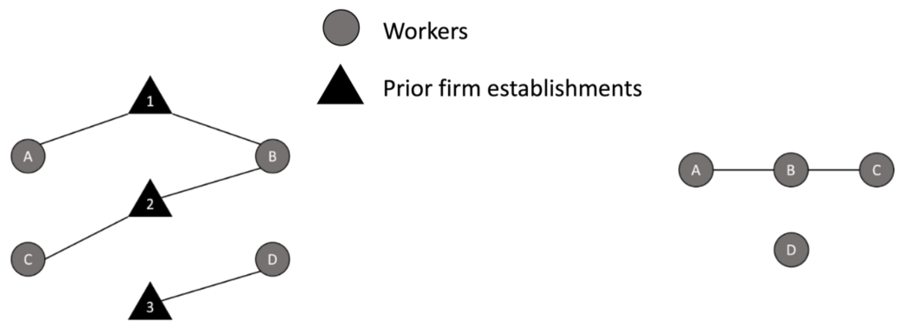
FIGURES

1. Senior members of government, leaders of companies, managers
    - 11. Senior members of government
    - 12. Heads of enterprises (other than public interest organizations)
        - 121. CEOs
        - 122. Directors of production and operations
            - 1221. Directors in agriculture, fisheries, aquaculture, and forestry
            - 1222. Directors and managers in the mining industry, processing, and public utilities
    - 13. Directors and managers in healthcare, education, or cultural, social, or personal services
    - 14. Managers
        - 141. Production and operations managers
            - 1411. Managers in agriculture, fisheries, aquaculture, and forestry
            - 1412. Managers in the mining industry, processing, and public utilities
            - 1413. Managers in construction
            - 1414. Managers of commercial operations and technical assistance
                - 141415. Store and supermarket managers
            - 1415. Managers of service operations in tourism, lodging, and restaurants
                - 141505. Hotel manager
        - 142. Managers of support areas
            - 1421. Administrative managers, financial, risk, and similar
2. Professionals in the arts and sciences
    - 21. Professionals in the hard sciences, physics, and engineering
    - 22. Professionals in biological sciences, health, and related fields

Note: This diagram illustrates the occupational hierarchy and the level of detail typical of occupation codes in RAIS. It is not a comprehensive listing of occupations because Brazil has more than 2,500 occupational codes. The word "director" in Portuguese (*diretor*) does not refer to the board of directors, but to upper-level managers. Readers interested in the complete hierarchy of occupation codes should consult the 2002 revision of the *Classificação Brasileira de Ocupações*, available from the Ministry of Labor at http://www.mtecbo.gov.br/cbosite/pages/home.jsf.

Figure 1. Illustration of the Occupation Hierarchy

Figure 2. 4-digit versus 6-digit *Distinct occupation* Expansion



(a) Prior experience (b) Shared experience connections

Note: Triangles represent establishments that employees A, B, C, and D worked at before joining a focal organization. Employee A worked at organization 1, B worked at organization s 1 and 2, and D worked at organization 3. These work experiences are shown in subfigure (a). The resulting connections between workers are depicted in subfigure (b), which has two connected components: one component linking A, B, and C through their shared experiences at organizations 1 and 2, and another, trivial, component consisting only of employee D, who did not work together with any other employees at prior organizations.

