Abstract

A principal often needs to match agents together to perform coordinated tasks. However, agents can quit or slack off if they dislike their match. We study two approaches for matching agents, both widely-used in practice: Centralized assignment by firm leaders, and self-organization through market-like mechanisms. Our model connects the choice of method to the degree of specialization in a firm’s workforce, the firm’s production technology, worker/CEO information asymmetry, incentive alignment, and firm size. We then study these topics using data from a large organization’s internal labor market. Centrally-assigned matches are highly productive. Using the organization’s preferred metric, the firm-dicated match is 36% more productive than randomly assigned matches within job categories. By contrast, preference-based matches (using deferred acceptance) are only 3% better than random, but are ranked more favorably by the workforce. A key driver of results is the degree of assortative matching: The self-organized match is positively assortative, and the most productive match is negatively assortative.

JEL Classification: M5, D47, J4.

Keywords: Internal labor markets, assortative matching, assignment mechanisms, team formation, matching.

*The authors thank Russ Coff, Bob Gibbons, John Hatfield, Zoey Jiang, Navin Kartik, Yash Kanoria, Fuhito Kojima, Scott Kominers, Jin Li, John Morgan, Parag Pathak, Tayfun Sonmez, Alex Teytelboym and Brian Wu for helpful comments, as well as seminar participants listed in additional acknowledgements (7). Cowgill thanks the Kauffman Foundation. Earlier versions of this paper were called, “Matching for Strategic Organizations,” and “Preferences and Productivity in Job Matching.”
1 Introduction

Principals are often required to coordinate agents by matching. For example, workers and managers in companies must be assigned to each other to perform tasks (Gardensfor, 1973; Roth et al., 1993). In these settings, agents’ preferences are a critical consideration. Workers with unfulfilled preferences could quit or become demotivated. However, worker preferences are not the only consideration. Workers may not fully internalize their organization’s success. Left to their own devices, agents may pursue other goals without knowing (or caring) about the principal’s objectives.

This paper is about how organizations navigate these tensions in matching and team formation. We study two approaches to matching agents, both widely-used in practice: Centralized assignment by firm leaders, and self-organization through market-like mechanisms. Since 2000, a growing number of companies have adopted market-based systems for internal assignments, allowing workers and managers to self-organize into matches based entirely on their preferences. Organizations such as Google, Wal-Mart, Accenture, and the United States Army have adopted these marketplaces. An ecosystem of venture-backed software startups exists to facilitate these market-based matching systems,1 with clients around the Fortune 500 and a combined market capitalization of over $400M.2 Some of these systems explicitly borrow mechanisms developed in the market design literature.3

Our model builds on existing techniques and results to examine the strengths and weaknesses of these market- or preference-driven systems as compared to centrally-planned hierarchical assignment (“command-and-control”). We derive boundary conditions for when each method is better for a principal facing a matching problem. Our approach is to initially simplify the problem by making strong assumptions and then to explore how sensitive our results are to relaxing the assumptions. Our theoretical model connects this

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1These startups include Gloat (http://gloat.com), Fuel 50 (http://fuel50.com), and Hitch Works (https://hitch.works/). Avela (https://avela.org/) is another social impact software and consulting company with academic ties which offers organization marketplaces software to organizations.

2Gloat’s clients including Wal-Mart, PepsiCo, Vanguard, Unilver, and Nestlé. For Gloat’s valuation, see https://techcrunch.com/2021/06/16/gloat-raises-57m-to-reinvent-the-internal-job-board/.

3For an overview of market design, see Roth (2015). We review a list of organizations using market design tools for internal labor markets in Section 2. The list includes Google (Cowgill and Koning, 2018), the US Army (Greenberg et al., 2020; Davis et al., 2020), Teach For America (Davis, 2022), and the International Monetary Fund (Barron and Vardy, 2005) (Vardy confirmed in private correspondence the IMF proposal was implemented).
choice to key firm characteristics, including the degree of specialization among the workforce, the production technology, worker/CEO information asymmetry, incentive alignment, and firm size. Our model makes predictions about what types of organizations will adopt either approach. We can also use it to study how important secular trends in the labor market affect team formation, internal organization, and principal-agent problems inside firms.

We then turn to a large organization for an empirical case study of the forces in our model. The structure of the organizations’ internal labor market – and particularly its use of the deferred acceptance algorithm – allows us to study detailed ranking data by workers and managers about each other. We also use the firm’s preferred metric for estimating the productivity of each match.

Our results show a relatively high degree of worker-specialization, and thus matching can be incredibly productive. Using our company’s preferred measure, the firm-dicated match is 36% more productive than randomly assigned matches within job categories. This is a multiple-standard deviation improvement. To achieve the same improvement by training or replacement, the bottom 75% of workers must perform as well as the 75th percentile employee. Despite these productivity improvements, workers and managers are lukewarm towards these assignments; they rank their partners in this match approximately the same as randomly assigned partners.

We then contrast these results with matches using worker/division preferences, implemented using the deferred acceptance algorithm. Preference-driven matches are much less productive: only 3% more valuable to the firm than the average random match. However, workers and managers rank their assignments better by an average of about two slots, and are 85 percentage points less likely to be assigned to a role they ranked as tied for last place (but better than quitting) in deferred acceptance.

Why does the preference-respecting mechanism perform so poorly? In our setting, we show that maximizing firm productivity results in slightly negative assortative matching: The firm’s best managers are not necessarily matched with the firm’s best workers (Becker, 1973; Shimer and Smith, 2000; Bandiera et al., 2007; Lazear et al., 2015; Adhvaryu et al., 2020; Kambhampati and Segura-Rodriguez, 2020). This result is driven by opportunity costs: Assigning a star worker to a top manager “wastes” the worker contributions on projects that will easily succeed without elite talent. In our setting, we thus find that disassortative matching is preferable to the firm.
By contrast, deferred acceptance produces greater assortative matching as high productivity workers and high-productivity managers rank each other favorably. Although pleasing workers can improve motivation and retention, several bits of evidence suggest that the magnitude of these benefits was not enough to offset the productivity loss from the DA. Despite the drawbacks we highlight, we cannot necessarily characterize the adoption of preference-based assignment as a mistake in our setting, as some benefits of these programs may be subtle or difficult to measure.

Although command-and-control and market-like delegation are both widely used in practice, we are aware that intermediate approaches can exist that may improve upon both. Although we do not study intermediates in this paper, they are a promising avenue of future research. The approaches we study can be viewed as extremes. This paper studies the gravitational forces tugging organizations closer to one extreme (or the other), and how large these forces are in a real-life setting.

Our analysis reveals some of the tradeoffs among intermediates. Command-and-control uses the information available to the CEO and not the workforce (such as information about match-specific contributions to firm objectives). Market-like delegation uses information available to the workforce and not the CEO (such as agents’ private match-specific preferences). As the CEO inches towards delegating, the organization may enjoy greater ability to incorporate the workforce’s distributed information. However, the CEO loses control, and workers may use part their discretion for private gains (at the CEO’s expense).

Our paper is related to several recent empirical papers in which preference-based matching generates unwanted externalities. In an educational setting, the introduction of the deferred acceptance algorithm increased competition for top schools and crowded out low-SES students (Terrier et al., 2021). In a political economy setting, the use of preference-based matching resulted in assigning low quality bureaucrats to disadvantaged regions (Thakur, 2021). In a workplace setting, the use of deferred acceptance raises the potential for gender segregation (Cowgill et al., 2020).

Our goal is to abstract away from the details of these settings, and study a more general problem: A principal has a set of matching objectives. These may include maximizing profits, avoiding gender segregation, and/or assigning workers to socially important tasks. Agents’ preferences enter the principal’s problem mainly as constraints on these objectives, and the principal then faces a choice of matching methods. Although we focus
on companies’ internal organization, there are parallel issues in other domains.

The remainder of this paper is organized as follows. Section 2 briefly discusses how our paper relates to prior literature. Section 3 presents a model of matching with organizational objectives and constraints. Sections 4 through 6 review our empirical setting, strategy and results, and Section 7 concludes.

2 Related Literature

Coordination within organizations. Our paper is related to decentralized management structures (Groves and Loeb, 1979; Arya et al., 2002; Ortega, 2001; Alonso et al., 2008; Christensen and Knudsen, 2010). We contribute a model of endogenous team formation (matching). This problem has many similarities with other principal/agent problems; for example, the choice to delegate in the presence of biased, informed agents (Dessein, 2002; Alonso and Matouschek, 2008). The two-sided nature of the problem requires new, stylized notions of “alignment” and coordination between multiple agents.

We connect this literature to the research about “happy workers are more productive” (Oswald et al., 2015; Bellet et al., 2019). A closely-related literature examines nonmonetary incentives, for example, workers who find intrinsic motivation or meaning in their assignments (Cassar and Meier, 2018). Keeping workers happy and motivated is not necessarily free. Our model places these tradeoffs at the center of firms’ resource allocation problems.

We also make connections to with the literature on information technology (IT) and organizations (Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002; Bloom and Van Reenen, 2011). Several comparative statics in our theory can be seen as modeling IT quality. We also study the link between routine-biased technical change (RBTC), employer demand for “generalists,” and the design of internal labor markets. Our results contribute to the understanding of IT, RBTC, and organizational structure (Lindbeck and Snower, 2000; Lindbeck and Snower, 2000).

4Some interventions increase happiness, but are neutral or even negative for productivity (e.g., by distracting workers, changing norms or misaligning skills). Notable examples include Bandiera et al. (2010) and Park (2019), in which workers’ productivity is correlated with those of the friends they work with. Concern about workers forming teams based on friendships (rather than output) plays a role in our empirical setting. Coviello et al. (2017) and Cowgill and Zitzewitz (2020) contain additional examples of higher happiness correlating with lower productivity. Psychology studies by Pacheco-Unguetti and Parmentier (2016) show that priming a better mood increases subjects’ vulnerability to distractions and increases sociability (Cunningham, 1988).
Matching. In this literature (Roth and Sotomayor, 1990; Roth and Peranson, 1999; Abdulkadiroglu and Sonmez, 2013), most markets are composed of autonomous agents who are free to match outside of a centralized mechanism. As a result, these papers often restrict attention to mechanisms which determine matches using agents’ preferences, and often restrict attention to mechanisms which yield pairwise stable matches (in the sense that no unmatched pair of agents would prefer to be matched together over their assigned match). As we discuss in Section 3, leaders in organizations are able to block matches. Centralized organizational leaders do face incentives to anticipate workforce preferences (because workers can choose to quit or withhold effort). However, the ability to block matches allows CEOs to address worker preferences without the constraints of pairwise stability.

Market design and policy goals. A smaller literature within market design considers non-choice policy goals. Several empirical papers in this literature examine counterfactuals in which allocations are dictated by a planner, rather through a market-like mechanism (Agarwal et al., 2020; Ba et al., 2021; Dahlstrand, 2021; Bates et al., 2022). We model the choice of planner versus market in a generic matching setting, and contribute an empirical personnel application.

Allocation constraints (such as quotas) are a major design tool for pursuing policy goals. Koijima et al. (2020) studies the set of all feasible constraints, and shows that constraints are particularly useful when a firm’s production function is group separable. We study a tool for policy goals (command-and-control) that is frequently used inside organizations, and highlight why group separability assumptions may not fit in some organizations.

\[5\] Self-organization has also attracted significant attention from management scholars (Raveendran et al., 2021; Lee and Edmondson, 2017) based partly on case studies of Valve, Zappos, and Morning Star (Martela, 2019). Our paper is conceptually related to these management practices, although we are focused on a particular stylized implementation.

\[6\] An incomplete list of constraints studied by economists includes ceiling constraints (Abdulkadiroglu and Sonmez, 2003; Fragiadakis and Troyan, 2017; Kamada and Kojima, 2018), floor constraints (Biró et al., 2010; Huang, 2010), proportionality constraints (Nguyen and Vohra, 2019), type-specific constraints (Hafalir et al., 2013; Ehlers et al., 2014; Ellison and Pathak, 2016; Kominers and Sonmez, 2014; Goto et al., 2017; Dur et al., 2018; Aygün and Turhan, 2020), multidimensional resource constraints (Delacrétaz et al., 2016; Noda, 2018; Nguyen et al., 2021), and joint constraints imposed on multiple entities (Kamada and Kojima, 2015, 2017, 2019).
First, group separability requires that divisions within an organization must face disjoint, non-overlapping labor markets. This restriction limits internal competition between divisions for the same workers. Internal competition appears in many organizational settings, including ours (Section 4), and others in the matching literature (e.g., cadet-branching, Greenberg et al. 2021). We do not rule out internal competition, and a key benefit of command-and-control is the ability to coordinate competing divisions.

Second, group separability requires that a CEO’s utility can be expressed as the sum of the individual division utilities. This limits the possibility of misalignment between the CEO and divisions. However in many settings, alignment is limited by principal/agent issues. Division leaders may be tempted to withhold information (Prendergast, 1993), sabotage rivals (Lazear, 1989), hoard talent (Haegele, 2021) or otherwise pursue private interests at the expense of the larger organizational goals. Our theoretical setup allows for misalignment, and we find empirical evidence of misalignment in our applied setting.

Internal labor markets. Although our model is more general, internal labor markets are our leading example (Baker et al., 1994; Baker and Holmstrom, 1995). Markets explicitly using market design tools have appeared at Google (Cowgill and Koning, 2018), Teach for America (Davis, 2022), the United States Military Academy (Sonmez and Switzer, 2013; Sonmez, 2013), the US Army (Greenberg et al., 2020; Davis et al., 2020), the International Monetary Fund (Barron and Vardy, 2005), and others. In July 2021, a report by Georgetown and Harvard Universities (Zúñiga et al., 2021) indicated that the US State Department is collaborating with the National Resident Matching Program (NRMP) to develop a similar system for assigning diplomatic officers to overseas posts.

In addition, firms such as McKinsey (Bryan and Joyce, 2007) and Deloitte (Erickson et al., 2018) have adopted formal internal talent marketplaces and advocated them for clients (sometimes in collaboration with the aforementioned software vendors). Although the microstructures behind these marketplaces are not disclosed in detail, their descriptions indicate that respecting participants’ preferences (the key property in our theoretical results) is a guiding principle.

7Other examples include Cowgill et al. (2020), which studies a large Asian bank with “millions of customers, billions of dollars in assets and in revenues, and thousands of employees” that uses deferred acceptance to match and re-allocate workers, managers and projects. The United States Military Academy uses a cumulative offer mechanism to assign cadets to branches (Sonmez and Switzer, 2013; Sonmez, 2013; Greenberg et al., 2020). The International Monetary Fund used the deferred acceptance algorithm to assign new economists to research teams (Barron and Vardy, 2005).
3 Theoretical Framework

We begin our framework with preliminaries. An organization (or firm) consists of a principal (a CEO) and two types of agents: workers and divisions (the latter led by middle managers). Although the workers and managers are differentiated, we refer to them collectively as “agents,” “participants,” or “the workforce.” There are \( I \) workers \( i \in \{1, \ldots, I\} \) and \( J \) divisions \( j \in \{1, \ldots, J\} \). Each potential worker-division pair yields an output \( v_{ij} \). The CEO’s utility is equal to the sum of the productivity of all matches which we call \( V \). For a private company, \( V \) could represent total firm profits, and for non-profits or governments \( V \) could represent other social objectives. Both workers and divisions can be matched with a single member of the other side of the market.

Without any other constraints, the CEO will maximize her utility by selecting a match using the Kuhn-Munkres linear programming algorithm (Kuhn 1955, a.k.a. the “Hungarian algorithm”). This solution finds the set of assignments that maximizes the sum of all \( v_{ij} \)'s. However, most CEOs are not so unconstrained. Workers and divisions may have preferences over their match partners, and may quit or slack off if assigned to a match they dislike. There are many ways to model how a CEO could be penalized for ignoring workers’ or managers’ preferences. Below, we develop a model in which unhappy agents exit the company and create retention problems. Unhappy workers could also exert lower effort, or demand higher wages for compensating differentials, or create other problems with similar negative payoffs to the CEO. Analogous issues arise for divisions: although an entire division is unlikely to quit, the manager leading them can. For these reasons, the CEO may consider incorporating the workforce’s preferences into matching.

