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Division of Labor Through Self-Selection

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Abstract. Self-selection–based division of labor has gained visibility through its role in varied organizational contexts such as nonhierarchical firms, agile teams, and project-based organizations. Yet, we know relatively little about the precise conditions under which it can outperform the traditional allocation of work to workers by managers. We develop a computational agent-based model that conceives of division of labor as a matching process between workers' skills and tasks. This allows us to examine in detail when and why different approaches to division of labor may enjoy a relative advantage. We find a specific confluence of conditions under which self-selection has an advantage over traditional staffing practices arising from matching: when employees are very skilled but at only a narrow range of tasks, the task structure is decomposable, and employee availability is unforeseeable. Absent these conditions, self-selection must rely on the benefits of enhanced motivation or better matching based on worker's private information about skills, to dominate more traditional allocation processes. These boundary conditions are noteworthy both for those who study as well as for those who wish to implement forms of organizing based on self-selection.

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Q: 5, 6 In formal organizations, the division of labor is a centralized process in which managers exercise the right to design tasks, as well as the right to assign tasks to workers (Simon 1951). The traditional version of this process is embodied in staffing practices that follow a typical sequence: analyze the task structure, design positions according to job analysis, make a job evaluation and assess the availability of current employees (or post a call to get external applicants), and then, select the most fit individual (Baron and Kreps 1999, chapter 14). In broad terms, this process is characterized by the attempt by managers to match the best-available individual to vacant tasks as soon as possible.

Q: 7 Yet, a notable trend in today's business world is to
Q: 8 allow individuals to self-select into their tasks. There are an increasing number of prominent instances in which the principle of self-selection by individuals has replaced traditional staffing processes as the basis for division of labor within a firm (Puranam et al. 2014). Self-organizing teams (Laloux 2014), less hierarchical firms (Lee and Edmondson 2017), and holacracies (Robertson 2015, Bernstein et al. 2016) all incorporate this element, in addition to well-known instances outside firms such as open-source software development (Von Hippel and von Krogh 2003, Shah 2006) and problem-solving contests (Jeppesen and Lakhani 2010).

In principle, division of labor through self-selection Q: 9, 10
depicts individuals who select tasks (based on their skills) that in their understanding contribute to the overall goals of the team or organization. The scope of application of self-selection–based division of labor within firms can vary, ranging from the entire workforce (e.g., all teams at the Dutch nursing services provider Buurtzorg or at the United States-based video game developer Valve) (Laloux 2014, Puranam and Håkonsson 2015) to organizing particular project teams (e.g., in global management consultancies such as McKinsey or BCG or in "agile" software development teams). For example, in Buurtzorg's nursing services organization, teams of 10–15 nurses self-select tasks within their district. The team manages and conducts all tasks from providing at-home care to hiring, administration, scheduling, and training, and each nurse can choose which portfolio of activities to take on (Laloux 2014). As a result, tasks are created and "crafted" (Wrzesniewski and Dutton 2001) by the individual team members, and task definition and scope can differ across teams in different locations.

Proof Only

At Valve or the French auto-component maker FAVI, self-selection occurs at two levels—into particular project teams as well as into particular tasks within a team (Laloux 2014, Puranam and Håkonsson 2015, Bernstein et al. 2016). Despite these variations, what is common across these instances is the existence of self-selection into tasks by employees based on their own perceptions of best fit (Lee and Edmondson 2017; also see Robertson 2015 on holacracy).

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However, we believe it is hardly time to bring the curtain down on traditional staffing processes in organizational hierarchies, in which managers with the authority to do so decide how to allocate work among employees. Even scholars who are intrigued by self-organizing processes as alternatives to hierarchical structures are nonetheless careful to note that the latter are still the dominant form in the economy today and continue to flourish even in innovation-intensive sectors (Puranam et al. 2014, Lee and Edmondson 2017, Freeland and Zuckerman 2018). In this research, we theorize about the conditions under which self-selection would outperform traditional staffing processes as a basis for division of labor.

When managers allocate work to workers, a degree of sacrifice by workers of discretion regarding task selection is presumed (Simon 1951). This sacrifice is compensated through extrinsic motivators such as cash, status, power, and promotion opportunities. It follows that if individuals can gain intrinsic motivation, such as greater task enjoyment, fulfilling use needs, or achieving recognition and reputation through self-selection into tasks (Von Hippel and von Krogh 2003, Lee and Edmondson 2017), then the need for these extrinsic motivators should decline. Thus, one benefit of self-selection could simply be greater motivation. Similarly, the observability of skills should surely matter because in many situations, the worker knows her own skills better than any manager can observe (e.g., Spence 1973, Salop and Salop 1976). In such cases, self-selection should produce a better match between employees and the work they do, as long as employees are incentivized to select work they are competent at (Rullani and Haefliger 2013, Haas et al. 2015).

Motivation and observability of skill are intuitive considerations at the individual level that help explain the advantages of self-selection. However, as we argue, division of labor is essentially a matching process between workers and the work they do. Which matches occur and their resulting value should therefore depend not only on these *individual* attributes but also, on the *relational* attributes of workers and tasks with respect to each other. Factors such as the distribution of skills among workers (e.g., Von Krogh et al. 2003) and the interdependence between the tasks they select (Baldwin and Clark 2006), as well as the constraints on the matching process in terms of simultaneous or serial availability of workers and work to be matched (e.g., Cohen et al. 1972), should thus play a significant role in understanding the conditions under which self-selection is beneficial (Baldwin 2015, Zenger 2015).

The complexity involved in how these factors interact to shape the allocation process is considerable, pointing to the limits of verbal theorizing. Thus, although it is obvious that autonomous individual choices of tasks may enhance motivation and exploit superior private information about own skills for employees, how (and when) these are offset by the advantages of decision makers who can take an organization-level view of possible matches between available work and available workers, under varying conditions of decomposability, specialization regimes, and availability of work and workers, is less obvious.

We build a computational agent-based model to examine under what conditions different approaches to division of labor may enjoy a relative advantage. We compare a procedure in which employees freely pick the tasks they are best skilled at (a stylized representation of self-selection) with one in which each vacant task is filled with the best-skilled available employee (a stylized representation of traditional staffing policies). Given the same set of employees and tasks, we compare how the two procedures differ in terms of aggregate task performance, task completion, and match quality. In our analysis, we hold observability and motivational effects constant by assuming that the productivity of an employee in a task is easily observable and does not depend on the allocation regime.

We find that letting employees pick the tasks they are most skilled at is advantageous in regimes involving staffing for growth (i.e., all tasks are available, but employees become available at unforeseen times—as is typical in project-based organizations), with strong specialization (i.e., where most employees are very skilled at a few tasks each) and low interdependence (i.e., where each task contributes independently to overall performance). If these conditions do not hold, self-selection can only be advantageous through motivational effects, by overcoming observability challenges, or both. Note that although staffing by vacancy filling and task self-selection is usually associated with different governance modes (such as authority versus decentralized self-organization), in our model we are comparing paradigmatic task assignment procedures and not governance modes (one might find examples of self-selection within a hierarchical governance system and centralized traditional allocation among nonhierarchical collectives).

As we show by comparison with an ideal benchmark that features optimal allocation under complete information, both procedures noted suffer from important coordination problems. Workers allowed to pick their own tasks may suffer from interpersonal coordination failure as each worker selects his most preferred task myopically; this leaves some tasks unallocated and others overstaffed. In contrast, the procedure that fills vacant tasks with the best-available employee suffers from a form of intertemporal coordination failure as it may end up blocking better future matches by irreversibly matching the available tasks and employees today. Surprisingly, these coordination problems result in different performance consequences across the two allocation procedures, creating conditions under which one can outperform the other. Although our exercise is purely theoretical, we show that the baseline results appear to have face validity when considering some of the exemplar organizations that use self-selection as a basis for division of labor (e.g., Laloux 2014, Lee and Edmondson 2017).

We also consider modifications to the procedures that mitigate their respective coordination failures. By allowing managers to defer allocation or to allocate employees to tasks where their added value is highest (including possibly to already staffed tasks), traditional staffing processes that follow the norm of only filling vacant tasks with best-available employees could be improved upon. Conversely, developing norms that encourage employees to pick tasks where they can make the biggest difference or to avoid crowded tasks can improve on self-selection processes that simply let employees pick what they are most skilled at.

We conclude that the enthusiasm for self-managed and nonhierarchical forms of organizing that emphasize self-selection must be tempered by a consideration of our results. Our results may also indicate areas that currently do not use self-selection but could gain from doing so. The contribution of our analysis is to offer a formal conceptualization of division of labor as a matching process and to identify a trade-off between interpersonal and intertemporal coordination failures. The latter helps understand the conditions under which self-selection may prove superior to more traditional allocation processes and suggests ways to improve both processes. We also suggest directions for future theoretical development as well as possible refinements to practice involving the trade-offs between different approaches to task allocation.

The rest of this paper is organized as follows: we first review prior literature on self-selection and its individual-level and relational attributes and explain our view of the division of labor in terms of a matching problem with unique features. We then describe our model and report our key result about the trade-off between interpersonal and intertemporal coordination failures. We then examine modifications to the basic processes that may mitigate their respective coordination failures. Finally, we discuss three contingencies (skill observability, task interdependence, and the size of the talent pool) to study the impact of key contextual features that should affect division of labor. Our analyses give rise to a number of findings amenable to future empirical tests, possibly through (field and laboratory) experiments. We conclude with a discussion of our results and implications for future research.

Division of Labor Through Self Selection: Prior Literature

Self-selection is a central feature of various forms of nonhierarchical organizing both within firms (Laloux 2014, Puranam and Håkonsson 2015, Bernstein et al. 2016) and outside firms (Von Hippel and von Krogh 2003, Shah 2006). Under self-selection, by definition, contributors select for themselves what tasks (or bundles of tasks constituting a "role" or a "job") to perform, rather than being assigned to their tasks or job by hierarchical processes (Kogut and Metiu 2001, Baldwin and Clark 2006).