Figure 3. Measuring Shared Prior Experience

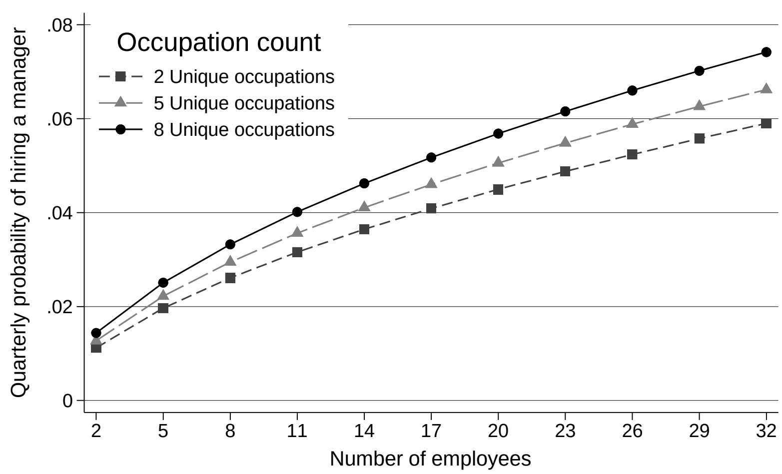
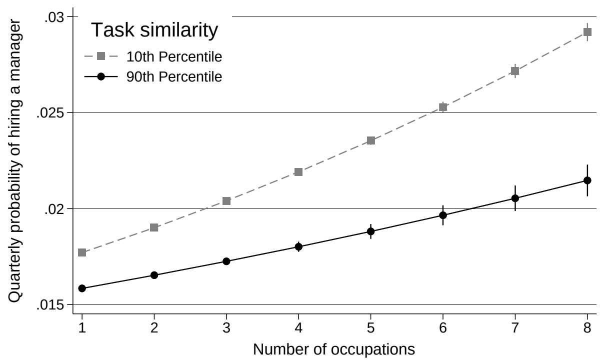
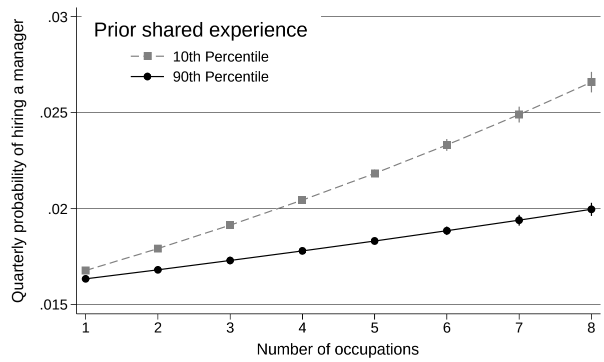


Figure 4. Size and Knowledge Scope Effects on Hierarchy Expansion



(a) Task Similarity Effect



(b) Shared Prior Experience Effect

Note: Vertical lines represent 95% confidence intervals. Some lines are smaller than corresponding points.

Figure 5. Knowledge Scope Effect for Varying Task Similarity and Shared Prior Experience

TABLES

Table 1. Summary Statistics

(a) Summary statistics, all quarters

Variable	Mean	SD	Percentiles 10th	25th	50th	75th	90th
Non-founder manager	0.16	0.86	0	0	0	0	1
Firm age (in quarters)	12.5	10.2	2	4	10	18	28
Ln employees	0.95	0.97	0.0	0.0	0.7	1.6	2.3
Ln founding team size	0.40	0.64	0.0	0.0	0.0	0.7	1.4
Multi-founder	0.35	0.48	0	0	0	1	1
Founder experience	3.71	4.28	0.0	0.3	2.3	5.6	9.8
Founder education	0.56	0.47	0	0	1	1	1
Distinct occupations	2.28	2.32	1	1	1	3	5
Task similarity	0.61	0.30	0.2	0.4	0.6	0.9	1.0
Shared prior experience	0.06	0.17	0.0	0.0	0.0	0.0	0.3
Founder prior wage	7.16	1,385	1.6	2.0	2.8	3.8	5.5

(b) Summary statistics, founding quarter

Variable	Mean	SD	Percentiles 10th	25th	50th	75th	90th
Ln employees	0.41	0.66	0.0	0.0	0.0	0.7	1.4
Ln founding team size	0.35	0.61	0.0	0.0	0.0	0.7	1.1
Multi-founder	0.31	0.46	0	0	0	1	1
Founder experience	3.77	4.39	0.0	0.3	2.3	5.6	9.9
Founder education	0.60	0.47	0	0	1	1	1
Distinct occupations	1.37	0.96	1	1	1	1	2
Task similarity	0.67	0.33	0.2	0.4	0.7	1.0	1.0
Shared prior experience	0.04	0.16	0	0	0	0	0
Founder prior wage	9.54	3,437	1.8	2.4	3.3	4.4	6.3

Note: "Founding quarter" refers to firms in their first quarter. See Section 3 for definitions of variables.