To formalize the workforce’s preferences, we say that worker \( i \)'s utility from matching with division \( j \) is \( \mu_{ij} \) and division \( j \)'s utility from this match is analogous \( u_{ji} \). We also make two substantive assumptions.

**Assumption 1** (Quits Reduce Output). A match is acceptable to a worker or division if it yields greater utility than their outside option \( u \). If either the worker or the division finds the match unacceptable, the agent quits and their abandoned match yields zero output for the CEO.

**Assumption 2** (Private Information). The CEO knows the productivity of all pairs of workers and managers \( (v_{ij}) \), the outside option \( u \). The CEO does not know the agents’ preferences \( \mu_{ij} \) and \( u_{ji} \), but does know the distributions from which they were drawn.
Using the information in Assumption 2, the CEO can calculate the prior probability that each match is acceptable or not. The workforce’s private information about quits captures the idea that relevant knowledge is often distributed across agents in an organization. As we shall see later, a key benefit of delegating comes from using this distributed knowledge (although there are sometimes other costs). Let \( a = 1, 2, \ldots, N! \) index all possible ways to assign \( N \) workers and \( N \) managers. Let \( R(a) \) for a proposed assignment equal its retention rate, or the proportion of the \( N \) paired assignments where neither side quits (resulting in zero output). The CEO does not know \( R(a) \), but has beliefs about it.

In addition, \( V(a) \) is equal to the sum of all productivities \( v_{ij} \) that are assigned in match \( a \), assuming that no worker quits. Formally, \( V(a) = \sum_{i=1}^{I} \sum_{j=1}^{J} \alpha_{ij}(a) v_{ij} \), where \( \alpha_{ij}(a) \) is equal to 1 if worker \( i \) and division \( j \) are matched in assignment \( a \), and 0 otherwise. Across all \( N! \) actions, \( V(a) \) has a discrete frequency distribution \( \mathcal{V} \) with finite support.

\( \mathcal{V} \) is an expression of the firm’s production function and output technology. The support of \( \mathcal{V} \) measures how sensitive a firm’s output is to changes in matching. A firm whose \( \mathcal{V} \) places all mass on one point will have the same output, as long as nobody quits, irrespective of how workers are assigned. A \( \mathcal{V} \) with wider support represents a firm whose output depends heavily on matching. We will later show that the properties of \( \mathcal{V} \) affect the CEO’s choice of assignment mechanism.

3.1 The CEO’s Problem

The risk-neutral CEO’s problem is to select a matching mechanism \( M \) to maximize the expected productivity of the selected assignments:

\[
\max_{M} U = \sum_{i=1}^{I} \sum_{j=1}^{J} \alpha_{ij}(M) v_{ij} P(i \rightarrow j \text{ acceptable}|M),
\]

\[\text{s.t.: } \sum_{i=1}^{I} \alpha_{ij}(M) = 1, \quad \sum_{j=1}^{J} \alpha_{ij}(M) = 1. \tag{1}\]

One possibility is for the CEO to influence preferences by offering conditional pay raises. However in many cases, wages are not flexible. The US Army and State Department set wages according to government pay scales that do not always permit assignment-specific pay (NEED A CITE HERE). Many other public employees, like teachers, are paid using
union pay scales. Even in settings where wages seem negotiable, they may be inflexible in practice because of fairness considerations (Fehr et al., 2009). The case study of Google’s deferred acceptance states that pay raises “were legally required to go through Google’s centralized HR system,” rather than be settled by the internal market.

We contrast the CEO’s problem from other two-sided matching problems that appear to be similar. The key property of our setup is that participants’ propensity for quitting (or slacking, etc) is private information. Without access to this information, the CEO could use prior beliefs about quits, and incorporate these into payoffs into assignments. Workers in this case would have no input, outside of their influence on the CEO’s priors. Because of the lack of input or choice, we call this “command-and-control” (or “CC”) in our analysis below.

If the CEO’s priors are uninformative, the CEO may consider steps to gather workers’ private information. This would give workers input and allow the CEO to better anticipate (and avoid) the assignments that trigger quits. However, this task faces an elicitation problem: Workers and divisions may be tempted to misrepresent their preferences in order to manipulate their assignment.

In other settings, market- and mechanism-designers have developed strategy-proof mechanisms for eliciting preferences. However, the CEO’s problem is distinct from the market designer’s. We highlight two key reasons: First, the CEO has preferences over the assignment. In typical applications of stable matching, the match institution is broadly indifferent towards outcomes (subject to stability constraints). Second, although CEOs cannot stop workers from exiting, they do have the power to stop unwanted matches (even if both worker and division care to proceed). For this reason, typical stability considerations may be less critical for the CEO.

Because of these differences, the CEO has the ability (and the incentive) both to commandeer matching and to solicit input. However, the CEO can do too much or too little of either. It is possible to become too concerned with worker happiness, at the expense of firm output. Similarly, it is possible to be too insensitive to workforce preferences so that

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8One law, California’s Fair Pay Act requires “Requiring equal pay for employees who perform ‘substantially similar work,’ when viewed as a composite of skill, effort, and responsibility.’ https://www.dir.ca.gov/dlse/california_equal_pay_act.htm

9For example, the National Medical Residency Match does not attempt to match agents according to its own views about which doctors should work where, but rather in a way that pleases doctors and hospitals (subject to stability constraints).
workers quit. As such, the CEO may want to engage in tradeoffs between i) the benefits of incorporating private information, ii) the information loss and elicitation challenges of incorporating it, and iii) the coordination benefits of central assignment. In this paper, we study two somewhat extreme institutions: Centralized command-and-control and full delegation.

3.2 Matching Protocols and Preferences

As specified above, the CEO’s problem is highly general. To proceed with our analysis, we add some additional structure to the CEO’s options. To implement command-and-control (“CC”), the CEO must calculate the highest payoff assignment, balancing the potential payoffs $V(a)$ of any assignment against the distribution of quits. Appendix A.1 shows how to calculate this solution generically using the Kuhn-Munkres method. For delegation, several mechanisms exist for matching with preferences. We study one in particular:

**Assumption 3** (Deferred Acceptance). The CEO implements delegated matching using the deferred acceptance algorithm (*Gale and Shapley, 1962; Roth, 2008a*).

We use deferred acceptance (DA) as our delegation mechanism for two reasons. First, DA gives us a tractable model of delegated matches that is strategyproof for the proposing side (and both sides in many models of large markets),\(^\text{10}\) which simplifies the user’s experience and addresses the CEO’s elicitation challenges. Second, we use DA because it is widely-used in practice (*Roth, 2008a*), including many of the organizations discussed in Section 1 and in our empirical setting. Our results will be framed in terms of workers-proposing DA, but we will highlight where the proposing side matters. While we proceed using DA, many of our results are likely more general than DA. We suggest a few cases where our results seem to be particularly detached from DA, and may apply to a wider variety of preference-driven mechanisms.

Finally, we add structure to participant preferences.

**Assumption 4** (I.I.D. Preferences). Workers’ utilities $\mu_i$ and division utilities $u_i$ for each match partner are independently drawn from a common, absolutely continuous distribution $G$ ($G(u) < 1$).

\(^{10}\)See e.g., Immorlica and Mahdian (2005); Kojima and Pathak (2009); Azevedo and Budish (2019).
Under Assumption 4, all preference profiles (i.e., ways for workers to rank managers and vice versa) are equally likely. This type of random matching market is a workhorse model in the literature, particularly when applied to deferred acceptance (Knuth, 1976, 1997; Pittel, 1989; Knuth et al., 1990; Pittel, 1992b; Ashlagi et al., 2017). Adopting this formulation allows us to connect with the prior literature, and makes some results more tractable. However, I.I.D. is a very strong assumption; among other things it rules out i) vertical preferences on either side of the market, ii) correlated preferences across the market (mutual attraction or repulsion), and iii) correlations between the firm’s objective and worker/manager preferences. We relax this Assumption in Section 3.6, and examine what happens when the workforce’s preferences are correlated within and across the market, and with the CEO’s preferences.

Under Assumption 4, the probability that both sides in an assigned pair find the match acceptable is \((1 - G(u))^2\). We call this the expected retention rate of the pair. All \(N!\) possible matches have the same expected retention rate \(R\) ex-ante from the CEO’s perspective, so the average across all possible matches is the same. We denote this retention rate as \(\bar{R}\).

### 3.3 Delegation vs Command-and-Control

We now have the technology to compare CEO payoffs under delegation and command-and-control. All proofs are in Appendix A.5.

**CEO Payoffs from Command-and-Control.** Under command-and-control, the CEO must select a match that maximizes output, conditional on expected retention. Because retention rates are the same for all possible matches, the CEO’s choice under command-and-control will be based on the productivity \(V(a)\) of each match. Under command-and-control, the CEO will pick the match with the highest output out of all \(N!\) possible matches. We call the output of this assignment \(V_{CC}\); under Assumption 4, it equals the output of the assignment that maximizes \(V\). To express the overall performance of CC, we need to integrate the possibility of quitting. Because all matches have the same ex-ante retention rate \(\bar{R}\), the performance of command-and-control is the product \(\bar{R}V_{CC}\).

**CEO Payoffs from Deferred Acceptance.** Under Assumption 4, the deferred acceptance algorithm produces all \(N!\) potential assignments with equal probability. As a result, the
CEO’s expected output of DA (without quits) is $\bar{V}$, the average output over all $N!$ possible matches. Let $R_{DA}$ be the retention rate under DA. The expected output of DA is therefore the product $R_{DA} \bar{V}$.

The merits of DA depend on retention, which leads to our first lemma:

**Lemma 1.** Given Assumption 4, the expected retention rate of the match selected by DA is higher than the average of all matches, $\bar{R}$.

The proof for this in Appendix A.5 uses a key property of DA: the distribution of agents’ utilities from DA has a lower hazard rate than the unconditional distribution of utilities at all utility levels. Therefore, DA will yield a higher retention rate than $\bar{R}$. Lemma 1 is an example of a result that we expect extends to many two-sided matching algorithms that incorporate workforce preferences in some way. To improve retention above $\bar{R}$, a matching approach would simply need to rule out some bad matches for either side.

**Delegation vs. Command and Control.** Together, this analysis implies CC is expected to yield greater output than DA when the following inequality holds:

$$\bar{R}V_{CC} \geq R_{DA} \bar{V}. \quad (2)$$

Rearranging, we can see that CEO’s choice of CC or DA depends on whether improvements in productivity or retention are more important:

$$\frac{V_{CC}}{\bar{V}} \geq \frac{R_{DA}}{\bar{R}}. \quad (3)$$

The left hand side is a property of $V$, the firm’s output technology; it essentially measures how sensitive a firm’s output is to changes in matching. The right hand side is a function of $G$, the distribution from which workers’ and managers’ preferences are drawn. Using these, we can derive our first set of results.

### 3.4 Match-Specific Output: The Benefit of Command-and-Control

The benefit of CC from the CEO’s perspective is that output – conditional on expected retention – is higher. Our next set of results are about how this conditional output could
vary. We begin by studying specialization: if workers’ productivity is homogenous across matches, then there are no potential gains to be had from CC.

**Definition 1** (Specialization). A workforce is unspecialized if the outputs \( (v_{ij}) \) for each worker \( i \) are equal for all possible assignments \( j \). The workforce is specialized if workers’ outputs vary across assignments.

**Proposition 1.** The performance of delegation will equal or exceed that of command-and-control in firms where the workforce is completely unspecialized.

The intuition behind Prop. 1 is that rearranging unspecialized workers generates no productivity benefits for the CEO. If workers are equally productive in all divisions, then the most productive match \( (V_{CC}) \) is equal to the average match \( (\bar{V}) \). All the mass in \( V \) is concentrated in a single point, and the LHS of Equation 3 is equal to 1. This is a property of the production function, and is not affected by the choice of assignment mechanism. By contrast, rearranging an unspecialized workforce could generate retention benefits. As long as baseline quit rates \( G(u) \) are above zero, then the retention rate of DA will exceed that of CC. For these reasons, an unspecialized workforce makes delegation more attractive for the CEO.

Prop. 1 suggests one reason why certain firms are organized like markets: unspecialized workforces reduce the gains from command-and-control. A variety of firms have unspecialized workforces. At the extreme are “gig economy” companies such as Uber, Doordash, and competitors. Prop. 1 suggests these firms are organized like markets because there is little match-specific productivity across tasks. If these firms view workers as perfectly substitutable across tasks, there is no benefit from CEO-imposed assignments. As a result, these firms offer flexibility to accommodate workers’ preferences around the timing, location, and total amount of driving (Hall and Krueger, 2018).

Non-specialization also appears in more traditional workforces. Google and the U.S. military, two organizations that use deferred acceptance mechanisms for personnel assignment, both have an openly advertised preference for generalists.\(^{11}\) Although Google’s engineers may be specialized within the overall economy, they may be less specialized to

any of their employers’ internal tasks. Employers who hire generalists emphasize the flexibility, adaptiveness, and robustness that it affords; theory models by Dessein and Santos (2006) and Deming (2017, 2021) formalize some of these intuitions. Our results suggest that hiring generalists and delegating assignments are complementary.

A variety of empirical papers document a secular trend toward less specialized job assignments. A related economics literature studies how information technology influenced job design, finding that IT caused work to move away from fixed categorization and towards job rotation and “multitasking” by workers. One alleged cause of this is routine biased technological change, which made work in many occupations less routine (Autor et al., 2003).

**Corollary 1.** For command-and-control to outperform delegation, it is necessary (but not sufficient) for the workforce to be specialized.

Eq. 3 shows why specialization alone is not sufficient. Specialization must also generate enough extra output to justify the retention loss of command-and-control. Both results (Prop 1 and Cor. 1) are driven partly by our I.I.D. assumption, particularly the lack of correlation between each agent’s preferences and their productivity to the firm.

In Section 3.7, we allow workers preferences to be correlated with their output. However, a degree of uncorrelatedness appears elsewhere in many settings. In our empirical setting, we study an internal mobility program created in response to worker unhappiness with their current specialization. Fear of “overspecialization” is a chronic topic of career advice. More generally, misalignment between principals and agents’ is a classic problem in the economics of organizations.

**Extension 1 (Noisy CEO Beliefs.)** Until now, we have assumed that CEOs have perfect
describes to generalist hiring within the US military. The Army describes the “Army Talent Alignment Process” as: “a decentralized, regulated, market-style hiring system that aligns officers with jobs based on preferences https://talent.army.mil/atap/.

12See Osterman (1994); Ichniowski et al. (1996); Brynjolfsson and Hitt (1998); Organisation for Economic Co-operation and Development Staff (1999); Caroli (2001); Caroli and Van Reenen (2001); Deming (2017, 2021). As Dessein and Santos (2006) note, the biggest management fad of the 1990s, reengineering (Hammer and Champy, 2009) prescribes “combining several jobs into one” and thus “putting back together again the work that Adam Smith and Henry Ford broke into tiny pieces.”

13For examples, see Bresnahan (1999); Lindbeck and Snower (2000); Caroli and Van Reenen (2001); Mobius and Schoenle (2006); Bloom and Van Reenen (2011).

14For an example, see https://www.fastcompany.com/3000791/how-specialize-yourself-right-out-job.
knowledge of workers’ match-specific productivities \( (v_{ij}) \). In Appendix A.2, we consider an extension in which the CEO observes these noisily. Even if workers are specialized, the CEO may be unable to observe the specializations.

Proposition A1 shows that noisy measurement diminishes the benefits of command-and-control. If the CEO does not know which matches are productive, then the firm is better off enjoying the retention benefits of delegating. One implication of this result is that better monitoring and/or analysis technology can tilt organizations toward command-and-control. If better technology allows CEOs to reduce measurement noise, the match-specific benefits of CC may outweigh delegation.

