# Delegation and Team Selection in Organizations: An Experimental Study*

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**Abstract**

We model a managerial decision environment in which a manager both determines the skill heterogeneity of her workers and determines whether to retain or delegate the ability to allocate tasks. The manager prefers delegating when uncertainty is sufficiently high relative to the incentive conflict with her workers, which is endogenously determined by her chosen team composition. Experimental data supports the direction of the main predictions, though it shows how and why participants deviate from expected behavior. Generally, the results highlight the difficulties in navigating complex managerial environments and illustrate potentially costly ways in which managers seek to simplify their decisions.

**Keywords: managerial decisions, delegation, team selection, task allocation, decision rights.**

**JEL Codes: C92, D23, D83, L22, M50**

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# 1 Introduction

Two managerial decisions of paramount importance in any organizational setting are who to hire and how much control to retain over decision-making. A recent example highlights both of these decisions. When Twitter founder Jack Dorsey was faced with mounting challenges at his new firm, Square, he drastically changed his management approach. As an exposé in online news magazine "re/code" describes [Del Rey and Wagner, 2015], he decided to turn over decision making power to a newly created group of division executives, allowing him to focus on big-picture projects. To fill these positions, he invested immense amounts of firm resources in identifying and hiring top executives with highly specialized skills.[1] Generally, in choosing the skillsets of workers (which we refer to as team selection), managers must determine whether broadly skilled or highly specialized team members will most effectively complete their anticipated tasks. In navigating this issue, organizations spend significant resources on their hiring processes.[2] The managerial changes at Square highlight our central questions: just how closely linked are these two aspects of managerial decision making? Should more specialized teams always be given greater autonomy? What if the manager is uncertain about exactly what objectives the firm will have in the future?

Personnel decisions depend critically on whether the manager will have final say in key matters or delegate decision rights to workers (Dorsey would not have spent so much on high-powered executives had he not planned to give them decision-making power over their division-specific tasks). The delegation decision is nontrivial, particularly in rapidly evolving business environments where managerial uncertainty about the nature of future tasks may change. With high managerial uncertainty (that is, uncertainty over what future tasks may arise), a decentralized organization that allows workers to allocate tasks among themselves may be the best option. Intuitively, this enables rapid response to changing local conditions. However, the composition of the team and the nature of the decision play an important role on the final outcome of a decentralized organization. For instance, divisions with overly similar specializations may struggle with how to divide tasks due to skill overlap.[3] When incentive conflicts among workers or divisions reduce firm performance, the manager may prefer a centralized organization where she keeps control over all task allocation decisions.

Despite the potential benefit for firms in modeling this decision environment, the interrelatedness of worker selection and allocation of decision rights has not been directly addressed in the academic literature. We develop a simple model incorporating these decisions to study a general problem faced by firms - namely, the efficient completion of multiple tasks. We char-

[1] Another good example recently is the acquisition of the Washington Post by Jeff Bezos, CEO of Amazon.com. See, for example, [Stone, 2014] or [Blodget, 2013].

[2] See the PWC Saratoga 2013/2014 Human Capital Effectiveness Report. Blatter, Muehlemann and Schenker [2012] finds that for executive hires the search costs amount to over 4 months' wages of the new position. These costs are in addition to actual wages paid, and so highly competitive markets necessitate the ability to hire workers whose skill sets closely match a firm's need.

[3] For instance, the coordination problem among divisions inside Sony Corporation was a major reason behind its lost of leadership on the production of electronic devices. In 2012, intradivisional mis-coordination left Sony with a catalog of 30 different TV's, none of which could argue that they had the most cutting-edge technology [Tabuchi, 2012].

acterize the optimal combinations of team composition and allocation of decision rights under varying levels of managerial uncertainty. The key component in our model is the ability for the manager to select her team composition. This decision endogenously determines the degree of conflict among workers in a task allocation framework. It also determines the potential harm from a manager mis-allocating tasks across workers. We use varying team composition to proxy different skill sets or roles in a work group.[4]

We aim to capture a broad range of managerial decision-making by highlighting this critical link between employee makeup and the allocation of decision rights within a firm. For instance, a research division may decide which types of engineers to hire before all of its projects are known. A hospital administrator must often decide which type of doctors to staff in an emergency room without knowing what patients may arrive. Lastly, when a manager in a consulting firm hires a new team member there may be a high degree of future project uncertainty, though the team's organizational structure is already well defined. Moreover, the total cost of a project and the quality of the team's output will depend on task allocation among consultants and how the team's capabilities fit the project requirements. Our model may also inform the organizational decision making process after a merger between firms, divisions or branches. The decision of which workers to retain and how to adjust the organizational structure is closely related to the new potential projects or tasks given to the newly merged firm. These stylized vignettes all highlight the importance of team selection commonly faced in managerial decisions and its connection to an organization's level of decentralization.