Table 2. Correlations

Variable		(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Firm age	0.170	-0.085	0.006	-0.069	0.167	-0.064	-0.050	-0.001
(2)	Ln employees		0.421	0.015	-0.080	0.744	0.011	0.318	0.000
(3)	Founder experience			-0.133	-0.111	0.270	0.051	0.166	0.000
(4)	Ln founding team size				-0.011	0.053	-0.049	0.148	0.001
(5)	Founder education					-0.020	-0.054	-0.072	0.000
(6)	Distinct occupations						-0.333	0.184	0.000
(7)	Task similarity							0.126	-0.001
(8)	Shared prior experience								0.000
(9)	Founder prior wage								

Note: Observations are firm-quarters for 2003Q1–2014Q4. See Section 3 for definitions of variables.

Table 3. Knowledge scope and hierarchy expansion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm age	-0.110	-0.111	-0.111	-0.111	-0.112	-0.112	-0.113	-0.113
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm age squared	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln employees	0.686	0.553	0.694	0.717	0.626	0.651	0.599	0.615
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Ln founding team size	-0.050	-0.046	-0.045	-0.047	-0.042	-0.043	-0.041	-0.042
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Founder experience	-0.011	-0.013	-0.013	-0.008	-0.011	-0.011	-0.011	-0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Founder education	0.235	0.226	0.229	0.231	0.222	0.221	0.22	0.219
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Founder prior wage								
1st Quartile	0.052	0.064	0.056	0.053	0.063	0.062	0.055	0.056
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2nd Quartile	0.144	0.156	0.147	0.149	0.157	0.157	0.148	0.148
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
3rd Quartile	0.201	0.208	0.199	0.205	0.206	0.206	0.197	0.197
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
4th Quartile	0.235	0.235	0.227	0.24	0.233	0.233	0.223	0.223
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
5th Quartile	0.303	0.285	0.282	0.308	0.281	0.28	0.273	0.273
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Distinct occupations		0.062			0.042	0.066	0.078	0.091
		(0.001)			(0.001)	(0.002)	(0.002)	(0.002)
Task similarity			-0.390		-0.229	-0.129	-0.161	-0.104
			(0.006)		(0.008)	(0.011)	(0.008)	(0.010)
Shared prior experience				-0.338	-0.289	-0.286	0.044	0.030
				(0.010)	(0.010)	(0.010)	(0.013)	(0.014)
Distinct occupations × Task similarity						-0.060		-0.036
						(0.004)		(0.005)
Distinct occupations × Shared prior experience							-0.102	-0.097
							(0.003)	(0.003)
Constant	-4.661	-4.571	-4.368	-4.641	-4.402	-4.479	-4.487	-4.529
	(0.061)	(0.061)	(0.062)	(0.061)	(0.062)	(0.062)	(0.062)	(0.062)
Firms	1,971,615	1,971,615	1,947,718	1,971,615	1,947,718	1,947,718	1,947,718	1,947,718
Observations	18,933,056	18,933,056	18,566,690	18,933,056	18,566,690	18,566,690	18,566,690	18,566,690

Note: Table shows coefficients from the survival model for hiring the first non-founder manager. All models include month, industry, and micro-region fixed effects. Standard errors in parentheses are clustered by firm.

Table 4. Average predictive margins

	Percentiles					
Continuous variable	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	$90^{th} – 10^{th}$
Firm age	3.42	2.58	1.73	1.10	0.90	-2.52
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Ln employees	1.15	1.15	1.47	2.22	3.18	2.03
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
Ln founding team size	1.93	1.93	1.93	1.85	1.83	-0.11
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Founder experience	1.95	1.94	1.90	1.84	1.77	-0.19
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Founder education	1.66	1.66	1.91	2.05	2.05	0.39
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Distinct occupations	1.66	1.66	1.76	1.86	2.08	0.42
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Task similarity	2.04	1.94	1.84	1.71	1.71	-0.33
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
Shared prior experience	1.97	1.97	1.97	1.97	1.75	-0.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)