### 3.5 Retention: The Benefit of Delegation

Our next set of results are about retention and the right hand side of Equation 3.

**Proposition 2.** The retention benefits of DA relative to CC are higher as the unconditional quit probability \( G(u) \) increases.

The intuition for this result is that if \( G(u) \) is low, few participants are at risk of quitting. As a result, the CEO sees limited benefits to putting participants into arrangements that prioritize their preferences. These workers are happy enough to remain, even in less preferred assignments. By contrast, when \( G(u) \) is high, workers and managers will quit unless they get their top choices. As a result, there are larger returns to arranging workers using their preferences.

The base level of retention \( G(u) \) can vary for reasons with economic interpretations.

**Corollary 2 (Workforce-Unfriendly Firms).** Let \( G' \) represent a distribution such that \( G \) first-order stochastically dominates \( G' \). DA is more attractive under \( G' \) than \( G \).

The shift in \( G' \) can be interpreted as making the firm less attractive to workers (since draws from \( G' \) are more likely to lie below \( u \)). Defined this way, workforce-unfriendliness could either be a common trait to an entire industry, or a firm-specific characteristic (possibly part of a strategy to tradeoff retention for other benefits). Workforce-unfriendly firms are not necessarily unsuccessful; they may be highly profitable by keeping costs low. Worker unfriendliness raises the retention benefit of placing workers in attractive jobs, and makes DA more attractive. DA and worker-unfriendliness are complementary; or
conversely, being an attractive destination for workers is complementary with command-and-control.

**Corollary 3** (Outside Options). *DA is more attractive as $u$ increases.*

Corollary 3 suggests that even firms that are relatively worker-friendly may find DA attractive if outside options are high enough. One example of this is Google, a company that regularly appears at the top of Forbes’ *Best Places to Work* list and offers workers free gourmet lunch and subsidized massages. Despite this, Google opened an internal talent marketplace in 2014 based on the deferred acceptance algorithm (Cowgill and Koning, 2018).

**Corollary 4** (Asymmetric Information). *Let $G'$ be a mean-preserving spread of $G$, so that $G'$ has the same mean of $G$ but higher variance. Unless $G(u)$ (the base rate of quitting) is too high, DA is more attractive for $G'$ than $G*."

Corollary 4 addresses the variance of $G$. Higher variance corresponds to greater CEO uncertainty about workers’ (privately-known) tastes, and thus an environment of greater asymmetric information. The CEO’s view of expected quitting is higher amid this uncertainty (as long as the base rate of quitting is sufficiently low). This increases the expected returns to DA.

Finally, we can model the effects of higher quitting costs. Suppose every successful match has a benefit of $c_N$ in addition to its productivity $v_{ij}$. This additional benefit $c_N$ can be interpreted as a quitting cost (it is lost if the match is unsuccessful).

**Lemma 2** (Quitting Costs). *Higher quitting costs attenuate the relative benefits of CC over DA, $\frac{V_{CC}}{V_{DA}}$.*

The results above offer some suggestive evidence for why internal talent marketplaces have grown popular in particular settings (high turnover, potentially workforce-unfriendly firms, industries with high outside options and/or retention costs). Although the results are discussed in terms of cross-sectional differences (i.e., differences in firms or industries), we can also apply them to intertemporal changes. Internal talent marketplaces have grown in the last decade, particularly during the pandemic. The last decade included record high quitting rates (Prop. 2), both before the pandemic (Fuller and Kerr, 2022), as well as the subsequent “great resignation.”
During this time, work may have become unattractive either because work becomes worse (e.g. all-day Zoom meetings, social distancing at work, Corollary 2), or because non-work becomes more attractive (e.g. rising quality of leisure, Aguiar et al. 2021; post-pandemic attractiveness of self-employment, Fazio et al. 2021; Haltiwanger 2021, Corollary 3). Faberman et al. (2022) documents a reduction in labor supply during the pandemic across most demographic groups, and particularly for workers with a high degree of social contact in their jobs. Tight labor markets increase quitting costs (Lemma 2). Some researchers allege a secular trend in higher quit rates, noting the steady rise in quit rates since 2009 (Fuller and Kerr, 2022).

The last decade also featured rising uncertainty including several uncertainty shocks (Altig et al., 2020, culminating with the pandemic). As workers were reallocated to new tasks under new circumstances, a CEO’s understanding of workers’ satisfaction with potential assignments (Corollary 4) may have become less clear, as did workers’ productivity $v_{ij}$ in those assignments (Extension 1). Both these trends favor delegation. Some researchers have documented a secular shift towards employers’ hiring generalists (Proposition 1) as a way of mitigating shocks such as those mentioned above.

All of these factors increase the attractiveness of delegating matches. Companies offering talent marketplace software have gained traction in the last decade and claim the pandemic has been good for business;\textsuperscript{15} market leader Gloat.com’s reached its peak valuation in June 2021 of $400M.\textsuperscript{16}

**Extension 2 (Firm Size.)** Our model also permits us to show how the retention benefits of delegating are increasing with the size of the firm. Our result essentially adapts a well-known result from Pittel (1992a) showing that as a random market enlarges, agents are more likely to be paired with a match partner they rank highly. In our setting, this translates into higher retention.

Besides retention, there may be additional reasons for large firms to prefer internal markets. Setting up a DA marketplace involves fixed costs (creating a match database, training workers and managers). In addition, a central executives’ ability to monitor match-specific details may attenuate as a firm becomes large, thus reducing the benefits of

\textsuperscript{16}https://techcrunch.com/2021/06/16/gloat-raises-57m-to-reinvent-the-internal-job-board/.
command-and-control (Extension 1). The empirical setting of the current paper contains little size variation; to conserve space, we have placed the details of our theoretical results about firm size in a separate mimeo (Cowgill et al., 2022).

Our results about firm size suggest reasons to expect talent marketplaces emerge in some organizations and not others. Many of the adopters of internal market places are large, including the world’s two largest employers, Wal-Mart and the US military. Like our other results, secular trends favor greater adoption; in recent decades, firm size has also increased, and a greater percentage of workers are employed in large firms (Hopenhayn et al., 2018).

3.6 Correlated Preferences

As noted above, our I.I.D. assumption is strong. It rules out i) vertical preferences on either side of the market, ii) correlated preferences across the market (mutual attraction or repulsion), and iii) correlations between what the firm wants and what workers/divisions like. We now relax each of these restrictions.

Vertical Preferences. In many real world settings, agents on one side of the market agree on the ranking of agents on the other side (vertical preferences). Managers may all agree on the best workers, and workers may agree on the best managers/divisions. Vertical preference assumptions appear in many academic papers.\footnote{For example, Agarwal (2015) and Agarwal and Diamond (2017), consider the econometric identification of preferences in a two-sided market under vertical preference assumptions.}

To relax our I.I.D. assumptions and use vertical preferences, we need to introduce additional concepts. Vertical preferences can apply to one side, leaving the other I.I.D., or to both sides simultaneously. In our formulation, the CEO knows that preferences are vertical for one or both sides. However, the CEO does not know exactly which options are ranked $1^{st}$, $2^{nd}$, $3^{rd}$, (... etc.) by the vertical side(s).\footnote{In practice, this may be easy for a CEO to find out. If the CEO learned the vertical preferences, this would decrease the value of DA, insofar as it would allow the CEO to incorporate information about quitting without using DA.}

We begin by assuming one side of the market has vertical preferences.

**Proposition 3** (Vertical Preferences). If one side of the market has vertical preferences, DA does not increase that side’s retention.
The intuition of this result is that if preferences on one side of the market are vertical, then all participants on that side have the same first choice, second choice, etc. No matter how these agents are matched or who proposes, exactly one agent will match with her $k^{th}$ choice for all $k$, so CC and DA have identical expected retention rates. If the other side’s preferences are I.I.D., there may still be benefits from using DA from retaining that side, particularly if the I.I.D. side proposes. These benefits may be high enough to outweigh the coordination benefits of command-and-control. However, the DA retention bonus will be lower than if both sides had I.I.D. preferences.

**Semi-Vertical Preferences.** The results above show that perfectly vertical preferences eliminate the potential benefits of DA. However, most preferences are not perfectly vertical; they may be highly correlated but not completely. Are the retention benefits of DA monotonically decreasing in workers’ preference correlation? Although we do not have analytic results on this question, we present simulation results in Figure 1. The figure suggests that the DA retention rate increases initially as preferences become slightly correlated, but converges to the unconditional retention rate as preferences become highly correlated.\(^{19}\)

**Cross-Sided Correlations.** Preferences can also be correlated across sides. Workers’ and managers’ preferences may exhibit a high degree of reciprocity. If preferences are correlated across sides, but are otherwise I.I.D. (i.e., no vertical preferences), then the results in our I.I.D. model all hold. None of our results from this model rely on uncorrelated-ness across sides. They are mainly driven by the lack of correlation between workforce preferences and the production technology.\(^{20}\)

\(^{19}\)As we show in Appendix Figures E3 and E4, the initial increase in retention rates on the left hand side of Figure 1 is a result of the receiving side of the market receiving a better match. But as preferences become more correlated, overall retention declines because more workers are matched with less preferred divisions. Appendix Figures E3 and E4 contain the overall retention rate broken out by the workers and divisions side.

\(^{20}\)The addition of cross-sided correlations does not change expected retention rate under DA, and thus Equation 3 is the same. This is partly because of our formulation of the problem, in which the CEO’s penalties are the same irrespective of if an agent quits, or if the agent’s match partner quits, or both quit. If the penalty for both quitting is higher, then cross-sided preferences would result in a higher degree of both-sides quitting than in our standard I.I.D. setup, and the benefits of DA would be higher (since the CEO gets extra credit for avoiding both sides quitting).
3.7 Alignment: Correlation Between CEO & Workforce Preferences

The final way we relax the I.I.D. assumption is to allow alignment between the workforce’s preferences and the CEO’s. The I.I.D. model in Section 3.2 assumed these were independent. In reality, a CEO and his workforce may desire very similar assignments. Workers may care about the CEO’s goals if they have intrinsic motivation for the company’s mission, or they may be compelled to care through an incentive contract.

To formalize this type of alignment, we introduce two definitions:

**Definition 2 (Broad Alignment).** An agent is said to have broadly aligned preferences with the firm if their utility over matches is of the form $f(V) + \varepsilon_{ij}$ where $f(V)$ is an increasing function and $\varepsilon_{ij}$ is uncorrelated with productivity. We say an agent has strictly broadly aligned preferences with the firm if their utility is of the form $f(V)$.

Broad alignment means that agents gain utility from the company succeeding as a whole, and strict broad alignment means that the firm’s overall success is the agent’s only source of utility. Broad alignment would appear to be favorable for the use of deferred acceptance, as it would give workers a vehicle for using private information in a way that is productive for the firm. However, specifying the format of this alignment features some challenges. Broad alignment means that workers care about the output of the organization as a whole. This requires them to have preferences about what other workers do (i.e. preferences over all $N!$ possible ways of assigning all workers to divisions). However, deferred acceptance only permits workers to rank $N$ members of the other side. As such, agents’ rankings will be a function of beliefs about what other workers and divisions will do. We analyze the Nash equilibrium of this setup in the following proposition.

**Proposition 4.** If workers and divisions have strictly broadly aligned preferences, the CEO’s optimal match is the surplus-maximizing Nash equilibrium of deferred acceptance, but is not generally a unique Nash equilibrium. Deferred acceptance can equal the performance of command-and-control, but cannot exceed it.

The result exhibits two key aspects of deferred acceptance as a management tool. First, the benefit of deferred acceptance comes from retention. The mechanism helps CEOs by incorporating workers’ private information about when they will quit. However, if workers are strictly aligned, there would be no private information and no quitting anyway,
thus eliminating this benefit. The CEO can implement the optimal match, achieving the same outcome, without delegation.

Second, when the workforce is broadly aligned, multiple equilibrium problems arise. Although Prop. 4 examines an extreme case (strict broad alignment) similar multiple equilibria issues would arise if workers and divisions had private values for each match and were paid a percentage of total firm output. Prop. 4 highlights the coordination aspect of the CEO’s problem; even when agents are maximally aligned, multiple equilibria could exist. Command-and-control could perform an equilibrium selection role in this setting.

Broad alignment is a very strong assumption, and in many other settings researchers have found strong firm-wide incentives difficult to introduce (Holmström, 1979; Holmström, 1982; Oyer, 2004). In practice, firms sometimes face a different form of alignment.

Definition 3 (Narrow Alignment). An agent is said to have narrowly aligned preferences with the firm if their utility over matches is of the form $f(v_{ij}) + \varepsilon_{ij}$ where $f(\cdot)$ is an increasing function and $\varepsilon_{ij}$ is uncorrelated with productivity. We say an agent has strictly narrowly aligned preferences with the firm if their utility is of the form $f(v_{ij})$.

Narrow alignment means that agents gain utility from the productivity of their own matches (irrespective of their co-workers’ matches). This is similar to paying salespeople for their own production, and not the success of the firm as a whole. Under this form of alignment, agents do not have to consider the behavior of others; each agent can rank all $N$ possible match partners considering how productive they would be in the match (individually). However, there are limitations to this form of alignment.

Proposition 5 (Talent Hoarding). Narrow alignment is not sufficient or necessary to guarantee that DA yields output as high as CC.

Even if all workers aspire to their most productive uses (individually), the result may be a suboptimal overall match. The intuition for Proposition 5 is about hoarding. Narrow alignment encourages each manager to seek (and retain) the most productive workers, even if these workers would have better use elsewhere in the company or are likely to quit in these jobs.\footnote{Our setting is motivated by horizontally differentiated placements, but managers could also “hoard” talent by denying promotions to deserving workers (Haegele, 2021).} Similarly, narrow alignment by workers produces the reciprocal “project hoarding” (seeking out the most productive projects, even if other workers would
be more productive in these jobs). In the extreme case, narrow alignment on both sides of the match could produce an assortative match, which is only optimal for output if the production technology is supermodular (Becker, 1973), and whose retention is no better than command-and-control (because both sides’ preferences are vertical, Prop. 3).

In more general terms, the problem with narrow alignment is externalities. Even when a worker performs a job well, their assignment may leave others in the company without productive uses, leading to suboptimal overall output. Maximizing an organization’s performance may require some workers to perform in roles where they are not individually their most productive. Through these opportunity costs, each worker’s assignment imposes a displacement externality that affects other workers, divisions and the CEO’s objectives. The CEO can incorporate these externalities in command-and-control, while delegating to narrowly-aligned agents does not automatically achieve this.

Prop. 5 shows how aligned preferences are insufficient for preference-respecting mechanisms to perform well. Appendix A.3 shows that narrowly-aligned preferences are not necessary either. In this example, deferred acceptance leads to an optimal configuration, despite worker preferences not being aligned according to our definition.22

Despite these limitations, narrow alignment can be sufficient for DA to perform well for certain types of production technology. For example:

Corollary 5. Suppose that workers and divisions have strictly narrowly aligned preferences, and that match productivities are the result of a production function that is supermodular in workers’ and divisions’ types. Then the worker-proposing deferred acceptance algorithm selects the CEO-optimal assignment. However, the CEO can select this without deferred acceptance using command-and-control.

These results show settings where delegation performs well. Unlike our previous results, there is no coordination or multiple equilibria problem. However, like the previous results, there is no tension between CEO and worker wants so workers are placed in their most preferred matches under command-and-control with there is no quitting under strict narrow alignment. As a result, there is no benefit to incorporating workers’ preferences. The CEO can obtain the same result by command-and-control, without delegation.