The main intuition behind the model can be captured with a simple illustration: A more heterogeneous or specialized team allows the manager to better respond to a more dissimilar task profile in a centralized organizational structure. However, if the task uncertainty is very high, the manager may be unable to make an informed decision. To minimize the ex-ante impact of these mistakes, the manager may instead prefer a team with greater overlap focused around the most common task addressed by the firm. On the other hand, in a decentralized organization, workers have perfect information about tasks but a potential conflict of interest may arise between workers and manager. Workers with similar specializations may have difficulty agreeing on the efficient division of tasks. The manager can reduce the potential incentive conflict by selecting a more heterogeneous team in terms of specializations.

Two main predictions from the model are worth noting here; for high or moderate levels of informational uncertainty, decentralization is the manager's optimal allocation of decision rights. Also, the worker types should be more heterogeneous under decentralized (as in the case with Square) than under centralized organizations regardless of the level of uncertainty. Worker types will converge under centralization as managerial uncertainty grows, but will be unaffected by the manager's uncertainty in a decentralized structure.

We test these predictions in a controlled laboratory experiment with three main results. First, we find that managers correctly delegate decision rights more often as information uncertainty

[4]Firms may change their allocation of decision rights and team composition, but those processes take time and resources, making the initial team composition and organizational structure decisions critical.

grows. However, we also find that there is a general tendency to centralize more than is optimal. So, while the response to uncertainty is in line with the model's predictions, our data suggest that managers may suffer from a desire for control, retaining allocation rights in low information conditions, which can be a costly decision [Fehr, Herz and Wilkening, 2013; Owens, Grossman and Fackler, 2014]. Second, we find that managers tend to select less specialized teams in centralized organizations than in decentralized, as predicted by the model. Teams are generally less heterogeneous than those predicted by the model, though they converge with experience toward optimal team composition. Interestingly, we find that those managers who select teams closest to the optimum perform much better in the organizational structure decision. These managers benefit greatly in payoffs. In fact, managers with near-optimal team composition but sub-optimal organizational decisions earn significantly more than managers who get the delegation choice right, but with far from optimal teams. Lastly, we show that when managers observe that a worker's decision goes against their interest in previous rounds, they overreact by choosing a more homogeneous team in subsequent rounds. As uncertainty is reduced, this effect becomes more evident. In relation to this, the data are consistent with managers using fixed team compositions to simplify the delegation choice.

These findings together tell us much about how individuals in managerial positions may use team selection to help navigate uncertainty, but they also highlight the challenging nature of these environments. Even when managers successfully find an optimal team composition, a single unforeseen negative outcome can make them abandon their strategy. In doing so, they adopt strategies that may seem safer, but prove very costly. Those managers who conssitently choose ideal teams without overreacting to bad short term outcomes also tend to make better organizational choices, and consequently, leave less money on the table. Many firm executives struggle with these decisions, and those who master them can expect greater likelihood of success. Our data suggest that a critical difficulty may be consistency, to sustain profitable strategies over the long term when short-term losses arise.

The rest of the paper is organized as follows: We discuss related literature more thoroughly in section 2 before developing our theoretical model in section 3. Our experimental design and specific hypotheses comprise section 4 and we discuss our results in section 5. Section 6 introduces simulation results from a variant of the model to help explain our team composition effects and Section 7 concludes with general comments and discussion of further study.