Individual-Level Attributes: Motivation and Observability of Skills

Researchers have noted that self-selection has the obvious benefit of enhanced motivation. For example, some of the reasons for contribution through self-selection in online communities include satisfying a quest for learning, gaining recognition and visibility, fulfilling use needs, and personal enjoyment (Lerner and Tirole 2002, Lakhani and Wolf 2005). Contributors' choices in a self-selection regime reflect their own needs, skills, and preferences in terms of where to contribute (Wasko and Faraj 2000). Because an individual's skills are not always easily observed by others (e.g., Spence 1973, Salop and Salop 1976), managerial allocation of workers to tasks may not produce an accurate match. This gives self-selection an advantage when the worker presumably knows his or her own skill better than an external observer would (e.g., Rullani and Haefliger 2013, Haas et al. 2015).[1]

Higher job motivation and better match between individual skills and tasks have also been observed when self-selection occurs during the course of job crafting—the process through which individuals alter the task, relational, and cognitive boundaries of their jobs (Wrzesniewski and Dutton 2001). Job crafters alter their tasks—whether formally or informally—thus incorporating an element of self-selection into their sphere of responsibilities (Berg et al. 2010b). Self-selecting into crafted tasks enables job crafters to contribute to their organization in ways that their formal job does not anticipate and simultaneously enables job crafters themselves to learn new skills or apply skills they own but rarely get to exercise (e.g., Berg et al. 2010a, b). As a result, job crafting has been positively linked with increased job satisfaction (a sense of personal fulfillment derived from the job), job effectiveness (a person's ability to fulfill the goals and expectations of her job), organizational commitment (a person's psychological attachment to the organization), work engagement (a positive state of mind while performing the job), and an enhanced sense of self-worth (Ghitulescu 2007, Bakker et al. 2012, Wrzesniewski et al. 2013).

Although the match of skill to tasks is also important in traditional staffing processes, the match between workers' intrinsic enjoyment of a task and their allocated task may not be particularly high. The payment of salary is in part precisely a compensation for this (e.g., Simon 1951). Further, managers may not be able to observe worker skills as well as workers themselves do. As a consequence, two important benefits of self-selection that arise from individual-level attributes are a higher level of motivation and greater alignment between skills and tasks than what
Q: 12 would be obtained under authority-based allocation (Lakhani and Von Hippel 2003, Laloux 2014, Lee and Edmondson 2017).

Relational Attributes: Specialization and Interdependence

The benefits from enhanced motivation as well as superior self-assessment of skill (relative to a third-party allocator, such as a manager) are both instances of individual characteristics that give self-selection an advantage over traditional staffing processes. However, division of labor is a matching process that matches individuals to tasks (or bundles of tasks combined into a role or a job). This suggests that the relational attributes of both workers and tasks (and not only their individual attributes) should also play an important role in determining when self-selection enjoys an advantage. However, although there are hints of what such factors might be in prior literature, particularly based in the open-source software development context, we do not yet have a definitive analysis that is more generally applicable beyond this context.

For instance, specialization is both an antecedent and a consequence of the division of labor (Smith 1776) and has both individual-level and relational aspects. As an individual-level attribute, it refers to the attainment of higher skill on some tasks by some workers, mainly through focus and repetition (Becker 1962). If we consider an individual's skills across multiple tasks, increasing specialization implies an increase in skill at a few tasks at the expense of most others. Thus, highly specialized individuals tend to be skilled at fewer tasks, whereas generalists tend to have more moderate skills at a greater number of tasks (Teodoridis 2018).

Researchers studying open-source communities have speculated that self-selection is aided by high levels of specialization in skills among workers. Specialization may enable entry into the community by letting individuals make specific focused contributions (e.g., Wasko and Faraj 2000, Von Krogh et al. 2003). This assumes that workers are specialized before self-selecting into tasks. Alternatively, workers might start out with equal skills for all tasks but different preferences. Task selection would, in this case, be driven by preferences, and specialization would develop endogenously via learning by doing.

Further, specialization also has important relational attributes. Unless every individual is uniquely highly skilled at a distinct task, a consideration of the relative skills of individuals across a set of tasks should also play an important role in allocation of tasks to individuals. Such a consideration may not arise naturally in self-selection because it typically ignores information about the suitability of other workers for the task that a worker selects. When worker X selects task 1, it is because for X, his or her own skills are best suited to task 1. Because of self-interest or myopia, X does not consider the possibility that another worker may in fact be better suited to undertake task 1 than X. This can occur because of nonsimultaneous entry—as in project initiation at Valve, which consciously mimics open-source processes (Baldwin 2015, Zenger 2015). However, even when all employees are simultaneously present (as when a team decided on how to self-allocate tasks among themselves) (e.g., Raveendran et al. 2016), there is a significant collective action problem: optimal matching of tasks and employees requires coordination such that some employees end up with suboptimal (for them) tasks in order to maximize overall skill values. This problem can be the result of imperfect alignment of interests, of inability to communicate information about relative expertise, or both. The evidence on teams is quite conclusive that such problems are very common indeed (e.g., expertise recognition) (Littlepage and Silbiger 1992, Littlepage et al. 1997, Argote and Ren 2012, Argote and Fahrenkopf 2016). It may therefore be useful to understand the relational implications of specialization beyond the individual, specifically how the relative skill distributions of individuals may affect self-selection for a given regime of specialization. Q: 13

Second, the nature of linkages between tasks is potentially an important relational attribute that should shape the efficacy of matching. In the context of open-source software communities, relatively low levels of interdependence between tasks (i.e., task structure decomposability) have been argued to allow for parallel and distributed (i.e., nonphysically collocated) work (Kogut and Metiu 2001, p. 258) as well as attract contributions because of the possibility of exchange and reuse of work among contributors (Baldwin and Clark 2006, p. 1116). However, these effects may well be idiosyncratic to open-source software development, as more generally self-selection does not need to involve either distributed work or exchange/recombination of contributions; for example, Buurtzorg's nursing delivery system relies on self-selection for team organization, yet team members are collocated, and the core tasks—in-home patient visits—cannot be recombined.

Further, in the case of open-source software development, the founders do *not* lay out a fully specified task structure as a menu from which subsequent entrants choose tasks. Instead, the very act of selecting what to do may specify the task division, just as the slices of a cake become defined as individuals cut themselves portions. Thus, tasks can remain latent and undefined until they are instantiated through the interest of a contributor with the requisite skills and motives to contribute (Lakhani and Panetta 2007). How individuals self-select some tasks therefore may also shape the interdependence between those and remaining clusters of tasks. However, the bundling of elementary tasks may be independent of the self-selection of the job to execute. In a more general setting, we could imagine a separation between task division—which may be authority based—and task allocation—which can occur through self-selection.

In sum, we know that division of labor through self-selection appears to differ from traditional allocation of workers to tasks in terms of the freedom to independently choose tasks that are deemed suitable for self (versus having them allocated by another individual such as a manager) and the consequent benefits to motivation and observability of skills that arise. On the flip side, employees may be less coordinated in self-selection, compared with traditional staffing processes in which the authority to make decisions about allocating individuals to tasks based on organization-level considerations is invested in managers. To understand the implications of these differences, we first develop the idea of division of labor as a matching process. This then sets the stage for the analysis of the conditions under which self-selection, despite being less coordinated, may nevertheless outperform traditional staffing processes.

Division of Labor as a Matching Process with Unique Attributes

Although it is intuitive to consider procedures for conducting division of labor as types of matching processes between tasks and workers, there are also significant differences between them as well as from matching problems in general. An extensive literature on matching exists in economics and operations research, starting from the seminal contribution of Gale and Shapley (1962). Algorithms have been developed in economics to solve matching problems, often grounded in rigorous mathematical analysis (for a review, see Niederle et al. 2008). In operations research, there is also a tradition of analyzing sequential matching problems that began with Derman et al. (1972) and Albright (1974) (also see Bearden et al. 2005, Chun and Sumichrast 2006). There are three unique features of division of labor within organizations that make the insights of these prior matching models a useful reference point rather than a complete solution: multidimensional skills, serial entry with limited information, and switching costs.[2]

First, employee skills are multidimensional (Becker 1962). Each employee can be skilled at multiple tasks but to varying degrees (e.g., Teodoridis 2018, Teodoridis et al. 2018). The distribution of employee's skills across tasks can vary across different regimes of specialization. For instance, individual workers will differ in their skills across tasks (intraagent specialization), and workers will also differ in the tasks for which they are best skilled (interagent specialization). In the limit, if each agent is maximally skilled at a single task that no other agent is maximally skilled at, then matching between tasks and agents would be trivial under almost any procedure. However, in the more general case of varying distributions of skills across tasks for agents (i.e., different regimes of specialization), the nature of these distributions is likely to be a critical parameter in the process of division of labor (Smith 1776, Mintzberg 1979). Prior matching models do not accommodate the comparative study of different allocation procedures under different regimes of specialization, conceptualized as varying skill distributions over multiple tasks.

Second, the serial and unforeseeable entry of employees and tasks into the system makes the problem different from the matching processes typically modeled, where both sides of the matching process are simultaneously present or if arriving sequentially, they do so with a known arrival distribution. In practice, it is often the case that tasks become available for allocation in an unforeseeable sequence (e.g., a basic HR process in most large corporations involves staffing newly vacated or created positions), employees "come off" other projects and become available to work on new projects in an unforeseeable sequence (e.g., in project-based software and R&D organizations), or both. As we will elaborate, nonsimultaneous and unforeseeable arrival of tasks and employees has different and surprising performance implications across different task allocation processes.