22 Of course, this raises the possibility that “negatively aligned” preferences could result in the optimal organizational match, even if preference-respecting mechanisms were used. In Appendix A.4, we provide an example that this is possible. In our example, workers and managers want to avoid working on the projects where they are individually most productive. Nonetheless, preference-respecting mechanisms produce the optimal assignments.
Prop. 4 and Cor. 5 shows that deferred acceptance and command-and-control sometimes produce the same outcome. In these settings, one may be preferable for reasons outside of our model. Delegating often requires a costly process of soliciting input. The case study of Google’s internal mobility program discusses both infrastructure (an internal website for browsing options and submitting preferences) and training programs to teach workers about the system. However, delegation may also have benefits outside the model. A longstanding view in organizational psychology and other disciplines is that workers have intrinsic, non-instrumental value for decision rights (Bartling et al. 2014, in addition see the psychology literature about “procedural justice” Cropanzano 1993; Brockner 1996). Anecdotes from Google suggest that workers value the pageantry and symbolism of workers’ choice, separately from its instrumental value. These issues are outside of our model, but may be an important consideration in practice.

4 Empirics

4.1 Setting and Institutional Details

Our theory model suggests that neither command-and-control nor delegation are optimal for all firms; instead, the CEO’s choice depends on parameters that can differ between firms and industries (and across time). We now study how the forces in our model unfold in an applied setting.

Our data come from a Fortune 500 company that develops software for business clients. The software includes, for example, customized tools for organizing and indexing special files and/or importing and managing content libraries. Employees are organized in teams serving a product and/or client, and each team has a single manager. These teams are the divisions in our theory model, and new (and/or internally mobile) workers need to be matched to them. Prior to the adoption of an internal job marketplace, each participant was assigned to a team indefinitely. Initial assignments were chosen by centralized administrators who performed a role similar to the CEO in our theory model: While these executives considered workforce preferences, they also considered the broader needs of the company and each worker’s qualifications.

These teams featured a mixture of engineers and non-technical staff. Engineers on these teams held a BS in computer science, and non-technical staff held a BA in a social science,
professional, or humanities subject. A single manager oversaw each team. Some products had multiple such teams, each working on different clients or different aspects of the product (with two separate managers).

Our setting features several characteristics appearing in our theoretical setup. The company’s publicly stated recruiting philosophy included both generalists and specialists (Definition 1 and Cor. 1), but overall leaned more towards generalists (Prop. 1). We later measure specialization directly. Workers and managers are relatively skilled and have good outside options (Cor. 3), and replacement costs are high (Prop. 2). The overall retention rate was high compared to industry standards (Prop. 2), but concerns about retention led to the adoption of the jobs marketplace.

Workers are paid in part with stock compensation to align incentives with shareholder goals (broad alignment, Definition 2). However, workers and managers are also paid a similar amount in individual bonus based on their own performance (narrow alignment, Definition 3). For the workers in our sample, approximately 40% of their annual compensation is performance based, with about half coming from stock options (broad alignment) and the other half coming from cash performance bonuses. This percentage is higher for managers and more senior workers.

4.2 Internal Mobility

During the sample period, the organization’s leadership sought to change the system of indefinite assignment to increase internal mobility. Both workers and team managers had expressed a desire for greater mobility. After employees spent several years in an organization, they sought career growth on a new project. Similarly, some managers sought to update their roster of workers with workers whose skills or interests were better aligned.

The company’s leadership embarked on building a market-like structure. All project assignments were given a pre-established “term length,” measured in quarters. All workers whose term was ending – including those who were successful in their previous jobs – would go into the market to be reassigned. Those who wished to stay in their roles could remain, but only if they were matched again through the market system. Term lengths coordinated internal search around predictable points in the annual calendar in which lots of

23 “Term lengths” were created in part to avoid adverse selection in which only bad workers or managers sought new assignments.
workers and managers would be searching for new assignments. By aligning the timing, the exchange market was thicker and featured more options for both sides.

To avoid disruption, entry into the market was staggered. The firm aimed for no more than 25% of workers to be on the market at any time, so that the remaining 75% could focus on their day-to-day work. Partly as a result of the staggering, each manager was typically recruiting at most one new worker in any given quarter’s match. As a result the match was 1:1. Nearly all matches were unbalanced, and featured an excess of managers hoping to recruit new workers.

Each quarter, eligible participants were given access to a web application through which they could develop a profile to describe their interests, accomplishments, and skills. Managers also included their job opening and skill requirements. Profiles could be searched or browsed. Although we could not obtain a screenshot for this paper without revealing internal user information, Figure D1 includes a mockup that replicates a hypothetical user’s profile page.

Each side then submitted a rank-ordered list of their preferences before a deadline. Figure D2 contains a replica of the submission page. The workers and managers were then matched using the ranked preferences using the workers-propose version of the deferred acceptance algorithm (Assumption 3). The ranking tool also allowed workers to identify managers with whom the worker would rather go unmatched. For workers this would mean quitting, and for managers this meant having one fewer worker. As part of the introduction of match, the firm trained the workforce about deferred acceptance so that all sides could understand how their rankings would be used. The training emphasized that all rankings would be kept strictly confidential. During the early rounds of the match, participants were anonymously surveyed about whether their rankings reflected their true preferences. 90% of managers confirmed that it did, and the remaining 10% reported feeling “neutral” about whether the reported preferences were their true preferences.

4.3 Market Restrictions

Although the marketplace broadly welcomed workers on the market to transfer anywhere, the leadership imposed some limitations on the market. First, the market was segmented into (essentially) two submarkets per quarter based on workers specialization (Prop. 1) as either engineers or non-engineers. Workers in one submarket could not bid
on the other without special permission. In practice, a few engineers were permitted to
bid on non-engineering jobs but never the other way around.

Second, the firm centrally selected which project managers were allowed to enter the
market and match with a worker. The match’s original design allowed managers to enter
the market more freely. However, the firm’s executives quickly realized how many man-
gagers wanted additional headcount. Without restrictions, high-priority cash-cow projects
could (in principle) lose headcount as workers abandoned them for smaller projects that
were cutting-edge, but speculative (and typically lacked a business plan). This can be seen
as narrow alignment gone wrong (hoarding, Prop. 5) – workers and managers concerned
only with their personal success drawing key resources away from critical projects. The
company’s executives thus limited the amount and type of projects in the market.

Finally, the firm developed a user-interface cue to nudge workers towards firm-preferred
rankings (described more below). We have no way of measuring how segmentation, lim-
ited entry and nudging affected preference rankings and final assignments, 24 although we
assume they pushed them towards the leadership’s objectives. Without these measures,
our performance measures of DA might be even worse.

5 Empirical Strategy: Firm Productivity Estimates

Using data from this setting, we aim to measure several of the key properties in our theo-
retical section. For example:

• How specialized are workers? How does their productivity compare across different
  matches?
• Do workers and managers prefer to work on assignments that maximize their own
  productivity? (narrow alignment, Definition 3, Prop. 5)
• Do worker/manager preferences exhibit a high degree of vertical preferences (Prop.
  3) and/or cross-sided reciprocity (Sec. 3.6)?
• How assortative/disassortative are the dicated and delegated matches?

24 Even without segmentation, non-engineers might not have ranked any engineering jobs. Had they,
managers may not have ever ranked them highly enough to have generated a match. Similarly, small spec-
culative projects might not have pulled labor off of established, important projects.
• How productive is the self-organized match (via DA) vs the leadership-preferred match (Equation 2)?

• How does the workforce rank the firm-preferred match?

A key input into these questions is the firm’s productivity measures for matches, $V(a)$ in our theory model (particularly $V_{CC}$ and $V_{DA}$, the outputs under command-and-control and DA). We now lay out our strategy for measuring these productivities. We begin by mentioning some important challenges of this problem. We then describe our strategy conceptually, and finally detail our implementation. The next sections contain our analysis plan and results.

**Measurement Challenges.** Measuring $V(a)$ involves several empirical challenges, but we mention two in particular. The first is “omitted payoffs.” If a match yields strong performance on CEO objectives easily visible to the researcher, how can researchers be certain it improved overall outcomes? Second, two-sided matching faces an enormous set of potential assignments ($N!$), only one of which will be realized. In our smallest market featuring 35 workers, this number is $35!$ or over $2.6 \times 10^{35}$. This makes it hard to know how a counterfactual match would have changed outcomes.

A key limitation is that interventions (such as a different matching technique) cannot be randomized at the individual employee level. Changing one employees’ match generates spillovers onto other employees’ matches, and other managers’ matches. The unit of treatment is the entire workforce.\(^{25}\)

These challenges are not unique to our setting. For example, empirical papers by Abdulkadiroğlu et al. (2020); Abdulkadiroğlu et al. (2021) are about “match quality” in between schools and families. “Match quality” in education is potentially hard to define, and there are a potentially enormous number of match-specific outputs to measure. The researchers overcome these challenges by developing models of match quality based on teacher/student value-added studies (Todd and Wolpin, 2003; Koedel et al., 2015; Abdulkadiroğlu et al., 2017) developed on observational data.\(^{26}\)

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\(^{25}\)One could sub-divide the market. However, existing matching theory (Roth, 2008b; Akbarpour et al., 2020) shows the value of larger, thicker markets. If markets are partitioned for measurement reasons, it may destroy the effect we are trying to capture.

\(^{26}\)In Abdulkadiroğlu et al. (2020), the researchers are able to validate these estimates by comparing a subset of them to value-added estimates using a lottery.
quality are not directly observed through experiments, but inferred through these models. Our approach is similar.

5.1 Conceptual Approach

The challenges above may appear in many other settings besides matching. Below we describe a more general problem in which researchers are interested in evaluating $K$ options and a conceptual strategy for measuring the benefits of the $K$. After, we describe how we operationalized this strategy in our setting. In short, our approach involves using modeled outcomes (similar to described above, Abdulkadiroğlu et al. 2020). However, instead of using prior observational data to train these models, we obtain incentive-compatible estimates of the leadership’s preferences (via direct elicitation). Our approach proceeds with two steps:

**Step 1 (Elicitation).** *Elicit an objective function for the CEO’s ranking or cardinal utility weights for the $K$ alternatives.*

A full discussion of elicitation techniques is beyond the scope of this paper, but one could use discrete choice experiments or conjoint methods (Green and Srinivasan, 1978). Should the $K$ options be too many to label individually, researchers could make and justify assumptions for labeling a subset of $K$, and using this labeled subset to extrapolate labels for the remainder.

**Step 2 (Intervention).** *Use the elicited objective function in Step 1 to intervene in the organization to encourage favored outcomes.*

In our design, the exclusive purpose of Step 2 is to make Step 1 incentive-compatible. Separately, researchers may want to study the intervention as a natural experiment and measure its effects, however that is not part of the strategy we outline here. Through the intervention in Step 2, executives must “live with their choices” (Ding et al., 2005) in Step 1, and thus face incentives to report their true objectives. The credibility of the strategy clearly depends partly on the strength of the intervention (and how seriously the CEO took the elicitation). The ideal intervention would not only encourage the CEO’s single most preferred option to be realized, but nudge favorable outcomes throughout the entire distribution. This would give the CEO incentives to Step 1 not only to identify the single
most preferred option, but to take seriously the ranking of the other \( K - 1 \). Our application meets this criteria.

Once elicited, the objective function addresses the earlier measurement challenges. If the CEO has payoffs that are “omitted” from typical data, the CEO can incorporate expectations about these in the Step 1 ratings. The resulting function can evaluate any arbitrary assignment among the \( N! \), producing the CEO’s \( V(a) \) for that match. This includes the DA match and a distribution of random matches. The objective function can also be used to construct the match that would maximize the firm’s objectives.

The procedure above shares some features with conjoint analysis (Green and Srinivasan, 1978; Ding, 2007), surrogate outcome methodology (Athey et al., 2019; Prentice, 1989), and “incentivized resume rating” (an alternative to resume audit studies, Kessler et al. 2019). Importantly, we make no claim that the elicited objectives are the “correct” ones for the firm (or other normative distinctions), only that the elicited objectives the elicited objective approximates (“surrogates” for) the leadership’s objectives \textit{ex-ante}. As such, it is useful for assessing tradeoffs between CEO objectives and other constraints.

5.2 Operationalization

In our applied setting, the leadership spotted a need to develop an objective score like the one described above. They were worried about the exact set of issues outlined in the theory section of this paper: A match based only on workforce preferences could produce highly unproductive teams. For example, participants could form matches to facilitate social connections or aspirational jobs, rather than qualified matches based on skills. The firm wanted to develop an \textit{ex-ante} metric of quality they could use to evaluate matches (once they were realized).

As a result, they developed a scoring metric like the one we described in Step 1 to assign a cardinal weight to any pairwise match between a worker and manager/team. The leadership then deployed this metric inside the web application in order to “nudge” the workforce (Step 2) towards ranking company-favored matches favorably. While each side of the market browsed the other’s profiles, the web application displayed an icon indicating the company’s assessed match quality. The icons not only displayed each user’s top recommended match, but also labeled degrees of company approval for each match using color-coded icons. These are visible in our Figure D2 & D1 screenshot mockups. Later, the
leadership evaluated the performance of the match based on this same metric.

To be clear, the creation of the firm’s objective score was initiated and executed by the firm itself, without our suggestion or encouragement. The two-step procedure described above describes why this is a useful approach, what challenges it solves, and how it could be replicated elsewhere. The independent development of the score makes it a better representation of the leadership’s priorities, as it shows the firm took this metric seriously. In addition, implementation choices about the metric were made in service of the goals above.

We use the firm’s objective score as part of our analysis of the broader topics of this paper. Because these scores were shared with workers and managers, they might have influenced rankings. We have no way to know how much this happened. Workers were free to ignore the recommended rankings. Insofar as the scores affected rankings, our results could be interpreted as a lower bound of the true level of misalignment between worker preferences and firm objectives.

Appendix B contains some implementation details of the firm’s objective score. The scoring algorithm used several input variables, but the most prominent were job skills and requirements, language requirements, and location. Among the many ways to optimize around these variables, the metric selected by the firm may have been chosen because it looked good on other dimensions. Although one can question the firm’s choices, we encourage readers to think of these scores as a reasonable proxy of the leadership’s objectives.

Data. The objective scores are the final piece of data necessary to study some of the questions motivating our paper. Our data consist of participant characteristics, preferences, objective scores for each pairwise match, and potential assignments under various matching regimes including the workers-propose DA match used by the firm. Appendix C describes all variables in greater detail. To calculate the firm-dictated match, we use the aforementioned Kuhn-Munkres algorithm that finds the matches that maximize the score, and we include some other matching algorithms for comparison (including random assignment with equal uniform probabilities). Each algorithm is run 50 times resolving ties randomly, generating a distribution of potential assignments.
6 Empirical Results

Table 1 displays summary statistics for our sample. Our data consists of 318 workers applying to 517 divisions/managers across seven submarkets. The average worker went on the market 1.67 times and submitted around three rankings, though some workers ranked up to 26 managers. Meanwhile, managers submitted just over two worker rankings on average.

From here, our analysis is straightforward. We show details below, but summarize our findings first: Our data about workforce rankings suggest preferences are relatively uncorrelated with where the leadership thinks they are individually most productive (i.e., little narrow alignment). Workers and managers also have a low degree of vertical preferences. In this respect, worker/manager preferences resemble the I.I.D. model, but with a high degree of cross-sided reciprocity.

Next, our data on the firm’s objective score suggests that workers and managers exhibit a high degree of specialization, and that the firm’s objective function is more submodular than supermodular. Partly for these reasons, the CEO preferred match experiences high gains from using this specialization, and produces a slightly disassortative match. By contrast, the DA match does not prioritize specialization as much (because participants did not rank their specializations highly). Furthermore, the DA match exhibits a slightly positive assortative matching.

As such, the DA output is only slightly more productive than random matching (\(\bar{V}\) in our theory model). However, the DA output is significantly better for workers preferences, while the centrally-planned match is approximately as good as random matching. We show these results in detail below, and then discuss their implications at the end.