## 2 Literature Review

***Decision rights, incentive conflict, and adaptation***: A rich theoretical literature in organizational economics studies the implications of modern property rights theory for the organizational structure within firms (e.g. Grossman and Hart [1986]; Hart and Moore [1990]).[5] Specifically, there has been a focus on how the allocation of decision rights affects a firm's ability to balance the trade-offs between "coordinated growth" (suggesting a centralized organization,

[5]Mookherjee [2006] provides a thorough overview of early work in this area.

as in Williamson [1996]) and rapid adaptation to local conditions, which favors a more decentralized organization as suggested by Hayek [1945]. These studies, like ours, develop models of incomplete contracts to derive predictions for when firms may benefit from centralized or decentralized decision making.[6]

A recent focus in this area has been the role of communication in helping firms manage the coordination-adaptation tension.[7] In a closely related theoretical paper, Dessein and Santos [2006] study organizations in which branches can change tasks to accomodate changing local tastes, but branch positions are fixed. The purpose of their study is to highlight the connection between communication technologies and adaptability. Other prominent theoretical examples are a closely related set of papers by Rantakari [2008] and Alonso, Dessein and Matouschek [2008, 2012], in which centralized firms may receive such distorted information that decentralization may be optimal even under situations with a strong need for coordination. Evdokimov and Garfagnini [2015] experimentally test a version of the models found in Alonso, Dessein and Matouschek [2008] and Rantakari [2008], and find results in line with the comparative statics of the model.

Brandts and Cooper [2015] experimentally test the behavioral assumptions behind many of these models; namely that divisions will successfully coordinate and that management will optimally utilize communication. They find that communication is not as strategic as predicted, and that managers struggle to optimally interpret communication. They also find that the coordination problem between divisions is non-trivial and leads to greater than predicted conflict.

Empirical studies of organizational structure are less common outside the lab due to identification challenges, though some important exceptions should be noted. McElheran [2014] finds that between-firm variation in decentralization is consistent with theoretical predictions based on the relative importance of adaptability or coordination within a firm. Thomas [2010], however, finds that adaptation to local preferences can lead to over-specialization of product lines at the expense of firm profits.

Our model differs from those mentioned above in several important ways. The primary distinction is that we endogenize the degree of coordination conflict by allowing the central manager to select her workers. To focus on worker selection, we exogenously determine the central manager's degree of informational uncertainty. This uncertainty is endogenous (though ambiguous) in Alonso, Dessein and Matouschek [2008, 2012] as well as in Rantakari [2008] and Dessein [2002].

***Team Composition***: Becker and Murphy [1992] theoretically establish that a more specialized team increases productivity, but it also increases the cost of coordination within teams. Other research shows that skill heterogeneity in manager-worker pairs [Mello and Ruckes, 2006] and

[6]For example, several related articles study the tension in multi-divisional firms between task-specific managers and managers who oversee multiple tasks (Dessein, Garicano and Gertner [2010]; Hart and Holmstrom [2010]; Hart and Moore [2005]).

[7]This work largely builds off of early models of communication by Crawford and Sobel [1982], Bolton and Dewatripont [1994], and Dessein [2002].

beliefs heterogeneity among workers [Van den Steen, 2010] may affect willingness to delegate due to incentive conflicts. The main trade-off in our paper differs from the trade-off analyze in these studies. Our study explores efficient task completion within an organization when workers are horizontally differentiated but vertically separated from management.[8]

***Delegation and the "Control Premium"***: The theoretical literature on strategic delegation establishes many scenarios in which firm managers may optimize by ceding decision rights to a more well-informed agent, even in the face of incentive misalignment [Aghion and Tirole, 1997; Alonso and Matouschek, 2008; Hart and Holmstrom, 2010; Holmstrom, 1982]. Additional benefits for the delegator have been revealed in recent experimental research. For example Hamman, Loewenstein and Weber [2010] find that delegation enables principles to seek out a self-interested outcome at the expense of others without feeling responsible taking actions via intermediaries.[9] However, recent experimental studies have demonstrated that even in the face of beneficial delegation, many principals have difficulty in transferring their decision rights. For instance, Fehr, Herz and Wilkening [2013] find that principals retain decision rights far too often and over-exert effort in a delegation game. Similar newly released studies quantify this preference for authority - the "control premium" - in hierarchical relationships. Owens, Grossman and Fackler [2014] find that individuals prefer to rely on their own performance in a quiz than another subject, even when their probabilistic earnings are much lower. Controlling for ambiguity aversion and overconfidence, among other factors, they find a control premium of $8 - 15\%$ of expected net assets. Bartling et al. [2014] design a lottery selection game that allows them to quantify the degree to which individuals intrinsically value control of their decision rights. They find a control premium of around 16.7% that persists over a wide range of parameterizations.

The current project therefore fits nicely into the broad literature on decision rights in firms. We provide a test of the trade-off between adaptation and incentive misalignment in an environment that also enables us to identify the degree to which firm managers prefer to retain decision rights when it is not in their material best interest. We also contribute to the theoretical and experimental literature on delegation by examining one-to-many delegation rather than one-to-one. We next discuss the theoretical model in more detail.