Third, in the case of division labor, switching costs are significant, and matches cannot easily be unmade. In the original discussion by Adam Smith (1776), three benefits of the division of labor in the pin factory were described: the improved productivity of the worker, the saving in time lost in switching tasks, and the development of new methods of working (including mechanization) arising from specialization. Mintzberg (1979, p. 70) noted that at the root of all three benefits is repetition: in particular, repetition of a task cluster that requires similar inputs of skill and efforts, which consequently entails narrow cognitive scope and allows rapid amortization of fixed costs. Put differently, switching can entail significant opportunity costs, lessening the advantages of division of labor, and may therefore not be feasible. In addition to these efficiency-based arguments, organizations likely take motivational consequences of task switching into account (e.g., the effect on employees of being replaced by better-performing colleagues).

In the next section, we describe an agent-based model of division of labor as a matching process that is sensitive to these issues.

Model Description

In our model, we compare two archetypical arrangements for division of labor: process "A" is a stylized representation of what one may observe in a traditional staffing process. A structure of tasks (we use this synonymously with jobs or roles, for our purposes) exists and is typically the result of formal design efforts around task structure and role specification. The consequences of different ways of defining the structure of tasks are expressed indirectly in our model in terms of attributes such as interdependencies between tasks and the resulting distribution of skills for tasks across employees. As tasks become available, either through new job creation or turnover, the allocator (e.g., the HR department) assesses the available labor pool internally and externally (e.g., by posting advertisements and reviewing candidates). The allocator's objective is to fill the vacancy as soon as possible picking the best-available candidate (i.e., the candidate with the highest skill for the task) from among available workers (e.g., Chadwick and Dabu 2009, Ethiraj and Garg 2012). Process A can therefore be characterized as one in which the allocator is aiming to "fill every vacancy with the best-available person."

Process "B" is a stylized representation of self-selection, in which employees are free to choose from the set of jobs or tasks based on personal preference. We assume that employees' skills align with their preferences (i.e., that employees prefer tasks for which their skill value is high (we also explore alternatives later)). If the tasks have been predefined, employees select their preferred task among all the tasks (irrespective of others' choices); if the task structure is ill defined, employees create their own task and thus, create the emergent task structure though their choices. The consequences of different ways of "carving up" the structure of tasks are expressed indirectly in our model in terms of attributes such as interdependencies between tasks and the resulting distribution of skills for tasks across employees. The key feature of process B is that all employees pick their tasks independently, without consideration of organization-level implications or the suitability of other employees for the task that they themselves select; each allocator (employee) is therefore free to "pick what they like."

In our baseline analysis, all other features are kept constant between processes A and B (for a summary, see Table 1). The costs of switching are assumed to be high enough to make allocations irreversible. Further, the individual-level attributes of motivation and observability of skills are held constant: we do not assume any information asymmetry between the allocator and employees in terms of assessing skill for a task, and worker productivity is assumed to be the same for a task in either allocation process. We assume that all allocators (whether employees or managers) are able to observe which tasks have already been staffed.

Task Environment

In our model, the task environment is characterized by a set of N tasks. These tasks can be interpreted as individual tasks or clusters of tasks bundled together into jobs or roles—we will refer to them as *tasks* for brevity, but the conclusions apply equally to settings where these tasks capture jobs or roles. Tasks are chosen by or allocated to M employees. In the baseline setting, we also assume that there is low interdependence between tasks. (Please refer to the appendix for information on technical details of the model.)

Timing of Task and Employee Availability. An important source of variation in the task environment is the timing of the availability of tasks and employees. A possible situation is one where all tasks in a project, as well as all employees available to work on it, are visible and can be *simultaneously* compared by an allocator in order to find matches. The initiation of a new project with a given set of employees is an instance of such a situation (it is equivalent to costless

Table 1. Baseline Assumptions About Different Archetypes of Division of Labor

Modeled allocation process	Empirical phenomenon	Unique assumptions	Common assumptions
Process A: allocator is aiming to "fill every vacancy with the best-available person"	Traditional staffing (e.g., typical HR process)	Allocator fills every vacancy with a person, by picking best-available employee for that task	1. High switching costs prevent reshuffling
Process B: each allocator is free to "pick what they like"	Self-selection–based allocation (e.g., self-organizing teams)	Allocator picks best-available task for themselves ignoring other workers' skill values	2. No periods without allocation 3. Arrival of task/employee is not foreseeable 4. Skills of available employees are visible to everyone 5. Allocations are visible to all

reshuffling of employees to tasks whenever a better match arises—something that is in practice ruled out by switching costs). The polar opposite case is the one where the tasks and employees arrive in random order (for simplicity, we assume one at a time). This is equivalent to a random pairing up of tasks with employees with no consideration of skills and specialization (Cohen et al. 1972, Lomi et al. 2012). This *garbage can* situation provides another benchmark for comparison. Neither is likely to be very realistic, with more typical situations involving project *growth* as employees become available at different and unforeseeable moments to staff a known set of tasks or *replacement* situations, where employees are selected from a known pool to staff tasks that fall vacant at unforeseeable points in time.[3] These four cases are summarized in Table 2 and illustrated in Figure 1.

Specialization Regime

We examine how performance in different allocation processes differs across specialization regimes. In high-specialization regimes, all employees tend to be highly skilled at relatively fewer tasks; which of the N tasks each employee is best at differs across employees and is determined randomly. In low-specialization regimes, employees are about equally skilled at all tasks, but the absolute level of skill at any task is lower, capturing the trade-off in skill between specialists and generalists (Becker 1962). We model this through a skill distribution for every employee in which their skills across all tasks sum to one, yet they have a nonzero skill value for each task. The overall shape of the distribution is the same for all employees within a regime, but across employees, the location of the peak skill differs randomly. By altering the shape of the distribution for all employees from flatter to more peaked, we can model regimes of low or high specialization. By modeling specialization regimes in this way, we ensure that each employee has the same degree of specialization in a given regime (intraagent specialization is the same for all agent) while allowing variation in interagent specialization (in which task each agent is best at).

For instance, assume that skill values in a specialization regime are drawn from a normal distribution, with mean = 0 and standard deviation $\sigma = 1$. We can take advantage of the reshaping of the curve with changes in the standard deviation $\sigma \in (0,1)$. As σ increases, the curve flattens, which captures lower specialization (Figure 2, panel (a)); as σ decreases, the curve steepens, which captures higher specialization (Figure 2, panel (b)). To generate each employee's skill values within a given specialization regime, we sample x values from that reshaped normal distribution at a fixed interval from the mean and normalize the resulting values to sum to one. This results in skill values denoted by s that are all quite close together for low-specialization regimes ($s1$, $s2$, $s3$ in Figure 2(a)). In contrast, in high-specialization regimes the difference between skill values across tasks for the same individual is initially large ($s1$, $s2$, $s3$ in Figure 2(b)). Figure 2 only illustrates how three skill values are drawn—for the model, we draw $N = 50$ skill values and normalize all 50 skill values to sum to one. Figure 2, panel (c) shows that the difference in skill values between each employee's best and worst

Table 2. Variations in the Timing of the Availability of Tasks and Employees

	All employees are simultaneously available	Employees become available in unforeseeable order
All tasks are simultaneously available	*Case I: simultaneous* (e.g., starting a new project with a team of available employees)	*Case II: growth* (e.g., projects grow in staff as employees become available)
Tasks become available in unforeseeable order	*Case II: replacement* (e.g., staffing a position that becomes vacant)	*Case IV: "garbage can"* (e.g., projects are staffed based on random availability of tasks and employees)

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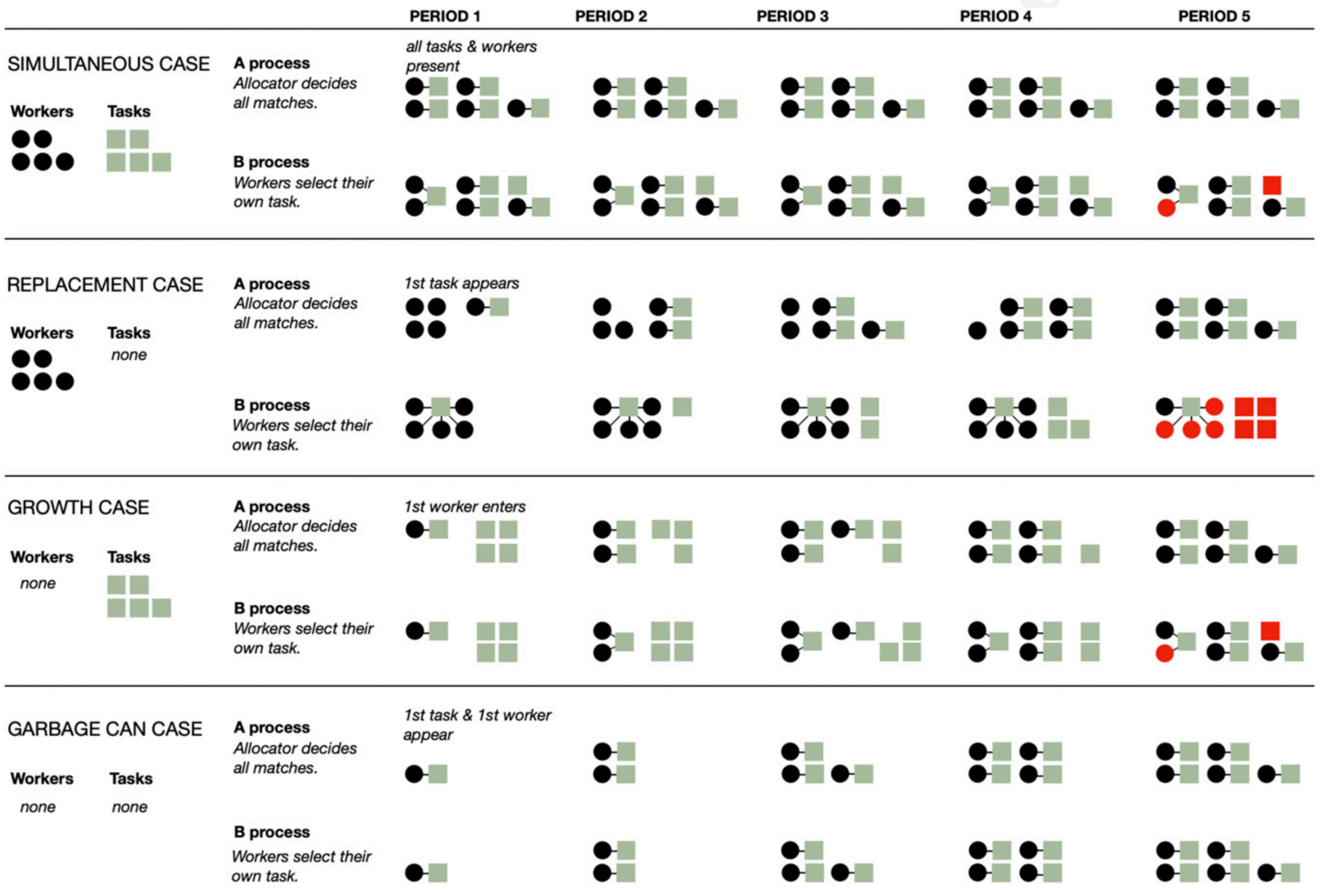
Figure 1. (Color online) Task Allocation Across Four Cases of Task and Employee Availability