6.1 Worker/Manager Preferences

Alignment. Are individual workers and managers preferences “aligned” with the firm’s objectives, either in the narrow (Def. 3) or broad sense (Def 2)? We aim to answer these questions in Panel B of Table 2. We run rank-ordered logits to describe workers’ (and managers)’ preferences. These regressions include all possible matches for each worker
and manager, and use the workers’ (or managers’) rankings as the dependent variables.\footnote{In Appendix Table E1, we run simpler OLS specifications predicting which option is each agent’s #1 choice.} We focus on two key explanatory variables. The first is the firm’s objective score (corresponding to the $v_{ij}$ in the model). The resulting coefficient suggests how much each worker is “narrowly aligned,” i.e., values matches that increase their own individual output. In addition, we include a variable measuring “broad alignment” for each $i, j$ match. Our measure of broad alignment is whether each $i, j$ match is present in the firm-dictated match (as calculated using the Kuhn-Munkres algorithm).\footnote{In some cases, there are multiple ways to achieve a maximum. In these cases, we express “broad alignment” of a match $i, j$ as the proportion of all optimal matches that include $i, j$.} We call this the “Firm dictated” assignment in the results table.

Panel B of Table 2 shows our results for both types of alignment. Columns 1–3 display the results for worker rankings while columns 4–6 display them for manager rankings. Across our results, we see some evidence for both narrow and broader alignment by managers and workers. However, the coefficients are economically small in magnitude, are marginally statistically significant, and do not explain a high fraction of variance in preferences. Workers and managers are at best weakly aligned with the firm’s objectives, both in a narrow and broad sense.

**Vertical Preferences** We now analyze the extent to which (i) workers on average prefer the same managers and (ii) managers on average prefer the same workers. Prop 3 shows that this would be relatively bad for deferred acceptance, insofar as such “vertical” preferences would create same-sided competition, prevent workers from obtaining their top choices, and thus reduce the retention (or effort) benefits of DA.

To measure vertical preferences, we create a dataset containing all possible pairs of workers, and calculate the Spearman’s rank-correlation $\rho$ for each pair of workers’ preferences over the same set of managers. We later repeat this analysis from the manager’s side, examining how correlated pairs of managers’ preferences are over the same set of workers. The $\rho$s in these analyses could in theory vary from -1 to +1.

For both workers and managers, the average $\rho$ is essentially zero (-0.01 and -0.02, respectively). This means that one worker’s preferences are uninformative about another’s; workers have independent uncorrelated views of the same set of managers. Our results suggest workers and managers have a highly idiosyncratic, personalized, and distinctive
set of preferences that do not come into conflict with other members of the same side. Prop 3 suggests that this is good for deferred acceptance, insofar as the workforce as a whole can obtain high rankings without competing.

Our results thus far somewhat resemble our I.I.D. model insofar as workforce preferences seem uncorrelated both with each other’s preferences, and with the leadership’s (above, at least in a narrow sense).

**Cross-Sided Reciprocity** Our results above suggest that workers and managers’ tastes are both highly idiosyncratic and personal. We now turn to cross-sided preference correlations. If a worker (idiosyncratically) likes a manager, does the manager like the worker in return (and vice versa)? We measure this by calculating Spearman’s rank-order $\rho$ for cross-sided preferences.

Our results suggest much stronger positive correlations (compared with our same-sided results), but still overall moderate correlations in cross-sided preferences. Among all preferences, the correlation is 0.25 (of a possible range of -1 to +1). Among pairs who ranked each other, the correlation is much higher (0.64). However, as we document in Section 3.6, the results of our I.I.D. model still hold if preferences are correlated across sides (but are otherwise I.I.D.).

### 6.2 Firm Objectives

Figure 2 shows the empirical version of $\mathcal{V}$, the distribution of output across matches. Because of the large number of possible assignments (over $10^{35}$ in our smallest market alone), we plot only a random sample of 10K possible matches in this figure. Although the density approaches zero near the edges of the graph, we will see that the full PDF extends much more broadly. The figure clearly shows that the different matches in $\mathcal{V}$ vary in their output.

**Specialization.** In Definition 1 of our theory section, we say that a workforce is unspecialized if the workers are equally productive in all matches. We can study this empirically, by examining how much a worker’s objective score changes with the assigned partner. Perhaps unsurprisingly, we can statistically reject the null hypothesis that workers are exactly equally productive in all assignments.
However, our data also show large economic significance. To measure degrees of specialization, we take the difference between the productivity of each worker’s best match and worst match. For ease of interpretation, we standardize these values using the standard deviation of the overall distribution of match qualities; this lets us measure differences in terms of standard deviations from the average match. Figure E11 in the Appendix contains a histogram of these differences. Sure enough, a small minority (≈10%) performs roughly the same in all jobs. However, for the vast majority (≈90%), the productivity difference between their best and worst job is over 1.5 standard deviations. The median is 2.16 deviations and about 10% of workers differ by 3 standard deviations between their best and worst match.

**Vertical Preferences by the Firm.** Although there is wide variability in a worker’s (and managers’) productivity (above), we also find strong worker- and manager- fixed effects. Regressions predicting the firm objective score for a match using workers FEs alone have an adjusted $R^2$ of 0.67. The adjusted $R^2$ is 0.49 for manager FEs alone and is 0.87 using both FEs together. The distribution of worker and manager fixed effects have the same means, but worker fixed effects are more variable. These numbers suggest the firm has a much stronger notion of “vertical preferences” over workers and managers, even if workers/managers do not have strong vertical preferences over each other. Some workers and managers have high (or low) output on average across all possible match partners.

**Complementarity and Production Technology.** What the CEO should do to maximize with high/low vertically ranked workers and managers is theoretically ambiguous, and depends on the degree of complementarity in the match production function (Becker, 1973). For supermodular production functions, the most productive match assortatively pairs the best workers with the best managers. For submodular production functions, the most productive match pairs the best worker and the worst manager.

The firm objective score allows us to measure this directly. Before directly measuring it, we mention some key features of the objective function. These features provide some intuition for our results. First, the firm’s objective score algorithm was programmed to have a maximum and a minimum which we scale to zero and one. This will shape some of our results. Because of the upper bound, the performance of the whole will often be

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29See Appendix Section E.3 for histograms of the distribution of worker and manager fixed effects).
“less than the sum of the parts” because performance has an upper bound that cannot be exceeded, no matter how great the parts are. Second, the upper and lower bounds are binding. 28% of all possible pairwise matches are at the maximum, and less than 1% are at the minimum. For the median worker, only 5% of his or her options are at the max, however, 69% of workers have at least one option that will place them at the maximum.  

To analyze the degree of complementarity, we analyze all 23K possible matches, using the fixed effects for workers and managers calculated above. For each match, we calculate the difference between the fixed effects and take the absolute value of this difference. This difference measures the average quality distance between the worker and manager in each match. We then use this difference to predict the firm objective score (along with worker and manager fixed effects). A positive coefficient on this variable means that greater differences are better for a match’s productivity (conditional on the fixed effects).

When we analyze our firm’s objective function in Panel A of Table 3, we find that match quality is increasing in the distance between workers and manager quality. Column 1 shows that a one standard deviation increase in the interaction between the worker’s average productivity (across all matches) and the manager’s decreases the firm’s objective by 0.21 standard deviations ($p=0.001$). Meanwhile, column 2 shows that the firm’s objective score increases as the difference in average quality between workers and managers increases. This suggests the firm’s optimal match will exhibit a degree of negative associative matching. Later, we will directly calculate the degree of associative matching under DA and the firm’s optimal.

### 6.3 Delegated vs Centrally-Planned Matchings

We now turn to our central empirical questions: How much does the firm sacrifice its objectives when implementing deferred acceptance (in our theory model $V_{CC}$ and $V_{DA}$)? Similarly, how much happiness do workers sacrifice by accepting the firm’s preferred assignments ($R_{DA}$ and $R_{CC}$)?

**Output.** Table 4 compares the distribution of firm objective scores obtained by the two main methods we study (deferred acceptance and command-and-control, implemented using the aforementioned Kuhn-Munkres). For comparison, we also report the scores for managers.  

30These numbers are 13% and 88% for managers.
several other matching methods. The results show that the firm-preferred match has a 36% higher objective score than random matches, while deferred acceptance is only about 3.6% higher. Table E3 places this comparison into a regression framework. Although we can reject the difference between random matches and DA, the size of the difference is small. In Appendix E.1, we show that the firm-dictated matching first-order stochastically dominates deferred acceptance.

We can use the manager and worker fixed effects to measure the size of our effects, relative to the quality of workers and managers. Rather than use the firm-dictated match, the firm could try to achieve the same productivity benefit by increasing the quality of hires. Our results indicate doing so would be difficult. Firm-dictated matching results in a 24% improvement in the firm’s objective score over deferred acceptance. Only 25% of workers and 16% of managers have fixed effects larger than this amount. Increasing productivity by 24% is about 55% of a standard deviation in the worker fixed effects and 66% of a standard deviation in manager fixed effects, suggesting that achieving the same productivity benefits through hiring would require a large increase in new hire quality.

Workforce Preferences. If the firm were to dictate matches instead of using those generated by deferred acceptance, how would workers and managers fare? Table 5 studies how favorably (or unfavorably) workers and managers ranked their assignments. Under deferred acceptance, the median worker and manager receive their first pick. On average, workers ranked their match 1.2 and managers ranked their match 8.2. However, under the firm-preferred match, workers receive their 2nd pick at the median and 3.4th pick on average, and managers get their 3rd pick at the median and 9th pick on average, respectively.

These may seem like small adjustments, but many participants labeled many options as “tied for last place.” In Appendix E.6, we examine these differences in terms of percentile rankings rather than the rankings themselves. Switching from deferred acceptance to the firm-dictated match means moving from the 3rd to the 45th percentile rank of choices for workers, and from the 17th to the 52nd percentile rank of choices for managers. More-

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31 Because the sample is unbalanced, all workers are matched but some projects/managers are not. Table 4 examines filled jobs only. Table E2 contains all matches (including unfilled jobs), giving unfilled jobs an objective score of 0 (the minimum). Our results are qualitatively the same in both tables.

32 The average ranking for managers is high because the table displays the average across all managers, including unmatched managers whose ranking is imputed as their last choice. If we only examine matched worker-manager pairs, the average manager ranking is 1.2 (see Table E5 in the appendix.)
over, in deferred acceptance matches, only 6% of workers and managers were assigned to a partner ranked as “tied for last.” By contrast, 91% are in such a match in the firm’s preferred assignment. Across measures, centrally-planned matches are about as equally attractive to workers/managers as random assignments. Table E4 places these comparisons in a regression framework, and shows these differences are statistically significant and robust to how “satisfaction” is measured.

**Assortative Matching.** Why does deferred acceptance produce relatively unproductive matches? In Panel B of Table 3, we assess the levels of assortative matching across different types of matches. As suggested by our earlier results, the firm-dictated solution is more likely to assign high quality workers with lower quality managers, and vice versa. We can now see also one of the reasons deferred acceptance was unproductive: it produced a positive assortative match. This is likely the result of workers being slightly “narrowly aligned” (Definition 2), as measured in our earlier results (Table 2). As Prop 5 indicates, this generates talent hoarding in which all participants want a productive partner, even if the firm prefers talent to be spread out (because of submodular production technology Becker 1973). Together, these results show how delegation failed to produce higher output in this setting.

**Discussion.** Our results show tradeoffs between optimizing the firm’s objectives and satisfying workers. Was delegation worth it? The sacrifice to firm productivity appears to be large. However, unhappy workers can also

Our data offers a few clues. First, workers were allowed to rank some jobs as “excluded,” meaning they would rather quit than be assigned to this position. Managers were similarly allowed to rank some workers as being worse than having no new worker. Despite the availability of this option, no manager or worker used this option to exclude any partnership. This suggests that the threat of quitting was not particularly strong.\(^{33}\)

Second, the firm did not report experiencing large changes in retention after the introduction of deferred acceptance, although they did feel the program was positively received by the workforce and continued operating it after making the investment.

Of course, it is possible that workers adjusted along another margin (for example, through

\(^{33}\)Of course, workers may have simply wanted to control the timing of their exit by accepting a bad job until they found employment elsewhere.
effort or intrinsic motivation) even if quits were not affected. Despite the drawbacks we highlight, we cannot necessarily characterize the adoption of preference-based assignment as a mistake in our setting, at least without knowing more about the firm’s objectives and costs. Some benefits of these programs may be subtle or hard to measure.

7 Conclusion

Leaders of organizations are often responsible for forming teams by matching agents. In these settings, worker and managers’ satisfaction are important constraints. However, principals may have additional goals relating to the mission of the organization as a whole. This paper has offered a model of the CEO’s choice of assignment mechanisms, and an empirical case study of many of the objects and outcomes in the model. We examine whether dictating or delegating is preferable as a function of workforce specialization, production technology, firm size, the level of vertical preferences and alignment with CEO interests (defined two ways).

Our findings suggest an obvious set of next steps in both theory and empirics. The first is to measure the prevalence of delegation, command-and-control, or other mechanisms for matching workers with tasks and colleagues. How do these covary with firm and industry characteristics? Our theory makes clear predictions about where these markets will appear.

The second is to measure change in the use of markets over time. Our research makes a connection between mechanism design and broader trends in the labor market. In particular, our theory suggests that hiring generalists is complementary with internal marketplaces. The pre-existing literature on routine bias technical change (discussed in Section 3.4) suggests that technology has pushed job design towards generalists. Prop. 1 suggests this should tilt organizations to look more like markets. Additional research could study the co-occurrence of preference-driven internal labor markets and RBTC.

Third, our paper makes connections between organizational design and non-financial compensation. The importance of non-monetary payoffs (such as being happy at work, having constructive relationships with colleagues, or having a meaningful job) appears to have risen over time (Cassar and Meier, 2018). The $\mu_i$'s and $u_i$'s in our model can be interpreted as non-monetary payoffs of different assignments. Our theory is about how firms
can navigate these desires alongside firm goals. The rise of non-monetary benefits may be related to firms hiring generalists and the subsequent flexibility around assignments.

Finally, future research should study mechanisms besides CC and DA. Other (or new) mechanisms may perform better than the options we study, either in general or in particular cases. In particular, allowing the CEO to target payments could improve alignment while compensating workers for their outside options. Neither command and control nor deferred acceptance were developed for the CEO's problem. There may be a rich set of research opportunities – with broad practical applications – at the intersection of principal-agent problems and matching.