# 3 The Model

We focus on organizations comprised of three members, a principal and two agents. The principal has a managerial role (manager) while agents have an operational one (workers). Worker

[8]Friebel and Raith [2010] highlights ways in which centralization affects the allocation of capital to projects proposed by well-informed division managers. Garicano [2000] focuses on the importance of knowledge acquisition and the cost of communication as determinants of task allocation inside a firm, while Garicano and Santos [2004] study how to match the tasks or projects with horizontally-differentiated talent focusing on market solutions but not on organizational ones.

[9]In a similar context, Bartling and Fischbacher [2011] and Coffman [2011] find significant reduction in punishment towards the principal when she delegates an unfair act, which is true even if the intermediary has transparently no decision making ability [Drugov, Hamman and Serra, 2014; Oexl and Grossman, 2013].

heterogeneity is modeled by different specializations $\theta_i$, and each receives a task $t_i^0$ to complete that period. The manager selects the worker's specialization, $\theta_i$, which determines how costly it is for the worker to complete $t_i^0$ for worker $i$.[10]

We assume that $\theta_i$ and $t_i^0$ have the same normalized support, $[0, 1]$. The original task realizations for each worker are independent and identically distributed based on the cumulative $F(t_i^0)$. The pair $(t_1^0, t_2^0)$ determines the state of the world for the firm. We consider a task allocation framework where the manager wants to minimize the total cost of the firm defined by $\mathbb{E}\big[\sum_{i=1,2} C_i(t_i, \theta_i)\big]$, where $C_i(\theta_i, t_i) = |\theta_i - t_i^1|$ and $t_i^1$ is the final task assigned to the worker $i$.[11] Thus, the total cost to the firm increases linearly as the distance between the workers' abilities and their final assigned tasks increase. Critically, the manager and workers have imperfectly aligned incentives. We assume each worker receives a fixed payment that is high enough to cover her best outside option, where the firm strategically combines high wages with high dismissal rates as disciplinary devices [Shapiro and Stiglitz, 1984]. As a consequence the worker focuses on minimizing her cost, $C_i(\theta_i, t_i)$.

In this context, centralized organizations allow the manager to reallocate tasks. A decentralized organization, then, is one in which the workers decide unanimously whether or not to reallocate tasks. While the differences in objective functions may favor a centralized organization, the manager's information quality plays a critical role in the trade-off between organizational structures. In our model, we assume workers observe both tasks with certainty, but managers observe each task independently with some probability $p$ known ex-ante by all agents.[12]

Critically, we also allow managers to choose the type of workers in their teams. Thus managers make two decisions before tasks are reallocated or not. First, the manager determines the organizational structure in her team by retaining or delegating reallocation rights. After this, she selects the team composition that will maximize her payoffs given the structure selected and the level of information available. The timing of the decisions in the complete model is divided in four stages as follows:

1. Given $p$, the manager chooses whether to delegate the rights to reallocate tasks.
2. The manager chooses $(\theta_1, \theta_2)$ and the workers receive randomly drawn tasks, $(t_1^0, t_2^0)$.
3. The manager observes each task with an independent probability $p$. Workers observe both tasks.
4. The manager (centralized organization) or the team (decentralized organization) determines the final task assignment, $(t_1^1, t_2^1)$.

[10] Firms are often able to distinguish potential employee skill sets but it is more difficult to recognize ex ante a worker's productivity. We abstract away from heterogeneous productivities and simplify the model by assuming that all tasks are completed at the end of the period.

[11] We assume both manager and workers are risk neutral. However, we obtain similar results with risk averse agents if we consider strict monotonically decreasing utilities as functions of the distance between positions and tasks.

[12] This captures the intuition that informational accuracy may differ across sectors or geographical locations. The differences in information accuracy can also represent the experience or ability of the managers.

In this game, each agent has a dominant strategy that we show using backward induction. First, we solve the manager's problem in a centralized organization and explain the main trade off the manager faces. Then, we solve the manager's problem in a decentralized organization and underline the main incentive conflict between the manager and the workers. Finally, we compare the two organizational structures to determine the manager's optimal organizational structure given the level of information.