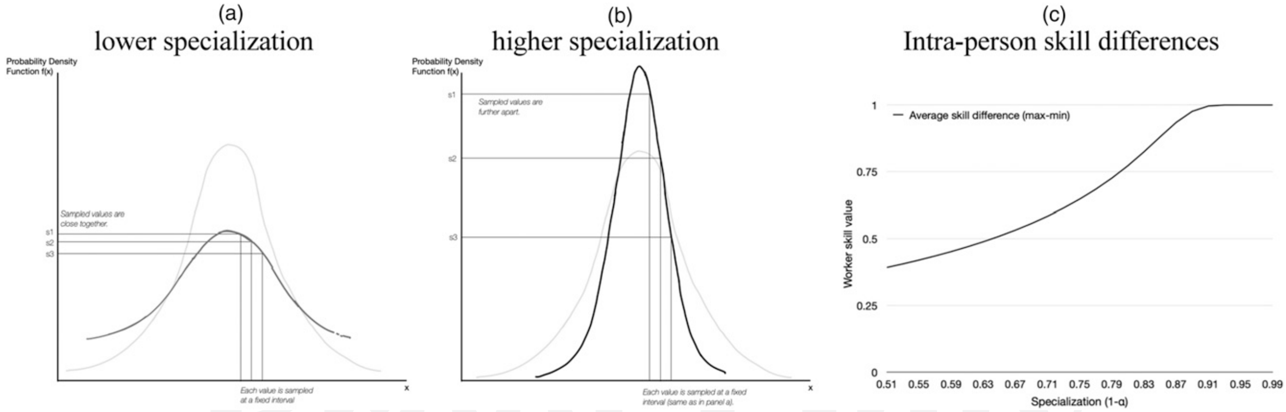


Notes. This figure shows the intuition of how task and employee availability affect the different task allocation processes with five tasks and five workers. On the far left, we show what is available for each case at the start: how many workers (black circles) and how many tasks (green squares). For example, in replacement, we start with all workers and zero tasks; in garbage can, we start with no workers and no tasks. For each case, we then show period by period how task allocation or self-selection unfolds. In our model, all four cases are based on the same underlying task structure; this means that the workers and the allocator make their decisions in each of these four cases based on the identical underlying skill distributions. At the end of some of these cases, some tasks are overstaffed (indicated by any red circles connected to the same one square), whereas some tasks are left unallocated (indicated by red unconnected squares).

task is very high (close to 1) for high-specialization regimes and significantly lower (under 0.4) for low-specialization regimes.

The parameter σ in the normal distribution thus tunes the nature of a regime of specialization, rather than the skills of any particular employee: at high

Figure 2. (Color online) Modeling Specialization Using the Normal Distribution



Notes. (a) Lower specialization. (b) Higher specialization. (c) Intraperson skill differences.

specialization, each employee is good at very few tasks but not necessarily the same set of tasks; at low specialization, each employee is fairly good at a greater number of tasks. This captures the trade-off in terms of depth versus breadth of skills within individuals while also allowing for differences across individuals in the tasks they are best skilled at. Analogous to the normal distribution, we can generate different specialization regimes using the Dirichlet distribution, using the parameter α.[4]

Choice Process

Choice by both the allocator and worker is assumed to involve the best match with certainty. We explore later the impact of other plausible assumptions (e.g., imperfect information about workers' skills). Under process A, allocators aim to choose employees from the available pool with the highest skills for each available unoccupied task. Effectively, each individual is allocated to an unoccupied task in which her skill is highest (or randomly allocated among two tasks if her skills are identical). If all tasks and employees are simultaneously available, the optimal match can be obtained using the well-known "Hungarian" algorithm, which forms the basis of a number of algorithms in network flows and matching theory[5] (Kuhn 1955, Frank 2005) (technical details are included in the online supplement). However, in all other cases (i.e., replacement, growth, and garbage can), the allocator in A must try to staff available tasks with best-available employees, aiming to ensure no tasks are left unstaffed. In process B, each employee selects tasks based on their own skills alone. Thus, the availability of other employees is not relevant in B. What matters for the employees in B is whether all tasks are simultaneously available to select from or not. Figure 1 provides a simple example to highlight how the choice process and the availability of tasks and workers interact.

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Outcome Variables

We compare the two systems of division of labor on three metrics: organization-level performance (which is increasing in skill match between employees and tasks), matching completeness (whether tasks or employees are left unmatched—unmatched tasks and employees are indicated in red in Figure 1), and matching quality (number of tasks staffed in a way that is nonoptimal for the individual (i.e., they do not get their first-preference match) and average skill of matched workers). To compute organization-level performance, we take the sum of the skill values across tasks of the employees allocated to those tasks. If a task is left unstaffed, it contributes nothing to organization-level performance (effectively imposing an opportunity cost of unstaffed tasks, which increases with task interdependence; the latter is equivalent to imposing a penalty for each incomplete task). If more than one employee chose the same task (overstaffing), we assume some effort is wasted. Thus, even though multiple employees chose that same task, only one value is entered into organization-level performance. We include only the maximum skill value (the "best shot") among the employees who selected the same task in the sum of skills across all allocated tasks (Kogut and Metiu 2001, p. 259).[6]

Results

Baseline Comparison Between Task Allocation Processes A and B

For all results, we compute the model for 1,000 iterations and present average results to eliminate any artefacts of random sampling (of task and employee entry order). In the baseline analyses, we set the number of tasks equal to number of employees, $N = M = 50$. Further, we assume independence between tasks. The baseline results thus look purely at task allocation differences in the two processes when the task division is identical, and the underlying task structure is fully decomposable. This analysis is useful to understand the key mechanism in the model, which we subsequently examine with more complex settings to understand the boundary conditions. In the analyses, we track changes in organization performance, matching completeness, and matching quality across all four cases of task and employee availability as we vary the specialization regime.

To determine how A and B perform relative to each other, it is not necessary to compute the model for all situations of task and employee availability (see Table 3 for a summary). In the simultaneous allocation situation (Case I), it is obvious that A will outperform B:

Table 3. Relative Performance of Allocation Processes A and B

	All employees are simultaneously available	Employees become available in unforeseeable order
All tasks are simultaneously available	*Case I: simultaneous*; A > B	*Case III: growth*; B > A under high specialization and low interdependence
Tasks become available in unforeseeable order	*Case II: replacement*; A > B	*Case IV: garbage can*; A and B perform equally

employees in B disregard the skills and choices of other employees, whereas A aims for completeness of matching (i.e., avoids understaffing and aims to staff each available task with the best-available employee). Because all employees and tasks are simultaneously available, we can assume that the allocator can apply the Hungarian algorithm (also denoted by "*H*"), which produces the optimal match. The computations required for this algorithm increase rapidly (to the cubic power) with the number of parameters (number of tasks and employees), so this conclusion does depend on computability constraints. Nevertheless, we can say that complete staffing using the Hungarian algorithm in A will outperform simultaneous allocation via B in Case I.

To determine the relative performance of A and B in Cases II and IV, computation is equally unnecessary. In Case IV (*garbage can*), both A and B are equivalent to a random pairing between tasks and employees as there is no information on either the entry of tasks or workers. Their performance must therefore be identical. In Case II (*replacement*), there is information about workers but not on the arrival of tasks, so A cannot invoke the Hungarian algorithm. Nonetheless, as tasks become available, A can pick the best-available worker. In contrast, the assumptions we make about B in the baseline analysis ensure that it will perform poorly relative to A because of a "pileup" problem, as all employees will take on the first-available task because they do not coordinate with each other. This is perhaps why, empirically, we do not seem to observe the use of pure self-selection (B) in situations involving staffing for replacement. This ability of the model to consider this unobserved counterfactual and reveal why we do not observe it is useful in its own right.

The interesting and ambiguous case is that of staffing for *growth* (Case III), where projects grow as employees become available to staff them. Here, information on all tasks is available, but employees enter in unforeseeable order, one at a time. This prevents A from applying the Hungarian algorithm but does allow matching of each arriving worker with the best-available task given the worker's skill values. On the other hand, B does not suffer a pileup problem as all tasks are visible simultaneously for the sequentially arriving workers to pick from. Here, it is hard to say whether A or B will dominate without actually computing the model, although it is noteworthy that almost every empirical instance of self-selection we observe lies in this quadrant.

The results shown in Figure 3 offer some insight into why this might be the case. Panel (a) compares organization performance of B(*growth*) and A(*growth*) (taking the performance difference, B – A) on the y axis with increasing specialization on the x axis. We find that A outperforms B for low and medium levels of specialization, whereas B outperforms A under regimes of high specialization. This is despite the fact that A always outperforms B in terms of match completeness (see Figure 3(b)): no tasks are ever left undone in A (100% of tasks are single matches; i.e., one worker, one task), whereas in B, about 36% of tasks are left unallocated across the range of specialization regimes. As a result, about one-quarter of tasks are overstaffed, with an average of 2.4 employees per overstaffed task in B and a peak of 3.8 workers on the most overstaffed one (versus zero overstaffed tasks in A).