Additional Acknowledgements. The authors also thank seminar participants at Carnegie Mellon, Columbia Business School, Cornell, MIT, Rochester, Stanford (CASBS), University of Minnesota, and University of Hong Kong, as well as participants at the NBER Economics of Organizations, NBER/CEME Decentralization, Wharton People and Organizations Conference, the Marketplace Innovations Workshop, the Academy of Management Annual Conference, the Workshop for Information Systems and Economics (WISE), the Strategic Management Society (SMS) Annual Conference, and the 2021 Causal Data Science Meeting.
References


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Tables and Figures

Figure 1: DA Retention Benefits with Preference Correlation

![Graph showing retention rates with preference correlation](image)

Notes: This figure shows average retention outcomes from 1,000 draws of a $50 \times 50$ matching market where underlying utilities over matches are multivariate normally distributed with mean zero, unit variance, and eleven different correlations. The x-axis shows the correlation in the proposing side’s preferences. The receiving side’s preferences are uncorrelated. The different colors of lines show different unconditional retention rates. Appendix Figures E3 and E4 contain the overall retention rate broken out by the workers and divisions side.
Notes: This figure displays the histogram of the total output across a sample of 10K random assignments of workers and managers in our sample. On the right is the CDF of this distribution.
Table 1: **Summary statistics**

<table>
<thead>
<tr>
<th></th>
<th>Workers N=318</th>
<th>Managers N=517</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Choices ranked</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>2.66</td>
<td>2.22</td>
</tr>
<tr>
<td>Min</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Max</td>
<td>26</td>
<td>11</td>
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<tr>
<td><strong># of times on the market</strong></td>
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<td></td>
</tr>
<tr>
<td>Mean</td>
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</tr>
<tr>
<td>Min</td>
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<td>1</td>
</tr>
<tr>
<td>Max</td>
<td>4</td>
<td>1</td>
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<tr>
<td><strong>Firm objective score</strong></td>
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<td></td>
</tr>
<tr>
<td>Mean</td>
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<td>0.54</td>
</tr>
<tr>
<td>Min</td>
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<tr>
<td>Max</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

**Notes:** This table examines summary statistics for our data.
Table 2: Preference Correlations and Alignment

**Panel A: Same-side & cross-side correlation of preferences**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std.Dev</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
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<tbody>
<tr>
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<td>-0.01</td>
<td>0.08</td>
<td>-0.20</td>
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<td>-0.02</td>
<td>-0.02</td>
<td>1.00</td>
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<td>Manager preferences</td>
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<td>-0.22</td>
<td>-0.03</td>
<td>-0.02</td>
<td>-0.02</td>
<td>1.00</td>
</tr>
<tr>
<td>Worker and manager preferences</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All pairs</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Mutually-ranked pairs</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

**Panel B: Preference alignment**

<table>
<thead>
<tr>
<th></th>
<th>Worker ranking of manager</th>
<th>Manager ranking of worker</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective Score ($v_{ij}$)</td>
<td>0.017* (0.0093)</td>
<td>0.011 (0.0093)</td>
</tr>
<tr>
<td>Firm-Dictated Assignment</td>
<td>0.060** (0.024)</td>
<td>0.056** (0.024)</td>
</tr>
<tr>
<td></td>
<td>0.060*** (0.023)</td>
<td>0.060*** (0.023)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Observations</td>
<td>23361</td>
<td>23361</td>
</tr>
<tr>
<td>Pseudo-R2</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

**Notes:** This table examines our preference data. Panel A displays the distribution of pair-wise Spearman correlations. It calculates the correlation of (i) worker preferences over managers, (ii) manager preferences over worker, and (iii) worker and manager preferences for each other. Panel B examines the alignment between worker/manager preferences and the firm’s preferences. Columns 1–3 display the results of a rank-ordered logit of each worker’s ranking on the firm’s objective score (column 1), their match in the firm’s preferred match (column 2), and both (column 3). Columns 4–6 display the results of a rank-ordered logit of each manager’s ranking on the firm’s objective score (column 4), their match in the firm’s preferred match (column 5), and both (column 6). Robust standard errors clustered at the worker level in columns 1–3, while robust standard errors clustered at the manager level in columns 4–6. In Appendix Table E1, we run similar analysis as Panel B, using simpler OLS specifications predicting which option is each agent’s #1 choice.

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$
### Table 3: Assortative Matching

#### Panel A: All possible worker-manager matches

<table>
<thead>
<tr>
<th>Interaction</th>
<th>0.21***</th>
<th>(0.0057)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abs[Worker - Manager Quality]</td>
<td>0.22***</td>
<td>(0.0066)</td>
</tr>
<tr>
<td>Worker Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Manager Fixed Effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td>Observations</td>
<td>23361</td>
<td>23361</td>
</tr>
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</table>

#### Panel B: Difference in worker-manager quality (absolute value), by matching algorithm

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean</th>
<th>Bootstrap S.E.</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
</tr>
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<tbody>
<tr>
<td>Command-and-Control</td>
<td>0.75</td>
<td>0.09</td>
<td>0.00</td>
<td>0.27</td>
<td>0.47</td>
<td>1.05</td>
<td>3.31</td>
</tr>
<tr>
<td>Random Assignment</td>
<td>0.69</td>
<td>0.07</td>
<td>0.00</td>
<td>0.28</td>
<td>0.48</td>
<td>0.96</td>
<td>2.98</td>
</tr>
<tr>
<td>Manager Draft</td>
<td>0.68</td>
<td>0.07</td>
<td>0.00</td>
<td>0.27</td>
<td>0.44</td>
<td>0.99</td>
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<td>Worker Draft</td>
<td>0.66</td>
<td>0.07</td>
<td>0.00</td>
<td>0.27</td>
<td>0.43</td>
<td>0.97</td>
<td>2.87</td>
</tr>
<tr>
<td>Workers-Propose DA</td>
<td>0.66</td>
<td>0.07</td>
<td>0.00</td>
<td>0.26</td>
<td>0.44</td>
<td>0.95</td>
<td>2.87</td>
</tr>
<tr>
<td>Managers-Propose DA</td>
<td>0.66</td>
<td>0.07</td>
<td>0.00</td>
<td>0.26</td>
<td>0.44</td>
<td>0.95</td>
<td>2.87</td>
</tr>
<tr>
<td>Firm Objective (minimizer)</td>
<td>0.65</td>
<td>0.08</td>
<td>0.00</td>
<td>0.27</td>
<td>0.43</td>
<td>0.89</td>
<td>3.25</td>
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</tbody>
</table>

**Notes:** This table investigates assortative matching in our sample. Panel A uses all possible worker-manager matches. Column 1 regresses the firm objective score on the interaction between worker and manager quality, while column 2 regresses the firm objective score on the absolute value of the difference between worker and manager quality. Worker and manager quality are normalized to have mean 0 and standard deviation one. Both columns include fixed effects for workers and managers. Panel B examines the average absolute value of the difference between worker and manager quality generated by various matching algorithms. Standard errors of the mean were bootstrapped by the quarter of the market.
Table 4: **Firm objective score by matching algorithm**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean</th>
<th>Bootstrap S.E.</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Command-and-Control</td>
<td>0.75</td>
<td>0.04</td>
<td>0.21</td>
<td>0.57</td>
<td>0.76</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Manager Draft</td>
<td>0.58</td>
<td>0.06</td>
<td>0.00</td>
<td>0.32</td>
<td>0.53</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Worker Draft</td>
<td>0.57</td>
<td>0.06</td>
<td>0.00</td>
<td>0.33</td>
<td>0.53</td>
<td>0.98</td>
<td>1.00</td>
</tr>
<tr>
<td>Managers-Propose DA</td>
<td>0.57</td>
<td>0.06</td>
<td>0.00</td>
<td>0.32</td>
<td>0.53</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Workers-Propose DA</td>
<td>0.57</td>
<td>0.06</td>
<td>0.00</td>
<td>0.32</td>
<td>0.53</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Random Assignment</td>
<td>0.55</td>
<td>0.07</td>
<td>0.01</td>
<td>0.29</td>
<td>0.48</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Firm Objective (minimizer)</td>
<td>0.34</td>
<td>0.09</td>
<td>0.00</td>
<td>0.12</td>
<td>0.22</td>
<td>0.36</td>
<td>1.00</td>
</tr>
</tbody>
</table>

**Notes:** This table displays the average firm objective score for matches generated by various algorithms. Standard errors of the mean were bootstrapped by the quarter of the market. Because there were more managers on the market than workers, some managers are unmatched. This table includes only complete manager worker/pairs (i.e., dropping managers who were not paired to workers). All matching algorithms left the same number of managers unmatched, but differed in their composition. A similar table including unmatched managers (containing a score of zero) is accessible in Table E2.
Table 5: **Worker/Manager Ranking of Assignment, by matching algorithm**

**Panel A: Workers’ Rankings of Managers**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean</th>
<th>Bootstrap S.E.</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worker Draft</td>
<td>1.15</td>
<td>0.03</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>5.08</td>
</tr>
<tr>
<td>Workers-Propose DA</td>
<td>1.17</td>
<td>0.04</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Managers-Propose DA</td>
<td>1.17</td>
<td>0.04</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Manager Draft</td>
<td>1.95</td>
<td>0.15</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>2.00</td>
<td>16.34</td>
</tr>
<tr>
<td>Random Assignment</td>
<td>3.36</td>
<td>0.39</td>
<td>1.00</td>
<td>2.00</td>
<td>2.00</td>
<td>4.00</td>
<td>22.40</td>
</tr>
<tr>
<td>Command-and-Control</td>
<td>3.39</td>
<td>0.38</td>
<td>1.00</td>
<td>2.00</td>
<td>2.00</td>
<td>4.00</td>
<td>16.00</td>
</tr>
<tr>
<td>Firm Objective (minimizer)</td>
<td>3.48</td>
<td>0.41</td>
<td>1.00</td>
<td>2.00</td>
<td>2.00</td>
<td>4.00</td>
<td>15.58</td>
</tr>
</tbody>
</table>

**Panel B: Managers’ Rankings of Workers**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean</th>
<th>Bootstrap S.E.</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manager Draft</td>
<td>8.05</td>
<td>0.84</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>3.00</td>
<td>106.00</td>
</tr>
<tr>
<td>Worker Draft</td>
<td>8.18</td>
<td>0.78</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>2.00</td>
<td>106.00</td>
</tr>
<tr>
<td>Managers-Propose DA</td>
<td>8.23</td>
<td>0.85</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>2.00</td>
<td>106.00</td>
</tr>
<tr>
<td>Workers-Propose DA</td>
<td>8.23</td>
<td>0.85</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>2.00</td>
<td>106.00</td>
</tr>
<tr>
<td>Command-and-Control</td>
<td>8.95</td>
<td>0.88</td>
<td>1.00</td>
<td>2.00</td>
<td>3.00</td>
<td>5.68</td>
<td>63.28</td>
</tr>
<tr>
<td>Random Assignment</td>
<td>9.00</td>
<td>0.93</td>
<td>1.00</td>
<td>2.00</td>
<td>3.00</td>
<td>5.36</td>
<td>76.56</td>
</tr>
<tr>
<td>Firm Objective (minimizer)</td>
<td>9.69</td>
<td>0.90</td>
<td>1.00</td>
<td>2.00</td>
<td>3.00</td>
<td>6.00</td>
<td>104.08</td>
</tr>
</tbody>
</table>

**Notes:** This table displays the average worker and manager rankings for matches generated by various algorithms. Standard errors of the mean were bootstrapped by the quarter of the market. Because there were more managers on the market than workers, some managers are unmatched. All matching algorithms left the same number of managers unmatched, but differed in their composition. The table above includes all managers, including some that were unmatched. A similar table studying only matched managers is accessible in Appendix Table E5.
A Theory Appendix

A.1 Formalization of Command-and-Control using the Kuhn-Munkres Algorithm

Any proposed match between worker $i$ and division $j$ has probability $P(i \rightarrow j \text{ acceptable})$ of being acceptable to both the worker and division, and payoff of $v_{ij}$, for an expected value of $v_{ij}P(i \rightarrow j \text{ acceptable})$. Because the principal’s objective in Equation 1 is to find matches that maximize the sum of these, the problem is equivalent to the assignment problem (Kuhn, 1955), even after integrating beliefs about quitting. It is thus solvable through the Kuhn-Munkres linear programming algorithm (a.k.a. the “Hungarian algorithm”). The input matrix to the Hungarian algorithm would be:

<table>
<thead>
<tr>
<th>Division 1</th>
<th>...</th>
<th>Division J</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worker 1</td>
<td>$v_{1,1}p_{1,1}$</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Worker I</td>
<td>$v_{I,1}p_{I,1}$</td>
<td>...</td>
</tr>
</tbody>
</table>

A.2 Noisy CEO Beliefs

Assumption 5 (Noisy CEO Beliefs). Suppose that match specific productivities $v_{ij}$ are drawn I.I.D. from a distribution $F$ with mean $\bar{v}$. CEO’s do not directly observe each $v_{ij}$ draw from $F$, but instead observe each $v_{ij}$ with noise; i.e. they observe $v'_{ij} = v_{ij} + \epsilon$, where $\epsilon \sim \mathcal{N}(0,\sigma^2)$ and drawn independently for each possible match.

Proposition A1. As the noise in CEO’s observations of match productivity ($\sigma^2$) increases, the relative productivity gain from command-and-control decreases.

Proof. When implementing matches with command-and-control, the CEO will select the match with the highest expected productivity because quit probabilities are identical across matches. Let $\tilde{v}_{ij} = v_{ij} + \epsilon_{ij}$ where $\epsilon_{ij}$ are I.I.D. $\mathcal{N}(0,\sigma^2)$.

The CEO perceives that arbitrary match $a$ has total productivity:

$$\tilde{V}(a) = V(a) + \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{ij}(a)\epsilon_{ij},$$
where $\alpha_{ij}(a)$ is equal to 1 if worker $i$ is matched to division $j$ in match $a$. Because $\epsilon_{ij}$ are I.I.D. across matches, this aggregate noise term is distributed $\mathcal{N}(0, N\sigma^2)$.

If $V(a) > V(b)$, the CEO correctly perceives the relative ordering of these two matches if:

$$V(a) + \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{ij}(a) \epsilon_{ij} > V(b) + \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{ij}(b) \epsilon_{ij}.$$  

This occurs with probability $\Phi(\frac{V_a - V_b}{\sqrt{2N}\sigma})$ which is decreasing in $\sigma$. Therefore the CEO is less likely to correctly rank any pair of matches when productivity is observed with more noise.

With command-and-control, the CEO will select the match with the highest perceived productivity. This is equivalent to the match being perceived as having higher productivity in every pairwise comparison. The probabilities of correctly evaluating each of these pairwise comparisons are not independent. The main difference between the impact of noise on the conditional and unconditional probability of correctly evaluating whether one match is more productive than another is that additional noise makes the conditioning less informative (e.g. the inverse-mills ratio is decreasing in $\sigma^2$).

\[\Box\]

### A.3 Narrow Alignment not Sufficient

We show this with a counterexample. Consider a $2 \times 2$ firm where the CEO’s $v_{ij}$ matrix is:

<table>
<thead>
<tr>
<th>Division A</th>
<th>Division B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worker 1</td>
<td>$x$</td>
</tr>
<tr>
<td>Worker 2</td>
<td>1</td>
</tr>
</tbody>
</table>

where $1 < x < 2$. The optimal assignment is $\{(\text{Worker 1, Division B}), (\text{Worker 2, Division A})\}$, which yields two for the CEO.

Suppose that workers and divisions rank their match partners based on $v_{ij}$ (narrow alignment). Then Worker 1 prefers Division A, who reciprocates (this is the consequence of narrow alignment). In a preference-respecting setup, the match will be $\{(\text{Worker 1, Division A}), (\text{Worker 2, Division B})\}$, which yields an output of $x$ (less than the optimal output of two). The expected output of a delegated mechanism is lower, despite workers and division being narrowly aligned.
A.4 “Misaligned” Participants Leading to Optimal Assignments

Consider a $2 \times 2$ firm where the CEO’s $v_{ij}$ matrix is given by:

\[
A = \begin{pmatrix}
1 & 4 \\
\frac{1}{2} & 2
\end{pmatrix}
\]

Assume preferences are misaligned, so workers and divisions both prefer to be in a match where they are individually least productive, but find all matches acceptable. The CEO’s optimal assignment is \{((Worker 1, Division B), (Worker 2, Division A))\}, which yields a total output of 4.5. If the organization delegates the decision to the market participants using a mechanism which respects agents’ preferences such as DA, it will achieve this assignment despite the nominally misaligned preferences of the participants.

A.5 Proofs

A.5.1 Proof for Lemma 1

Lemma 1. Given Assumption 4, the expected retention rate of the match selected by DA is higher than the average of all matches, $\bar{R}$.

Proof. The proof of Proposition 2 below implies that the distribution of utilities over DA matches has a lower hazard rate than the unconditional distribution of utility. This implies that the distribution of utilities over DA matches first-order stochastically dominates the unconditional distribution and so has a higher retention rate for all $u$ such that $G(u) < 1$.

A.5.2 Proof for Proposition 1

Proposition 1. The performance of delegation will equal or exceed that of command-and-control in firms where the workforce is completely unspecialized.

Proof. If workers are unspecialized under Definition 1, then $v_{ij}$ equals a constant $v_i$ for the worker $i$, and $V(a) = \sum_{i=1}^{N} \sum_{j=1}^{N} a_{ij}(a)v_{ij} = \sum_{i=1}^{N} v_i = V$ for all $a$. The most productive match ($V_{CC}$) is equal to the average match ($\bar{V}$). All the mass in $V$ is concentrated in a single point, and the LHS of Equation 3 is equal to 1. Lemma 1 shows that the RHS of Equation 3 is equal to or greater than one.
A.5.3 Proof for Corollary 1

**Corollary 1.** For command-and-control to outperform delegation, it is necessary (but not sufficient) for the workforce to be specialized.