Categorical variable	1st Quintile	2nd	3rd	4th	5th	5th–1st Quintile
Founder prior wage	1.72	1.88	1.97	2.02	2.12	0.40
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Note: Numbers reflect the average, quarterly hazard rate (multiplied by 100) at various points on the distribution for each variable. For example, the number 1.15 for *Ln employees* implies that if all sample firms were moved to the 10th percentile of the firm size distribution—holding all other variables constant—then 1.15% of them would hire a manager each quarter. Estimates are based on Model 8 of Table 3. Standard errors in parentheses are calculated using the delta method. All differences in the final column are statistically significant at the 0.01 level.

TABLE 5. Effects of size and knowledge scope on hired manager attributes

Dependent variable:	Prior Firm Size	Prior Jobs	Prior Firm Size	Prior Jobs
	(1)	(2)	(3)	(4)
Ln employees	0.111	0.077	0.129	0.088
	(0.012)	(0.002)	(0.012)	(0.002)
Ln distinct occupations	0.000	0.071	-0.012	0.057
	(0.016)	(0.003)	(0.016)	(0.003)
Firm age			-0.014	-0.016
			(0.003)	(0.000)
Firm age squared			0.000	0.000
			(0.000)	(0.000)
Ln founding team size			-0.030	-0.021
			(0.010)	(0.002)
Founder experience			-0.000	0.006
			(0.002)	(0.000)
Founder education			0.095	0.060
			(0.017)	(0.003)
Founder prior wage				
1st Quartile			-0.022	0.063
			(0.026)	(0.005)
2nd Quartile			-0.005	0.107
			(0.025)	(0.005)
3rd Quartile			0.065	0.124
			(0.026)	(0.005)
4th Quartile			0.042	0.144
			(0.027)	(0.005)
5th Quartile			0.125	0.170
			(0.027)	(0.005)
Constant	8.709	0.924	8.700	0.882
	(0.014)	(0.002)	(0.027)	(0.005)
Observations	462,633	462,633	462,633	462,633
Psuedo-R^2	0.050	0.040	0.052	0.048

Note: Dependent variable *Prior Firm Size* is the largest firm a manager previously worked in. The dependent variable *Prior Jobs* is the number of unique, non-managerial occupations previously held by the manager.

Table 6. Average predictive margins for alternative samples

	Percentiles					
	10th	25th	50th	75th	90th	90th – 10th
Distinct occupations						
Limited liability corporation	1.75	1.75	1.85	1.95	2.17	0.41
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)
No more than 100 initial employees	1.67	1.67	1.76	1.86	2.08	0.41
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
No more than 10 initial employees	1.67	1.67	1.76	1.86	2.08	0.41
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
External manager only	1.38	1.38	1.46	1.55	1.73	0.35
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Task similarity						
Limited liability corporation	2.16	2.05	1.93	1.78	1.78	-0.38
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
No more than 100 initial employees	2.04	1.95	1.84	1.71	1.71	-0.33
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
No more than 10 initial employees	2.04	1.94	1.84	1.71	1.71	-0.33
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
External manager only	1.74	1.64	1.54	1.40	1.40	-0.34
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Shared prior experience						
Limited liability corporation	2.06	2.06	2.06	2.06	1.83	-0.23
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
No more than 100 initial employees	1.97	1.97	1.97	1.97	1.75	-0.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
No more than 10 initial employees	1.97	1.97	1.97	1.97	1.75	-0.22
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
External manager only	1.64	1.64	1.64	1.64	1.47	-0.17
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Note: Table shows average predictive margins for varying levels of knowledge scope, task similarity, and shared prior experience, using alternative samples and dependent variables. *Limited liability corporation* limits the sample to limited liability companies. *No more than 100 initial employees* limits the sample to companies with 100 or fewer employees at the time of founding, and *No more than 10 initial employees* limits the sample to companies with 10 or fewer employees at the time of founding. *External manager only* uses hiring of the first manager from outside the firm—excludes people internally promoted to manager—as the dependent variable. Standard errors in parentheses are calculated using the delta method. All differences in the final column are statistically significant at the 0.01 level.