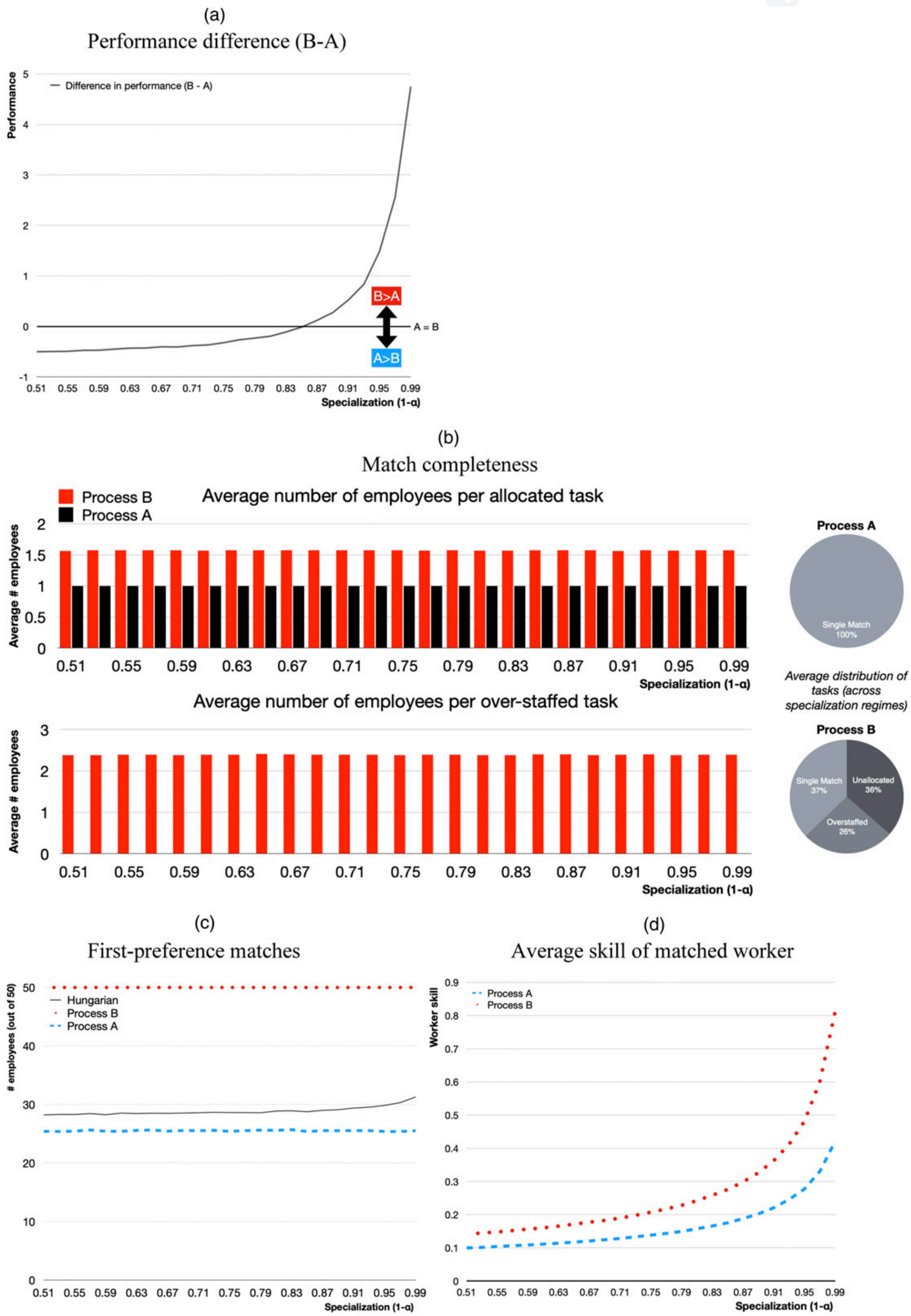
On the other hand, B always outperforms A in terms of match quality. In B, each employee always performs his or her best task, whereas only half the employees are allocated to their first-preference match in A, as shown in Figure 3(c). We contrast these results with the *organizationally* optimal allocation (Hungarian algorithm) as a purely theoretical benchmark as it requires information conditions unavailable in the growth case (also shown in Figure 3(c)). It is interesting to note that maximum organizational performance requires personally suboptimal allocation for a sizable number of employees. Finally, Figure 3(d) highlights the higher match quality in B over A by examining the average allocated worker skill across specialization regimes. Here, only workers who actually contribute to organization performance are counted in B (i.e., the maximum skill among the 2.4 workers for any overstaffed task). Across the entire range of specialization regimes, the average match quality in B is higher than in A—even though by construction there is no private information in the model as skills and allocations are freely observable by all in both processes.

To summarize, we find that process A, which models traditional staffing, outperforms process B, modeling self-selection, in allocation situations where tasks and employees are available simultaneously (Case I), as well as in staffing for replacement (Case II). A and B perform equally poorly under random allocation (Case IV), whereas B outperforms A in situations of staffing for growth (Case III), in regimes of high specialization and low interdependence. We discuss what gives process B, despite it producing poorly coordinated choices (because workers do not take any other workers' choices into account), an advantage over the choices of A.

Mechanism: Intertemporal Vs. Interpersonal Coordination Failures

The mechanism underlying the switch in performance in growth situations between A and B as specialization increases from moderate to high rests on a trade-off between (1) blocking—which is high

Figure 3. (Color online) Performance Comparison: Allocation Processes A and B in the Baseline Growth Model



Notes. (a) Performance difference (B – A). (b) Match completeness. (c) First-preference matches. (d) Average skill of matched worker.

in A and zero in B—and (2) over-/understaffing—which is high in B and zero in A. Blocking, or the opportunity cost of finding a better match for a given task in the future, is high in A because of its imperative to match one worker to every task and leave no task unoccupied. Because the growth case presumes that employees only become available with delay, the allocator may select a task for a certain employee now, even though a better-skilled employee for that task comes along later. Thus, he effectively faces an *intertemporal* coordination failure. B does not suffer from such an intertemporal coordination failure because every worker simply picks (once) the task at which he or she has the highest skills.

However, the opportunity cost of over-/understaffing is high in B because of the purely parochial way in which workers select tasks. Each worker simply picks her highest-skilled task, regardless of other workers' selection of the same. If multiple workers pick the same task, a number of other tasks will turn out to be unstaffed. The strong organization performance under high specialization for B is therefore driven by the possibility of incomplete but superior matching between individual skill and task despite the fact that B therefore suffers from *interpersonal* coordination failure among workers.

The relative performance advantage of A over B thus hinges on this balance between complete staffing and better skill matches. As long as the skill values for the forced matches are relatively high (as they are in low and medium levels of specialization), they add up to generate the performance advantage of A over B, even in the growth case. However, when skill values of forced matches fall, which is the case in high-specialization regimes, B dominates.

These baseline results seem to mirror empirical observations. For example, reviews of Valve on the employment website www.glassdoor.com suggest that successful and/or safe projects end up being *overstaffed*. Further, "because teams are intended to be self-forming, it's rare that enough people will want to assume risk to all collectively embark on a new project. It's too safe and too profitable to just contribute to something that's already successful." In other words, some projects can also end up being understaffed, leading possibly to many initiated but few completed projects, as public accounts suggest indeed has been the case at Valve (Keighley 2020).[7] Interestingly, at Buurtzorg, the Dutch nursing organization, procedures were explicitly designed to prevent any individual from being overburdened with too many undesirable (administrative) tasks, after it was realized that few nurses self-select into those tasks freely (Laloux 2014). The problem of over- and understaffing in self-selection is also well known in the open-source communities. It is often the core developers who have to step in to pick up those tasks that nobody else self-selected (Von Krogh et al. 2003). The fact that the model produces empirically consistent patterns in the baseline settings gives this theoretical exercise a degree of external validity and raises the plausibility of the rest of the analysis.