**Proof.** For command-and-control to outperform delegation, the LHS of Equation 3 needs to exceed the RHS. The right hand side of Equation 3 will be greater than or equal to 1 because of Lemma 1. If workers are not specialized, the LHS of Equation 3 will equal 1 under Proposition 1.

A.5.4 Proof for Proposition 2

**Proposition 2.** The retention benefits of DA relative to CC are higher as the unconditional quit probability $G(u)$ increases.

The unconditional quit probability on either side of the market is $G(u)$. This is increasing in $u$. Our proof below shows that the returns to DA are increasing in $u$. Then, all increases in $G(u)$ can be shown to be equivalent to an increase in $u$.

Suppose the distribution of utilities from DA matches is distributed according to $H(u)$ for the proposing side and $L(u)$ on the receiving side with densities $h(u)$ and $l(u)$, respectively. Then $R_{DA}(u) = (1 - H(u))(1 - L(u))$. The unconditional expected retention rate is $\bar{R}(u) = (1 - G(u))^2$.

Differentiating with respect to $u$ implies that the ratio $\frac{R_{DA}(u)}{\bar{R}(u)}$ is increasing if:

\[
\frac{g(u)}{1 - G(u)} \geq \frac{1}{2} \left( \frac{h(u)}{1 - H(u)} + \frac{l(u)}{1 - L(u)} \right).
\]

This says the relative retention benefits of DA are increasing if the unconditional hazard rate is greater than average hazard rate on the proposing and receiving sides. This is a form of stochastic ordering called the hazard rate ordering which is stronger than stochastic dominance.

The proof will require the following result.

**Lemma A1.** For any absolutely continuous distribution $F(\cdot)$ with density $f(\cdot)$ such that $F(u) < 1$:

\[
\frac{f(u)}{1 - F(u)} \geq \frac{\sum_{r=1}^{N} N!}{(r-1)!((N-r)!)} \frac{F(u)^{r-1}(1 - F(u))^{N-r} f(u)}{1 - F_r(u)}
\]

where $F_r(u)$ is the CDF of the $r^{th}$ out of $N$ order statistic for $r > \frac{N}{2} + 2$. 

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Proof. We will use a proof by contradiction. Suppose the lemma is false, so:

\[ \frac{f(u)}{1 - F(u)} \leq \frac{N!}{(r-1)!(N-r)!} F(u)^{r-1} (1 - F(u))^{N-r} f(u) \]

Cross-multiplying and canceling the shared terms implies:

\[ \frac{1 - F_r(u)}{1 - F(u)} \leq \frac{N!}{(r-1)!(N-r)!} F(u)^{r-1} (1 - F(u))^{N-r} \]

\[ 1 \leq F_r(u) + \frac{N!}{(r-1)!(N-r)!} F(u)^{r-1} (1 - F(u))^{N-r+1} \]

Now, note that:

\[ F_{r-1}(u) = F_r(u) + \frac{N!}{(r-2)!(N-r+1)!} F(u)^{r-1} (1 - F(u))^{N-r+1} \]

Therefore:

\[ 1 \leq F_r(u) + \frac{N!}{(r-1)!(N-r)!} F(u)^{r-1} (1 - F(u))^{N-r+1} \leq F_{r-1}(u) \]

Because \( r > \frac{N}{2} + 2 \), \( F_{r-1}(u) < F(u) \) because the distribution of an above median order statistic first order stochastically dominates the unconditional distribution. The above inequalities imply \( F(u) \geq 1 \) but we assumed \( F(u) < 1 \) so this is a contradiction.

Lemma A1 shows that the hazard rate of an order statistic above the median is lower than the unconditional hazard rate. We will show that both \( H(u) \) and \( L(u) \) are both distribution for above median order statistics.

Now, let \( Q_i \) be worker i’s rank of her assigned division in a worker-proposing stable matching, \( \mathcal{M} \). Define \( Q = \max_i Q_i(\mathcal{M}) \). Pittel (1992), Theorem 6.1 shows that \( P(Q \leq (2 + a)\log^2 N) \geq 1 - O(N^{-c}) \) for all \( c < c(a) \) where \( c(a) = 2a[3 + (4a + 9)^{1/2}]^{-1} \). In words, this says it is almost certain that the least preferred match of a worker in an \( N \times N \) random matching market using working-proposing deferred acceptance will be ranked less than \((2 + a) \log^2 N\). This suggests the worker who receives the least preferred match in the entire market is almost certain to match with utility draw at least in the \( p_N \) percentile, where \( p_N = \frac{N-(2+a)\log^2 N}{N} \). For a fixed \( a \), this is greater than \( \frac{1}{2} \) for sufficiently large \( N \). For example, if \( a = 0 \) this is greater than \( \frac{1}{2} \) if \( N \) is about 75. If \( a = 1 \) this is greater than \( \frac{1}{2} \) if \( N \) is about 150.

This result implies a lower bound on \( H(u) \) is the distribution of an above median order statistic in sufficiently large markets.
All that is left to prove the result is to show that:

\[
\frac{g(u)}{1 - G(u)} \geq \frac{l(u)}{1 - L(u)}.
\]

While the receiving side of the market fairs worse than the proposing side, they do better than random because they can choose their more preferred offer when they receive multiple offers. Pittel (1989), Theorem 2 shows that the number of proposals made by the proposing side of the market converges in probability to $N \log(N)$. Therefore, an average member of the receiving side of the market is expected to receive $\log(N)$ proposals. Each of these proposals allows for another I.I.D. preference draw. As a result, $L(u)$ is distributed like an above median order statistic. The result therefore follows from Lemma A1.

A.5.5 Proofs for Corollaries 2, 3 and 4

Corollaries 2, 3 and 4 are applications of Proposition 2.

**Corollary 2** (Workforce-Unfriendly Firms). Let $G'$ represent a distribution such that $G$ first-order stochastically dominates $G'$. DA is more attractive under $G'$ than $G$.

**Proof.** We need to show that for any $u \in \mathbb{R}$ and $\mu - K \sim G'$, there exists another constant $\epsilon$ such that $G'(u) = G(u + \epsilon)$. Then the statement would be true under Prop 2 and Cor. 3.

If $G$ first order stochastic dominates $G'$, then $G'(u) \geq G(u)$ for all $u$. Because $G$ is a continuous CDF between zero and one and 1 and is increasing in its argument, you can add a positive constant $\epsilon$ to $u$ until $G'(u) = G(u + \epsilon)$. As such, this statement is true under Prop 2 and Cor. 3.

**Corollary 3** (Outside Options). DA is more attractive as $u$ increases.

Note: This was shown as part of the proof for Proposition 2.

**Proof.** If $\tilde{u}$ improves, then $G(\tilde{u})$, the probability of quitting has increased because $G$ is increasing in its argument. DA is more attractive by Proposition 2.

**Corollary 4** (Asymmetric Information). Let $G'$ be a mean-preserving spread of $G$, so that $G'$ has the same mean of $G$ but higher variance. Unless $G(u)$ (the base rate of quitting) is too high, DA is more attractive for $G'$ than $G$.

**Proof.** We show that for any $u \in \mathbb{R}$ and $G'$ (a mean preserving spread of $G$), there exists a $\epsilon \in \mathbb{R}$ such that $G'(u) = G(u + \epsilon)$. Then the statement would be true under Prop. 2 and Cor. 3.

If $G'$ is a mean preserving spread of $G$, then the CDFs of $G$ and $G'$ intersect at a single point (Diamond and Stiglitz, 1974). Call this single crossing point $\hat{\mu}$ such that $G'(\hat{\mu}) =
If the outside option $u$ is not too high ($u < \hat{\mu}$), then $G'(u) \geq G(u)$. Because both $G$ and $G'$ are continuous and lie within [0,1], and because $G$ is increasing in its argument, a positive constant $\epsilon$ can be added to $u$ until $G'(u) = G(u + \epsilon)$. As such, this statement is true under Prop 2 and Cor. 3.

A.5.6 Proof for Lemma 2

**Lemma 2 (Quitting Costs).** Higher quitting costs attenuate the relative benefits of CC over DA, $V_{CC}/V_{DA}$.

**Proof.** To see this, assume every successful match has a benefit of $c_N$ in addition to its productivity $v_{ij}$. We can interpret $c_N$ as a quitting cost because it is lost if the match is unsuccessful. The ratio $V_{CC}/V$ is decreasing in $c$:

$$\frac{\partial}{\partial c} \left[ \frac{V_{CC} + c}{V + c} \right] = \frac{\bar{V} - V_{CC}}{(V + c)^2}. \quad (3)$$

This is negative whenever $V_{CC} > \bar{V}$. Therefore, increasing the costs of quits makes DA relatively more appealing than CC.

A.5.7 Proof for Proposition 3

**Proposition 3 (Vertical Preferences).** If one side of the market has vertical preferences, DA does not increase that side’s retention.

**Proof.** If one side has vertical preferences then regardless of which of the $N!$ matches is selected, exactly one agent on that side will match with her 1st, 2nd, …, Nth most preferred division because this is a one-to-one match.

Without loss of generality, suppose the worker side has vertical preferences. Let $P_{a,(i)}$ denote the expected retention of the worker who matches with her $i^{th}$ ranked choice in match $a$. The overall retention rate of workers will be:

$$\bar{P}_a = \frac{1}{N} P_{a,(i)}.$$
But the average across all order statistics is just the unconditional average so $E[\bar{P}_a] = G(\mu)$ is the unconditional retention rate. In expectation, there is no variation in retention among the $N!$ possible assignments $a$ with regards to the vertical side’s quit rates. \hfill \Box

A.5.8 Proof for Proposition 4

**Proposition 4.** If workers and divisions have strictly broadly aligned preferences, the CEO’s optimal match is the surplus-maximizing Nash equilibrium of deferred acceptance, but is not generally a unique Nash equilibrium. Deferred acceptance can equal the performance of command-and-control, but cannot exceed it.

*Proof.* Because workers and divisions have strictly broadly aligned preferences, $\mu^i_j = u^i_j = V(a)$ if matching together will yield overall match $a$ given all other workers’ and divisions’ preference reports. $V_{CC}$ is the output of the optimal match. Therefore it must be the case that $V_{CC} \geq V(a)$ for all $a \in 1, \ldots, N!$. Suppose all workers except worker $i$ rank their optimal match first. Then worker $i$’s best response is to also rank her optimal match, say $j^*$ first because $\mu^i_j = V_{CC} \geq V(a)$ for all $a \in 1, \ldots, N!$. The same logic applies to division $j$. This proves that the optimal assignment is a Nash equilibrium.

Now, suppose there is another Nash equilibrium that yields output $\hat{V} < V_{CC}$. If all workers except $i$ rank their match corresponding to this alternative equilibrium first, then it is a best response for $i$ to also rank this alternative equilibrium first by our assumption that it is a Nash equilibrium. The same logic applies to divisions. Together, these results prove that there are possibly Nash equilibria that yield the same output as command-and-control but there are possibly others that do not. \hfill \Box

A.5.9 Proof for Proposition 5

**Proposition 5** (Talent Hoarding). Narrow alignment is not sufficient or necessary to guarantee that DA yields output as high as CC.

*Proof.* This follows from the example in Appendix A.3. \hfill \Box

A.5.10 Proof for Corollary 5

**Corollary 5.** Suppose that workers and divisions have strictly narrowly aligned preferences, and that match productivities are the result of a production function that is supermodular in workers’ and divisions’ types. Then the worker-proposing deferred acceptance algorithm selects the CEO-optimal assignment. However, the CEO can select this without deferred acceptance using command-and-control.
Proof. Narrow alignment implies deferred acceptance will yield positive assortative matching. Assortative matching maximizes output when production is super-modular (Becker, 1973).

B Firm Objective Score: Additional Implementation Details

Several variables went into the firm objective score, but the most prominent were job skills and requirements, language requirements, and location. Using the aforementioned structured skill taxonomy, the company developed a distance metric between the skills sought on the manager’s job requisition, and the skills listed on the worker’s profile. Workers and managers’ self-reported skills and requirements were reviewed by a centralized third party for accuracy. Matches on specific skills (or the absence of a match) was weighted differently depending on the type of skill and how the skill was characterized in the manager’s requisition and on the worker’s profile. These weightings were hand-tuned by the central management to nudge workers and managers towards the outcomes preferred by the firm.

C Data

Our data consist of four tables about participant characteristics, preferences, pairwise match scores and potential assignments under various matching regimes.

Participant Characteristics. For both workers and managers, we have a set of individual covariates. Some of the manager characteristics are associated with the job he/she is hiring for. Note that some workers and managers are observed multiple times, as they finish one assignment and enter another one over our sample period.

Participant Preferences. For each worker and manager, we have a complete set of ordinal preferences over the opposite side of the market. For workers and managers who appear in the market multiple times, we have multiple sets of preferences. Note: We describe our as “complete,” although a large portion of possible matches were left unranked, or essentially tied for last place. We code such labels as expressing indifferences.\(^1\) Given our setting has more managers than workers, some managers will not be matched

\(^1\)For example, if a worker ranked seven out of a total of ten managers, we code the three non-ranked managers as choice 8. We also run a version where we randomize participant preferences among unranked choices.
to workers. Non-matches are coded as the least desirable choice for participants based on their inputs.\(^2\)

**Pairwise Match Scores.** For all possible pairs of workers and managers, we have several numeric scores characterizing the match. The most important in our analysis is the *firm objective score*. This is (roughly) the firm’s estimate of how productive each match would be for the firm’s goals. The firm would prefer the match that maximizes the sum of total pairwise scores across all assignments.

**Actual and Simulated Assignments.** Finally, our data includes the assignments generated by the worker-proposed match used by the company. We have also re-run this algorithm 50 independent times, resolving indifferences and ties randomly, to generate a distribution of potential assignments. In addition, we also use the preference data to generate counterfactual assignments based on a variety of other assignment methods. Specifically, we examine the managers-propose DA algorithm which is nearly always identical to the workers-propose. We also examine completely random assignments, as well as random serial dictatorship (\textit{Abdulkadiro\'glu and S"onmez, 1998}) led by the workers and managers (we call these the “workers’ draft” and the “managers’ draft”). Our goal using these latter two is to help us evaluate non-parametrically how much our results are driven by workers and managers preferences by examining matching based only on one side’s preferences. We similarly run each of these algorithms 50 times, resolving ties randomly. When running matches using participants preferences, we utilize the same random draws to break ties across all different assignment algorithms.

Finally, we calculate the “firm-optimal match,” which maximizes the firm’s objective (as described above). To calculate this, we utilize the aforementioned Kuhn-Munkres algorithm (aka the “Hungarian algorithm,” \textit{Kuhn 1955}). This algorithm identifies the set of assignments which maximize a numeric objective. We apply this algorithm to find the set of worker/manager assignments that maximize the total firm objective score (described above). Because this sometimes involves resolving ties between equally productive pairwise matches, we run this algorithm 50 times. We also run a version of the Kuhn-Munkres algorithm that minimizes the total firm objective to provide a lower bound of the firm’s objective function in our data (while still assigning all workers).\(^3\)

\(^2\)As described above, all participants were given the option to rank “prefer to be unmatched” ahead of some least-preferred. No participant chose to utilize this option.