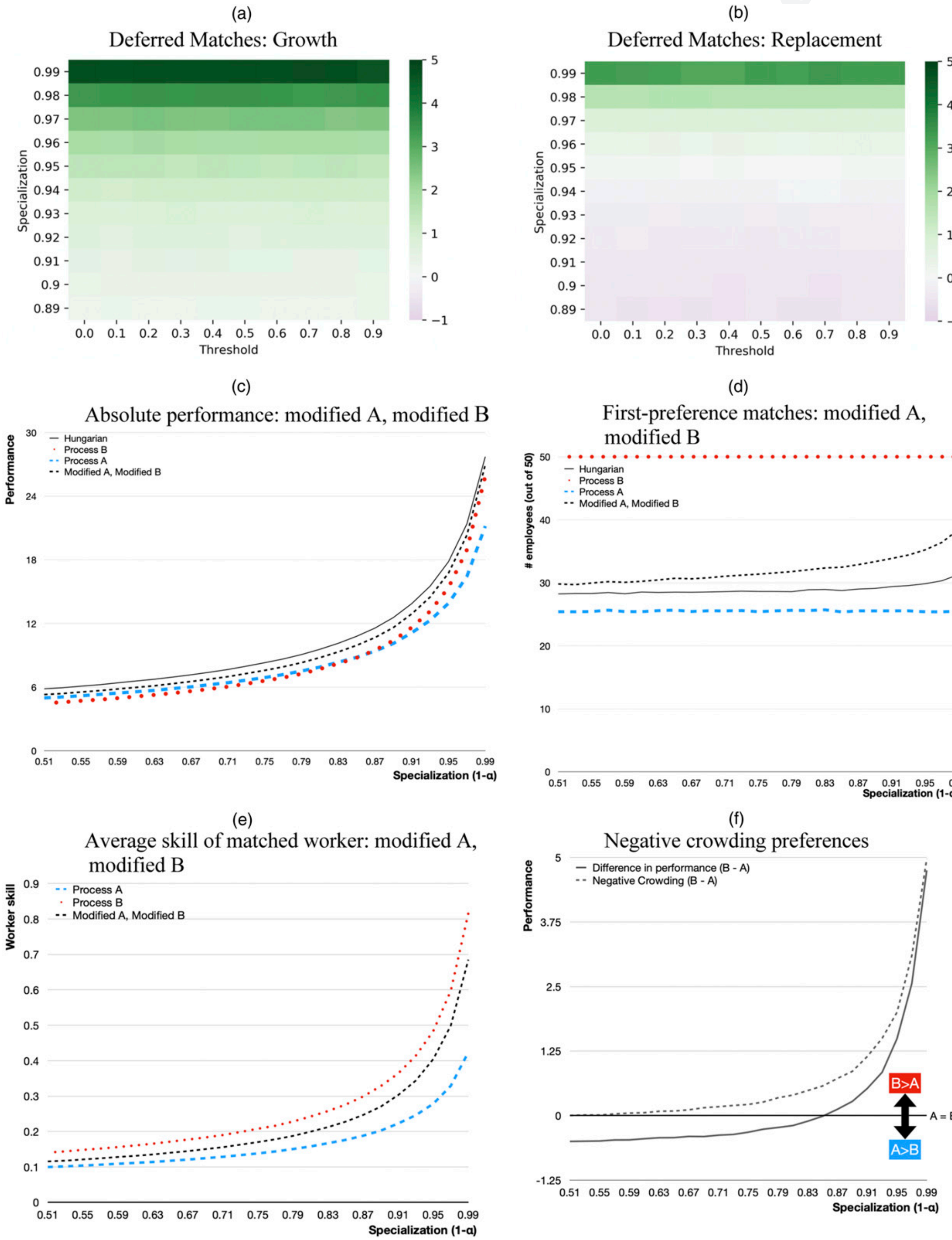
In sum, the differential performance between A and B in growth situations hinges on (1) the allocator's intertemporal coordination failure: the opportunity cost of finding a better match in the future, which is high in A and zero in B; and (2) the workers' interpersonal coordination failure: opportunity cost of over-/understaffing, which is high in B and zero in A. Under a high-specialization regime, the opportunity cost of foregone future matches in A is higher because the employees' second-best skill value is very low. As a consequence, B has the advantage over A in high-specialization regimes with staffing for growth. We now exploit our understanding of this mechanism to consider modifications of both processes to alleviate the intertemporal and interpersonal coordination problems of A and B. This also serves as a form of "mechanism test" of the model.

Mitigating the Intertemporal Coordination Failure in A. In the baseline analyses, we operate under the constraint that no period can pass without a match: allocators cannot defer staffing a task. This leads to intertemporal coordination problems for the allocators, effectively reducing A's performance because of blocking. Next, we relax this assumption. In process A, we give the allocator a threshold value r for staffing: in the growth case, this would leave a given employee unallocated if her skill levels do not exceed r for any of the available tasks, and in the replacement case, this would leave a given task unstaffed if none of the available employees' skill levels exceed r. Such a threshold model effectively mitigates the blocking cost that A faces in the baseline setting. In process B, we allow employees to wait for a task that matches their optimal skill value in B.

We find that allowing for deferred allocation in both A and B narrows the set of conditions under which B outperforms A in the growth case, as shown in Figure 4(a). Although the option to defer choices does not reduce the number of unstaffed tasks previously prevalent in B, it *does* improve the skill to task matching for the allocator in A. B therefore outperforms A across a smaller range of specialization regimes. The allocator can now strive for better matches first, at the cost of understaffing certain tasks. However, the deferral requires the allocator to hold accurate information regarding the arrival distribution of skills to be effective: only with an adequate threshold value will A outperform B for a wider range of specialization regimes.

In contrast, in the replacement situation (where all employees are present but tasks become available in random order) (Figure 4(b)), it is process B that benefits more from deferring matches. Compared with the baseline, where A outperformed B under *all* specialization values, B now outperforms A for very high-specialization regimes across all threshold values. In B, deferral effectively removes the pileup problem (but not the interpersonal coordination failure), such that each employee now waits for and selects the task with his or

Figure 4. (Color online) Modified Allocation Processes



Notes. (a) Deferred matches: growth panel. (b) Deferred matches: replacement. The heat maps in panels (a) and (b) show the performance differential between B and A (B − A) across specialization regimes under deferred matching and various threshold values *r*. Dark (green) shading shows areas where B clearly outperforms A; (light) purple shading shows negative areas, where A clearly outperforms B. (c) Absolute performance: modified A, modified B. (d) First-preference matches: modified A, modified B. (e) Average skill of matched worker: modified A, modified B. (f) Negative crowding preferences. Panels (c)–(e) show the effects across performance metrics in the growth case of modified A (highest added value) and modified B (make the biggest difference). Panel (f) shows the effect of negative crowding for B (compared with A) in the growth case in comparison with the baseline (B − A) result.

her highest respective skill value. The baseline and deferral analyses together highlight sharply the differential vulnerability of A and B to the lack of information in division of labor; B is most vulnerable to not seeing all available tasks at the same time (i.e., replacement situations) as it suffers from the pileup problem but is indifferent to the lack of information on other workers (because choice is parochial anyway by the allocators, the employees). In contrast, A is most vulnerable to not seeing all employees at the same time (i.e., growth situations) because of the possibility of better-skilled employees becoming available in the future, as well as the possibility of better tasks appearing later (i.e., replacement). Allowing for deferred matches in growth situations does not reduce B's performance per se. In contrast, allowing for deferred matches in growth and replacement situations can benefit A, but this depends on accurate knowledge of an appropriate threshold for deferral.[8]

An alternative modification of the A process is to allow for overstaffing (which in the baseline, is only allowed in B) and match employees to tasks based on their "highest added value," such that a highly skilled worker who arrives late could be allocated to an already staffed task, if the new arrivals' contribution to the occupied task is higher than any contribution she could make to unoccupied tasks. This hybrid of A and B (because it combines allocation that is mindful of other's choices with allowance for overstaffing) helps mitigate the intertemporal coordination failure by overcoming blocking while minimizing the cost of overstaffing. Figure 4(c) shows that this "modified A" process outperforms both basic allocation processes A and B (performance is displayed in absolute terms in this figure). We show that it is indeed the reduction in blocking (modified A facilitates a greater number of first-preference matches, which were blocked by early non-optimal matches in A) (Figure 4(d)) and the resulting higher match quality (average skill values of matched workers are above the baseline A) (Figure 4(e)) that lead to the performance increase. Offsetting this is an increase in the number of unallocated tasks (across specialization regimes) from 0 to a moderate 12% and an average number of workers per task from 1 in A to 1.2 in modified A, with a maximum of 2.2 workers on the most overstaffed task.

We recognize that modifying traditional staffing processes from A to modified A may have to contend with context-specific constraints—such as the possibility that employees might react negatively to having a higher-skilled colleague being added to their task, in effect setting the value of their own contribution to zero. It might therefore require careful piloting to assess whether the gain in allocation through such a modification sufficiently offsets any possible costs because of lowered morale.

Mitigating the Interpersonal Coordination Failure in B. The baseline results assumed that under B employees took no account of the choices of other employees and were indifferent to working with others on the same task. Instead of myopically picking their best task, one might consider norms such that employees might be motivated to self-select the task that they would "make the biggest difference" at. Thus, if their best task was already occupied but they are relatively highly skilled at a second unoccupied task, the employee would pick the latter. Figure 4(c) shows that this "modified B" process would outperform both basic allocation processes A and B (this modified B process is equivalent to the "modified A" process in its allocation and performance implications). Effectively, modified B would result in a reduction of overstaffing from an average of 26% overstaffed tasks and 2.4 workers per overstaffed task in the baseline to an average of 12% overstaffed tasks with 1.2 workers per overstaffed task in modified B. This reduction in overstaffing, however, would come at the cost of reduced match quality: the number of first-preference matches drops from 50 (of 50) to a range between 30 and 38.5 (from low to high specialization) (Figure 4(d)), and the average skill of matched workers in modified B is slightly lower than in the baseline B (Figure 4(e)).

Alternatively, employees may simply be motivated to pick tasks that are less crowded (without any consideration of where they can make the biggest difference). If we assume that employees prefer to pick tasks that have few or no occupants, then performance in this second modification of B matches or exceeds A's performance across the entire range of specialization regimes (Figure 4(f)). Although the positive effect of allowing employees to freely choose tasks based on their highest skill levels remains, the negative crowding preference introduces a disciplining mechanism that prevents extreme levels of crowding and reduces the number of unstaffed tasks. Effectively, employees are encouraged to look for their "second-best" task skill match if another employee already occupies their first task choice. The cost of over-/understaffing in these hybrid versions of B (which allow for overstaffing while adding a consideration of other's choices) is lower compared with the baseline case. However, we also acknowledge that creating norms for such mindful of others self-selection may not be easy in all contexts. Again, careful piloting may be required to assess whether such modifications produce benefits to offset the somewhat diminished autonomy in choice relative to baseline B.

In sum, both sets of modifications to A and B mitigate their respective weaknesses—intertemporal and interpersonal coordination failures—and bring them both closer to the optimal Hungarian algorithm (and therefore each other; these modified processes can be seen as hybrids of A and B).

Three Performance Contingencies: Observability, Interdependence, and Talent Pool

We conclude our analyses by examining three contingencies that influence the relative performance advantage of A and B allocation in growth situations: observability of skills, task interdependence, and depth of talent pool. The model implementation underlying these discussions as well as the figures is included in the online supplement.

Why Accurate Observability of Skills Is Critical for A. In the baseline model, we assumed that employees' skills could be visible equally well to themselves in B as well as a third-party allocator like a manager in A. One departure from such a baseline would be to introduce noise in matching for A but not for B (on the plausible assumption that it is easier for employees to know their own skills than it is for a third-party allocator because of information asymmetry). However, in such a case it is intuitive that we would create a strict disadvantage for A (we can show that B in this case outperforms A across all specialization regimes). One can also imagine scenarios in which allocators are better able to assess employee skills (through appropriate assessment and testing tools, for instance), in which case the advantage would tip toward A over B.

We can make a more subtle comparison of the two allocation processes under the assumption that both face the same levels of noise. Specifically, we examine the case when both allocator and employees may suffer from imperfect ability to observe employee skills: we continue to let allocators observe employee skills as well as employees themselves can observe their own skills, but the observations of both parties are now noisy. When noise affects the matching process, choice is assumed to involve the best match with some probability rather than with certainty.

Interestingly, we find that moderate increases in noise diminish the performance of A more than that of B, particularly as specialization increases. The reason for this differential effect is that in B, even if one employee misses his best choice under noise, another employee may select that task, compensating for the initial miss. Overstaffing creates redundancy that compensates for noise. However, this option is not available in A. Because the allocator in A leaves no task unstaffed, a miss on a high-skilled task for one worker has two effects. First, the opportunity cost of a high task to skill match and second, an early mismatched employee may now block a later high task to skill match. The negative externalities of these effects increase in strength with increasing specialization—higher-specialization regimes have fewer high-skilled tasks per employees, which significantly increases the opportunity cost of mismatches. Thus, although overstaffing in B compensates for noise, noise in A exacerbates the blocking problem.

Why Task Decomposability Is Critical for B. We confirm that task structure decomposability (i.e., task independence) produces a strong advantage for B. The baseline analysis assumes that the underlying task structure is highly decomposable so that task interdependence across employees is negligible. With greater task interdependence (more off-diagonal "1's" in the task structure), the overall system becomes less decomposable. The possible interaction costs between tasks allocated to different employees is one obvious issue to consider as a direct cost of reduced task decomposability. However, even if we ignore interaction costs (assume they are the same for employees in A and B), we find that A already has an advantage at dealing with interdependence: lower decomposability serves to increase the opportunity costs of unallocated tasks. Given that the allocator in A leaves no tasks unallocated, A will outperform B for highly interdependent task structures, even without the advantage such a system could hold in terms of managing interaction costs.

Why a Shallow Talent Pool Favors A and a Deep One Favors B. The baseline model assumes that the number of tasks and employees is the same ($N = M$). Here, we explore how changes in the depth of the talent pool influence relative performance in A and B; we continue to focus on the growth case.

We find that, overall, a shallower talent pool—where there are relatively fewer employees available for a given task (i.e., $N > M$, labor shortage)—effectively increases the probability of a high skill to task match in A. Given that all tasks are simultaneously available and the manager in A allocates the highest-skilled employee to each task, a wider selection of tasks for each employee will make a higher skill match more likely. As a result, performance in A is higher in a shallow talent pool compared with the $N = M$ setup. Although a shallow talent pool in B has the same effect of making more tasks available across employees, in B in the $N = M$ model each employee already selected her highest-skilled task, so that we see little impact of a shallow talent pool on organization performance. This differential effect of shallower talent pools (or labor shortage) on A and B effectively closes the performance gap between them at higher levels of specialization, such that B only outperforms A—under shallow talent pools—for the highest level of specialization.

A deeper talent pool (or $N < M$, labor surplus), on the other hand, overcomes the understaffing problem for B, increasing organization performance significantly above the initial results. Performance in A under a deeper talent pool remains unchanged compared with equal numbers of tasks and employees because A does not suffer an understaffing problem to begin with. In contrast, although B always suffers from tasks left undone, the greater number of available employees increases the likelihood that each task is chosen by someone and reduces the percentage of tasks left unstaffed in B.

As a corollary, the negative effects of interdependence in B described can be dampened by increasing the number of available employees. This effect is driven by the reduction in unstaffed tasks with increased depth of the talent pool.

Conclusion

Self-selection–based division of labor is a cornerstone of several systems of nonhierarchical organizing. The best studied of such systems so far has been online communities. Researchers have pointed to several factors that seem to be important in these contexts. Decomposability of task structures, exploited through fine-grained modular architectures for instance, may create independence of action, allowing for parallel contributions (Kogut and Metiu 2001, Lakhani and Panetta 2007), as well as opportunities for exchange of valuable work (Baldwin and Clark 2006). By attracting a large and diverse body of contributors, modular architectures may also stimulate and exploit specialization in skills (Wasko and Faraj 2000, Von Krogh et al. 2003) and improve the possibility of creating a close match between contributor skills and task requirements (Rullani and Haefliger 2013; also see Haas et al. 2015).

Self-selection has also gained popularity as a basis for division of labor within firms—with managerial application of the principle to holacracies, agile software development teams, and nonhierarchical organizations (Laloux 2014, Puranam and Håkonsson 2015, Lee and Edmondson 2017). However, unlike the open-source software context, self-selection within the firm does not need to involve either distributed work or exchange/recombination of contributions and implicitly always competes with the possibility of traditional staffing by managers. To understand the conditions under which self-selection may be advantageous, we developed a computational model of division of labor as an irreversible matching process. The comparison between different matching processes reveals that the intuitions derived from the study of systems with self-selection alone may be incomplete.

Our analyses help us understand why traditional staffing processes that embody the principle of "fill every vacancy with the best-available person" can be superior to self-selection processes where individuals "picks what they like" across a wide range of conditions. Unlike self-selection, which fails to coordinate choices across workers, traditional staffing explicitly takes an organization-level perspective, aiming to optimize organization performance rather than myopically looking for the best match possible for each worker. Nonetheless, we discovered that there are specific conditions under which self-selection has an advantage, even if we held individual-level attributes (such as motivation and observability of skills) constant across the allocation procedures.

We find that the traditional process outperforms self-selection when it pays to leave no task unstaffed, possibly at the cost of poor-quality matches because of blocking (i.e., matches made today are worse than what could be made later). Conversely, self-selection has an advantage when it pays to create better skill to task matches for individuals (i.e., employees work on tasks they are most skilled at, their first-preference match) but at the expense of under- and overstaffed tasks. The diverse results summarized in Table 4 can all be understood with respect to this basic trade-off between intertemporal coordination failure (leading to blocking) in traditional staffing and interpersonal coordination failure (leading to over-/understaffing) in self-selection.

With increasing *interdependence*, the costs of understaffing of tasks can be dramatic because any tasks left undone can harm the entire system. Interdependence thus creates a significant disadvantage for self-selection, which is prone to leaving some tasks unstaffed.[9] With increasing *specialization*, the cost of blocking increases—because the possibilities of far superior matching in the future increase—whereas those of overstaffing decline—because the best-skilled individual has very high skills. This is why self-selection gains an advantage under high-specialization regimes. *Deferred allocation* reduces the cost of blocking in situations of growth tilting the scales toward traditional staffing, whereas it increases the benefit of self-selection in staffing for replacement, by preventing pileup of employees on the first-available vacant task. Norms that *avoid crowding* benefit self-selection by reducing over-/understaffing. A *shallower talent pool* reduces the occurrence of blocking because of greater task availability per employee, whereas a *deeper talent pool* reduces the occurrence of understaffing because of more possible high-skill matches for the few available tasks. The former therefore benefits traditional allocation, and the latter benefits self-selection. *Noise* in the task to employee matching process gives self-selection an advantage because there are more opportunities for rectification through the choices of other employees—effectively an advantage of overstaffing. If the allocator gets it wrong in traditional staffing because of noise, this blocking effect cannot be rectified. Notably, all these effects would all hold *even if* there were no motivational or informational advantages to

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Table 4. Summary of Model Results and Propositions

		Division of labor: effect of allocation based on		Predictions	
		Process A (e.g., traditional staffing)	Process B (e.g., self-selection)	B advantage over A . . .	Notes
Individual-level attributes					
Motivation	Workers derive motivation from freedom to choose tasks		Increases task performance via intrinsic motivation	Increases when worker motivation improves because of the freedom to choose task	A by definition takes away the choice from workers
Observability of skill	Information asymmetry, workers know own skills better than allocators do	Worsens managers' match quality		Increases when workers know their own skills better than managers	Better match between worker skill and tasks in B if workers are incentivized to pick their highest-skill task
	Noise in the task to employee matching process for workers and allocators		Overstaffing rectifies any poor skill choices because of noise	Increases with moderate noise levels because overstaffing rectifies prior poor matches	Excessive noise is equally detrimental for A and B
Relational attributes					
Interdependence	Significant interdependence between tasks (i.e., the value of any task is contingent on other tasks being performed)		Penalizes unstaffed task	Decreases when tasks are highly interdependent	A ensures no understaffing and may also oversee interactions to ensure integration of effort
Specialization regime	Workers are highly specialized at few tasks	Increases the opportunity cost of blocking	Reduces the opportunity cost of overstaffing	Increases when workers are highly specialized	A suffers from higher costs of blocking; B benefits from lower cost of understaffing
Timing of choice	Deferral of allocation until multiple workers/tasks arrive	Reduces the opportunity cost of blocking	Prevents overstaffing in replacement	Diminishes in growth, increases in replacement with deferral possibility	In B, no effect on growth
Worker crowding preferences	Workers find tasks unattractive based on what others choose		Negative crowding reduces overstaffing	Increases when workers prefer working alone	In B, positive crowding worsens overstaffing
Depth of talent pool	Variation in the number of workers available per task match	Shallower talent pool reduces occurrence of blocking	Deeper talent pool reduces understaffing	Increases when the talent pool is deeper	In B, more workers than tasks increase high-skill matches; in A, more task options per worker improve match quality
Maximize contribution	Allocators and workers select matches based on where the new employee's contribution is maximized	In the presence of overstaffing, this improves match quality at the cost of (some) unstaffed tasks	Reduces overstaffing	Equals out; the two modified (A and B) processes perform equally well and better than both basic A and B	Implementation via staffing policy in A, via norm development or selective hiring in B

self-selection (which we know would shift the balance further in favor of self-selection).