\(^3\)One possible way to minimize the firm’s objective might be to leave them all unmatched; our implementation of the objective-minimizer forbade this.
D Screenshots of Internal Marketplace (Mockups)

Figure D1: Profile Screen

Notes. This figure portrays a mock profile screen of a manager.
Notes. This figure portrays a mock ranking screen for a manager ranking potential workers in the deferred acceptance algorithm.
E Additional Empirical Analysis

Figure E3: DA Retention Benefits with Preference Correlation: Proposing Side

Notes: This figure shows average retention outcomes from 1,000 draws of a 50 × 50 matching market where underlying utilities over matches are multivariate normally distributed with mean zero, unit variance, and eleven different correlations. The x-axis shows the correlation in the proposing side’s preferences. The receiving side’s preferences are uncorrelated. The different colors of lines show different unconditional retention rates.
Figure E4: DA Retention Benefits with Preference Correlation: Receiving Side

Notes: This figure shows average retention outcomes from 1,000 draws of a $50 \times 50$ matching market where underlying utilities over matches are multivariate normally distributed with mean zero, unit variance, and eleven different correlations. The x-axis shows the correlation in the proposing side’s preferences. The receiving side’s preferences are uncorrelated. The different colors of lines show different unconditional retention rates.
Table E1: **Analysis of Top Rankings (OLS)**

<table>
<thead>
<tr>
<th></th>
<th>Worker ranked manager #1</th>
<th>Manager ranked worker #1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objective Score ($v_{ij}$)</strong></td>
<td>0.0023 (0.0016)</td>
<td>0.0015 (0.0015)</td>
</tr>
<tr>
<td></td>
<td>0.0013 (0.0019)</td>
<td>0.00059 (0.0019)</td>
</tr>
<tr>
<td><strong>Command-and-Control Assignment</strong></td>
<td>0.026* (0.013)</td>
<td>0.025* (0.013)</td>
</tr>
<tr>
<td></td>
<td>0.021 (0.013)</td>
<td>0.021 (0.013)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Observations</td>
<td>23361</td>
<td>23361</td>
</tr>
</tbody>
</table>

**Notes:** This table is analogous to Table 2, which examines worker preferences using a rank ordered logit. In this table, we use OLS to predict which option agents rank #1.

Table E2: **Firm objective score by matching algorithm**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Bootstrap S.E.</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Command-and-Control</td>
<td>0.75</td>
<td>0.04</td>
<td>0.21</td>
<td>0.57</td>
<td>0.76</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Manager Draft</td>
<td>0.58</td>
<td>0.06</td>
<td>0.00</td>
<td>0.32</td>
<td>0.53</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Worker Draft</td>
<td>0.57</td>
<td>0.06</td>
<td>0.00</td>
<td>0.33</td>
<td>0.53</td>
<td>0.98</td>
<td>1.00</td>
</tr>
<tr>
<td>Managers-Propose DA</td>
<td>0.57</td>
<td>0.06</td>
<td>0.00</td>
<td>0.32</td>
<td>0.53</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Workers-Propose DA</td>
<td>0.57</td>
<td>0.06</td>
<td>0.00</td>
<td>0.32</td>
<td>0.53</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Random Assignment</td>
<td>0.55</td>
<td>0.07</td>
<td>0.01</td>
<td>0.29</td>
<td>0.48</td>
<td>0.99</td>
<td>1.00</td>
</tr>
<tr>
<td>Firm Objective (minimizer)</td>
<td>0.34</td>
<td>0.09</td>
<td>0.00</td>
<td>0.12</td>
<td>0.22</td>
<td>0.36</td>
<td>1.00</td>
</tr>
</tbody>
</table>

**Notes:** This table displays the average firm objective score for matches generated by various algorithms. Standard errors of the mean were bootstrapped by the quarter of the market. Because there were more managers on the market than workers, some managers were unmatched. This table includes all managers, labeling unmatched managers an objective score of zero. All matching algorithms left the same number of managers unmatched, but differed in their composition. A similar table including only complete manager/worker pairs is accessible in Table 4.
Table E3: **Effects on Firm Objectives**

<table>
<thead>
<tr>
<th>Match Type</th>
<th>Firm Objective Score</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deferred Acceptance</td>
<td>-0.15***</td>
<td>-0.15***</td>
<td>-0.15***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Assignment</td>
<td>-0.17***</td>
<td>-0.17***</td>
<td>-0.17***</td>
<td>-0.17***</td>
<td>-0.17***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.026)</td>
<td>(0.026)</td>
<td>(0.026)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Managers-Propose DA</td>
<td>-0.15***</td>
<td>-0.15***</td>
<td>-0.15***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workers-Propose DA</td>
<td>-0.15***</td>
<td>-0.15***</td>
<td>-0.15***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
<td>(0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.819</td>
<td>0.448</td>
<td>0.919</td>
<td>0.819</td>
<td>0.448</td>
</tr>
<tr>
<td>Observations</td>
<td>129250</td>
<td>129250</td>
<td>129250</td>
<td>129250</td>
<td>129250</td>
</tr>
<tr>
<td>Fixed effect</td>
<td>Worker</td>
<td>Manager</td>
<td>Both</td>
<td>Worker</td>
<td>Manager</td>
</tr>
<tr>
<td>P-values:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DA = Random</td>
<td>0.059</td>
<td>0.059</td>
<td>0.059</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>DA (MP) = Random</td>
<td>0.059</td>
<td>0.058</td>
<td>0.059</td>
<td>0.059</td>
<td>0.059</td>
</tr>
<tr>
<td>DA (WP) = Random</td>
<td>0.059</td>
<td>0.059</td>
<td>0.059</td>
<td>0.059</td>
<td>0.059</td>
</tr>
</tbody>
</table>

**Notes:** This table displays the results of a regression of the firm objective score on indicators for the match being generated through deferred acceptance or random matching. The excluded category is the optimal match. Each regression includes robust standard errors clustered at the simulation-submarket level. The bottom of the table displays p-values that test the difference in coefficients on deferred acceptance versus random assignment. The average firm objective score from the optimal matches is 0.62.

*** $p < 0.01$  ** $p < 0.05$  * $p < 0.10$
Table E4: Worker and manager losses from firm-dictated match

Panel A: Worker losses

<table>
<thead>
<tr>
<th></th>
<th>Manager unranked by worker</th>
<th>Worker ranking of manager</th>
<th>Simulated ranking of manager</th>
<th>Worker utility, z-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Command-and-Control</td>
<td>0.85***</td>
<td>2.22***</td>
<td>25.6***</td>
<td>-0.61***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.40)</td>
<td>(2.68)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.792</td>
<td>0.555</td>
<td>0.589</td>
<td>0.520</td>
</tr>
<tr>
<td>Observations</td>
<td>12840</td>
<td>12840</td>
<td>12840</td>
<td>12720</td>
</tr>
<tr>
<td>DA mean</td>
<td>0.063</td>
<td>1.173</td>
<td>1.403</td>
<td>0.770</td>
</tr>
<tr>
<td>Fixed effect</td>
<td>Worker</td>
<td>Worker</td>
<td>Worker</td>
<td>Worker</td>
</tr>
</tbody>
</table>

Panel B: Manager losses

<table>
<thead>
<tr>
<th></th>
<th>Worker unranked by manager</th>
<th>Manager ranking of worker</th>
<th>Simulated ranking of worker</th>
<th>Manager utility, z-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Command-and-Control</td>
<td>0.70***</td>
<td>0.73**</td>
<td>16.7***</td>
<td>-0.14*</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.24)</td>
<td>(2.63)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.768</td>
<td>0.423</td>
<td>0.564</td>
<td>0.458</td>
</tr>
<tr>
<td>Observations</td>
<td>15510</td>
<td>15510</td>
<td>15510</td>
<td>15300</td>
</tr>
<tr>
<td>DA mean</td>
<td>0.065</td>
<td>8.221</td>
<td>9.273</td>
<td>-0.660</td>
</tr>
<tr>
<td>Fixed effect</td>
<td>Manager</td>
<td>Manager</td>
<td>Manager</td>
<td>Manager</td>
</tr>
</tbody>
</table>

Notes: This table examines the effect of using the optimal matching system on worker and manager preferences. Panel A displays the results of regression of four measures of worker preferences on an indicator for the optimal match, with worker fixed effects. Panel B displays the results of regression of four measures of manager preferences on an indicator for the optimal match, with manager fixed effects. The regression drops worker-manager pairs obtained from random matching, so the comparison group is matching from deferred acceptance. Each regression uses robust standard errors clustered at the simulation-submarket level. Some workers did not rank managers and vice-versa. In column 2, we impute these as workers being indifferent among these choices (if a worker submitted N rankings, we impute the non-ranked managers as the worker’s N+1 choice. In column 3, we randomly assign preferences over unranked choices. Column 5 uses a standardized utility measure from a rank-ordered logit, and drops some workers/managers who only submitted one ranking.

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$
E.1 Distribution of match quality by algorithm

Figure E5 displays a cumulative distribution plot of match quality by algorithm for successful worker-manager matches (i.e., we drop instances when a manager is not matched to any worker). Meanwhile, Figure E6 displays the corresponding histogram.

Figure E5: Cumulative distribution plot of match quality by algorithm

Notes: This figure displays a cumulative distribution plot of match quality by the firm-optimal (Kuhn-Munkres) algorithm, deferred acceptance, and random matching.
Figure E6: **Histogram of match quality by algorithm**

Notes: This figure displays a histogram of match quality by the firm-optimal (Kuhn-Munkres) algorithm versus deferred acceptance.

### E.2 Distribution of match quality by algorithm

Figure E7 displays a histogram of each worker’s ranking of their matched manager by algorithm. Figure E8 displays the corresponding plot for manager ranking of their matched workers, excluding managers who are not matched to a worker.
Figure E7: **Histogram of worker ranking of matched manager by algorithm**

Notes: This figure displays a histogram of worker rankings of their matched manager for deferred acceptance and the firm-optimal (Kuhn-Munkres) algorithm.

### E.3 Distribution of worker and manager quality

Figure E9 displays a histogram of worker quality. We take the average firm objective score for each worker across all managers and de-mean this measure. Figure E10 displays the corresponding plot for manager quality.
Notes: This figure displays a histogram of manager rankings of their matched worker for deferred acceptance and the firm-optimal (Kuhn-Munkres) algorithm. The figure drops managers who were not matched to a worker.

Figure E9: **Histogram of worker quality (de-meaned)**

Notes: This figure displays a histogram of worker quality. We take the average firm objective score for each worker across all managers, de-mean this measure, and plot the distribution across all workers.
Figure E10: **Histogram of manager quality (de-meaned)**

Notes: This figure displays a histogram of manager quality. We take the average firm objective score for each manager across all workers, de-mean this measure, and plot the distribution across all managers.

### E.4 Distribution of worker specialization

In Definition 1 of our theory section, we say that a workforce is unspecialized if the workers are equally productive in all matches. We can study this empirically by examining how much a worker’s objective score changes with their assigned manager. We take the difference between the productivity of each worker’s best match and worst match, and then divide this difference by the standard deviation of the firm objective score across all matches. Figure E11 displays a histogram of this measure.
Figure E11: Histogram of worker specialization

Notes: This figure displays a histogram of worker specialization. We take the difference between the productivity of each worker’s best match and worst match, and then divide this difference by the standard deviation of the firm objective score across all matches.

E.5 Worker and manager ranking of assignment, by matching algorithm, for only successful matches

In Table 5 of the main text, we document that workers (managers) are matched to less-preferred managers (workers) in the firm-dictated match versus the DA-generated one. That table displays the average ranking across matching algorithms for all worker-manager pairs, including unmatched managers. In Table E5 below, we reproduce the same Table but limit our sample to only successfully-matched worker-manager pairs. The results are in line with Table 5.

E.6 Percentile of worker and manager ranking of assignment, by matching algorithms

In Table 5 of the main text, we document that workers (managers) are matched to less-preferred managers (workers) in the firm-dictated match versus the DA-generated one. In Table E5 below, we reproduce the same Table but using the percentile rank of each match. For each worker (manager), we calculate the percentile rank as $PR = \frac{CF - (5 \cdot F)}{N} \times 100$, where CF is the count of all rankings less than or equal to the rank of interest, F
Table E5: **Worker/Manager Ranking of Assignment, by matching algorithm**

### Panel A: Workers’ Rankings of Managers

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean</th>
<th>Bootstrap S.E.</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worker Draft</td>
<td>1.15</td>
<td>0.03</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>5.08</td>
</tr>
<tr>
<td>Workers-Propose DA</td>
<td>1.17</td>
<td>0.04</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Managers-Propose DA</td>
<td>1.17</td>
<td>0.04</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Manager Draft</td>
<td>1.95</td>
<td>0.15</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>2.00</td>
<td>16.34</td>
</tr>
<tr>
<td>Random Assignment</td>
<td>3.36</td>
<td>0.39</td>
<td>1.00</td>
<td>2.00</td>
<td>2.00</td>
<td>4.00</td>
<td>22.40</td>
</tr>
<tr>
<td>Command-and-Control</td>
<td>3.39</td>
<td>0.38</td>
<td>1.00</td>
<td>2.00</td>
<td>2.00</td>
<td>4.00</td>
<td>16.00</td>
</tr>
<tr>
<td>Firm Objective (minimizer)</td>
<td>3.48</td>
<td>0.41</td>
<td>1.00</td>
<td>2.00</td>
<td>2.00</td>
<td>4.00</td>
<td>15.58</td>
</tr>
</tbody>
</table>

### Panel B: Managers’ Rankings of Workers

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mean</th>
<th>Bootstrap S.E.</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Managers-Propose DA</td>
<td>1.19</td>
<td>0.04</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>6.32</td>
</tr>
<tr>
<td>Workers-Propose DA</td>
<td>1.19</td>
<td>0.04</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>6.32</td>
</tr>
<tr>
<td>Worker Draft</td>
<td>1.32</td>
<td>0.07</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>7.32</td>
</tr>
<tr>
<td>Manager Draft</td>
<td>1.62</td>
<td>0.08</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>2.00</td>
<td>10.20</td>
</tr>
<tr>
<td>Random Assignment</td>
<td>3.00</td>
<td>0.36</td>
<td>1.00</td>
<td>2.00</td>
<td>2.00</td>
<td>3.79</td>
<td>11.50</td>
</tr>
<tr>
<td>Command-and-Control</td>
<td>3.04</td>
<td>0.37</td>
<td>1.00</td>
<td>2.00</td>
<td>2.00</td>
<td>4.00</td>
<td>11.90</td>
</tr>
<tr>
<td>Firm Objective (minimizer)</td>
<td>3.15</td>
<td>0.40</td>
<td>1.00</td>
<td>2.00</td>
<td>2.66</td>
<td>4.00</td>
<td>11.22</td>
</tr>
</tbody>
</table>

**Notes:** This table displays the average worker and manager ranking for matches generated by various algorithms. Standard errors of the mean were bootstrapped by the quarter of the market. Because there were more managers on the market than workers, some managers are unmatched. This table includes only complete manager worker/pairs (i.e., dropping managers who were not paired to workers). All matching algorithms left the same number of managers unmatched, but differed in their composition. A similar table including unmatched managers (containing a score of zero) is accessible in Table 5.
the frequency of the rank,\(^4\) and \(N\) is the number of managers (workers) available for the worker (manager).

The results are also in line with Table 5.

Table E6: **Worker/Manager Percentile Ranking of Assignment, by matching algorithm**

<table>
<thead>
<tr>
<th>Panel A: Workers’ Percentile Ranking of Managers</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workers-Propose DA</td>
<td>2.73</td>
<td>10.88</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>58.93</td>
</tr>
<tr>
<td>Managers-Propose DA</td>
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<th>Panel B: Managers’ Percentile Ranking of Workers</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>Min</th>
<th>P25</th>
<th>Median</th>
<th>P75</th>
<th>Max</th>
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Notes: This table displays the average worker and manager percentile ranking for matches generated by various algorithms. Standard errors of the mean were bootstrapped by the quarter of the market. For each worker (manager), we calculate the percentile rank as \(PR = \frac{CF - (5\times F)}{N} \times 100\), where \(CF\) is the count of all rankings less than or equal to the rank of interest, \(F\) is the frequency of the rank, and \(N\) is the number of managers (workers) available for the worker (manager).

\(^4\)Some rankings appear multiple times given workers left some managers unranked, and we input these as tied.
References