These results also uncover some subtle aspects of both allocation procedures. Paradoxically, the effectiveness of "spontaneous coordination" seen in nonhierarchical organizations such as open-source communities and self-managed teams may actually depend on individuals' preferences for working alone on tasks. Absent such preferences, overstaffing is exacerbated in self-selection, resulting in opportunity costs. We can also infer that a valuable role for managers in traditional staffing—even if they do not undertake any dispute resolution or direction of subordinates—may simply be to prevent over- and understaffing in a nondecomposable system to avoid the ripple effects of leaving tasks left undone.

Understanding the nature of the coordination failures affecting our archetypical task assignment procedures allows us to address some of their shortcomings. Allowing managers to defer filling vacancies or allocating multiple employees to the same task (when that represents the best improvement in organization performance) can improve traditional staffing. Creating norms where employees allocate themselves to tasks where they can make the biggest difference or at least to avoid crowded tasks can improve self-selection.

Our results have face validity when we compare them with accounts of organizations that employ self-selection practices in their operations in that we see anecdotal evidence of over- and understaffing as predicted (e.g., Buurtzorg, Valve). The contribution of this theoretical exercise lies in (1) uncovering important boundary conditions that would not have been easy to detect from empirical data (e.g., the availability of tasks before workers, specialization, and independence for conferring an advantage on self-selection) and (2) providing a deeper understanding of the mechanism underlying the relative performance differences that go well beyond the expected motivational and informational advantages that intuitively characterize self-selection.

More generally, we think that our model may contribute to filling a relevant gap in the literature on skills and organizations. Most of the recent literature on matching in organizations has focused on firm-specific skills and the pairing of workers with firms (e.g., Lazear 2009). However, as Gibbons and Waldman (2004) have forcibly argued, task-specific skills are potentially more relevant for understanding the internal working of organizations. Too little is known about how the distribution and dynamics of task-specific skills affect the design and operation of organizations and the process of division of labor—notwithstanding the original focus of Adam Smith (1776)—at this level of analysis. We provide new insights into how task-specific skill specialization affects the dynamics of matching workers to jobs and its effect on performance under different organizational regimes. By doing so, our work brings new emphasis on a central—but underinvestigated—level of analysis of organizations.

The results of our analysis offer a first window into the conditions under which each form of intraorganizational division of labor may have relative advantages. They may be seen as hypotheses to be confirmed in data. Because the counterfactual comparison between the two regimes of division of labor is unlikely to be naturally observable in the field, the need for (laboratory or field) experiments seems clear to progress on this agenda. Pending such exploration, we hope our results can be used to inform, if not guide, managerial thinking on this matter.

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Appendix
Task Environment
The task environment is characterized by a set of N tasks and M employees. The *allocation* of employees to tasks at any point in time t is captured by the $M \times N$ asymmetric matrix L_t. If employee i is assigned to task j, then $L_{ij} = 1$; else, $L_{ij} = 0$. We assume that allocators are able to observe L_t (i.e., which tasks have been staffed at time t).

Interdependence. The set of tasks that collectively contribute to the organization's performance is represented by a square matrix T of size $N \times N$. The matrix captures the patterns of interdependence between tasks: $T_{ij} = 1$ implies that task i is dependent on task j, and this dependence can be unilateral. This is referred to as the *task structure* and denoted by T. In the baseline setting, tasks are assumed to have low interdependence (i.e., a staffed task can have nonzero value even if other tasks are left unstaffed).[10]

Specialization Regime
Employees have skills for every task. This is represented as the $M \times N$ matrix K, which gives measures of employee i's skill for task j. We explained the intuition behind the specialization regime with a normal distribution in the text. Here, we explain how to draw the specialization regime using a symmetric Dirichlet distribution of dimension N, with the concentration parameter $\alpha \in (0, 1)$ tuning specialization. This distribution is a useful representation of probability over a set of discrete states (e.g., Puranam et al. 2017, Haanigan et al. 2019). We adopt it to model the distribution of skills across tasks, subject to a constraint on total skill. We use the symmetric distribution as we do not mean to impose any particular prior for any of the workers to favor any of the N tasks. Although α can take on any positive value in the Dirichlet distribution, the distribution behaves differently for different ranges of concentration parameters (i.e., the range of values generated by α between 0 and 1 behaves differently from the range of values generated by $\alpha > 1$). We take advantage of the properties of the distribution for $\alpha \in (0,1)$: the values of the resulting distribution tend to be less evenly distributed compared with $\alpha > 1$. This is precisely what mimics the workers' tendency to be good at some, but not all, values: it is the variance of this property over the range of concentration

parameter values strictly between zero and one that allows us to mimic different degrees of specialization without additional parameters.

A given employee's skill values will always sum up to one across the range of N tasks. However, the specialization regime (tuned by α) changes both how skilled that employee is at any one of those tasks as well as how many tasks the employee is relatively good at. Under a high-specialization regime (a low value of α), each employee has high skills for only one or two tasks and very low skills for all remaining tasks. For example, at $\alpha = 0.01$ (highly specialized) in a task environment with 50 tasks, the maximum skill value (in the range (0, 1)) is 0.78, the second-highest skill value is 0.16, and the skill values for the remaining 48 tasks range between 0.04 and almost 0. However, given the nature of the Dirichlet distribution, the skill values of all workers remain strictly in the open interval *between* zero and one, even for extreme specialization, and sum up to one.[11]

Under a low-specialization regime (a high value of α), a given employee's skill values are more similar to each other across the N tasks. Given that her skill values across a particular task sum up to one, however, these skill values are all relatively lower compared with the high-specialization regime. For example, at $\alpha = 0.51$ (a low-specialization regime) in a task environment with 50 tasks, the maximum skill value is 0.14, the second-highest value is 0.10, and the remaining 48 skill values range between 0.08 and 0.00002.

Outcome Variables

To compute organization-level performance, we take the sum of the skill values (across tasks) of the employees allocated to those tasks. Thus,

$$\text{Organization–Level Performance } \pi = \sum_{n=1}^{N-n} \max\{s_i\}, \quad \text{(A.1)}$$

where N is total number of tasks, n is the number of unallocated tasks, and $\{s_i\}$ is the set of i employees' skill values for each task.

Endnotes

[1] If workers' preferences for tasks and their skills at those tasks are not aligned, this advantage would of course diminish. For instance, a tendency toward "hobbyism" may cause individuals to take on tasks they enjoy, not necessarily the ones they are competent at, diminishing the ability of self-selection to produce effective matches between skill and tasks. We have explored these factors in additional analyses, and the results are available from the authors upon request. Intuitively, a high divergence between preferences and skills hurts performance in self-selection.

[2] An interesting parallel literature models division of labor in social insects (see Beshers and Fewell 2001 for a review). Here, division of labor results from autonomous decisions made by each worker to perform a task. Workers are assumed to be adaptive rather than foresighted. Models try to accommodate for changing availability of tasks, heterogeneous predispositions to tasks (often represented by task-specific individual thresholds of activation), inhibition effects of others' choices, and decentralized communication.

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[3] For an instance of process B, a pool of internally available talent (such as the "bench" in IT services companies) might allocate themselves to tasks as they become available (https://medium.com/some-personal-thoughts/the-bench-in-it-companies-expense-or-investment-6f7511d28176; accessed on March 10, 2020).

[4] The normal distribution provides an intuitive and familiar basis for the drawing of skill values in varying regimes. However, it does require a number of assumptions and steps (e.g., drawing probabilities for equidistant x values, choosing the interval, and normalizing) to derive the skill values for each individual. Equivalent results can be achieved through a single parameter in the Dirichlet distribution. Details on the latter can be found in the appendix. All our results hold using either distribution; the results in the paper show results from the Dirichlet distribution.

[5] The Hungarian algorithm was originally developed to solve the assignment problem of jobs to workers and subsequently, employed for cost minimization (Kuhn 1955). We adapt this algorithm to our problem of division of labor (Kamrani et al. 2010, p. 42).

[6] The "best-shot" approach constitutes an unfavorable assumption for B, as the skills of others are simply ignored. One could make the case that a number of high-skilled employees working on the same task will improve the output. Hence, by relaxing this assumption, B performance will increase relative to A. On the other hand, if one assumes that overstaffing results in a reduction of skill for the task (such as taking the *average* of all allocated employees), performance for B will decrease.

[7] See https://arstechnica.com/gaming/2020/07/valve-secrets-spill-over-including-half-life-3-in-new-steam-documentary-app/.

[8] If delayed staffing is inconsequential, then the threshold can be set very high, and the allocator can wait until all candidates and tasks arrive and then apply the Hungarian—this cannot be improved upon. If delay is consequential and the skill distribution is unknown to the allocator, then the threshold cannot be set very high. Thus, without accurate knowledge of an adequate threshold value, the simpler and less accurate B allocation process may still outperform A.

[9] We have modeled a particularly strong form of interdependence (multiplicative such that any unstaffed task reduces its interdependent tasks' values to zero), which effectively stacks the deck against self-selection because it is prone to understaffing. Nonetheless, regimes emerge where it dominates.

[10] Our baseline assumptions therefore stand in stark contrast to Adam Smith's setting of functional division of labor (sequential steps in the production line) where any one unallocated task would bring overall performance to zero; they are more akin to an *nk* landscape with zero interdependence ($k = 0$). In additional analyses, we consider cases with interdependence (see the online supplement).

[11] We also explored the limit case of "perfect" specialization where skill values took on strictly zero or one; in this scenario, performance in B equals performance of the optimal Hungarian algorithm because avoiding overstaffing under the latter does not add any nonzero performance benefits to the B allocation choices. Under these conditions, A will always underperform B, unless interpersonal specialization is perfect such that each employee is highly skilled at a different, unique task, in which case A = B = H performance. We thank an anonymous reviewer for highlighting this case.

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