### 3.1 Manager's problem in a centralized organization

A manager may see one realized task, both tasks, or neither task, depending on $p$. Managers optimally respond to these different situations as follows:[13]

- If the manager observes both tasks, she reallocates tasks minimizing $\sum_{i=1,2} C_i(t_i, \theta_i)$.
- If the leader observes only one task, she would assign the task she observes to the worker with the closest position.[14]
- If the manager does not observe either task, she maintains the status quo (no reallocation).[15]

A manager without information ($p = 0$) is like a manager who cannot reallocate tasks. As a consequence, she will minimize the maximum expected distance each worker can face positioning them in the ex-ante expected tasks, $\theta_1 = \theta_2 = E[t^0]$. This somewhat trivial result becomes more interesting when we allow for task reallocation between workers. When there are reallocation possibilities and $p = 1$, the manager would not choose the same positions for both workers since reallocation can not change the final outcome with homogeneous workers. If the firm wants to take advantage of reallocation possibilities, the manager must select a more heterogeneous team. In particular, if we assume the distribution of each task is uniform, the optimal positions tend to $\theta_1 \approx 0.29$ and $\theta_2 \approx 0.71$.[16]

Figure 1 defines the probability that the manager decides to reallocate tasks as a function of $p$ for all the possible states of the world, $(t_1^0, t_2^0)$.[17] For this illustration, we analyze the case of two symmetric positions equidistant to $E[t^0]$ where $\theta_2 > \theta_1$. The shaded area represents the region where the manager would like to exchange tasks under perfect information. Since the

[13] A manager's optimal response is independent of initial task assignment in a centralized firm.

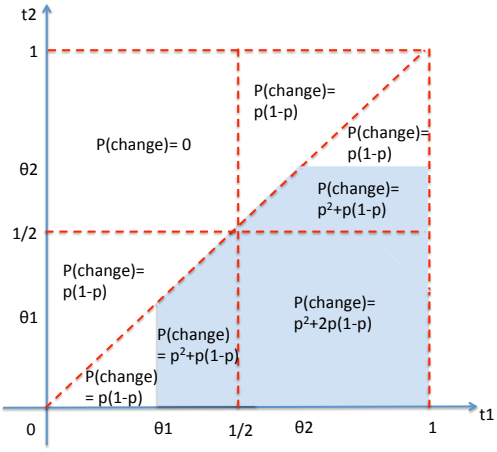
[14] This behavior is supported by the data we observe in the experiment. In 75% of the rounds where the manager observes exactly one task, she follows this behavior.

[15] Since managers have no information, any mixed strategy over the set of actions { Switch, No switch} would give us the same results. For simplicity, we assume a strategy assigning 0 to the *Switch* action and 1 to the *No switch* action - keeping the status quo.

[16] Intuitively, one can expect the solution to be closer to the values 0.25 and 0.75. That is true if we minimize the sum of the distance between the selected positions and the expected minimum/maximum tasks, $|\theta_1 - E[min(t_1^i, t_2^i)]| + |\theta_2 - E[max(t_1^i, t_2^i)]|$. However, our manager's problem is to minimize $E[|\theta_1 - min(t_1^i, t_2^i)| + |\theta_2 - max(t_1^i, t_2^i)|]$. Since, we are working with absolute value functions it is possible to show that both cases are not equivalent.

[17] The graph identifies the managers' probability to reallocate tasks given that managers are strictly better off following this strategy. If we include the situations where managers are indifferent, the probabilities on the upper right and lower left triangles become $p^2 + p(1-p)$ instead of $p(1-p)$. However, the final solution is unaffected by any of these approximations.

Figure 1: Reallocation Probabilities in a Centralized Organization




manager does not always observe both tasks, she is likely to make some errors $ex-post$ in her task reallocation. Two types of errors appear as a consequence of the established rule. The manager may fail to exchange tasks in a region where she would have preferred to do so (Type I error), and she may exchange tasks with some probability in the region where she would prefer not to change $ex-post$ (Type II error). Let $\delta(\theta_1, \theta_2) = \frac{\theta_2 - \theta_1}{2}$ be defined as the measure of heterogeneity of the team selected by the manager assuming that $\theta_2 \geq \theta_1$.[18]

**Proposition 1** *For any $p$, if $t_i^0 \sim \mathcal{U}(0,1)$ for $i = 1, 2$, there is a unique $(\theta_1^C(p), \theta_2^C(p))$ in a centralized organization, such that:*

1. *$(\theta_1^C(p), \theta_2^C(p))$ are symmetric with respect to $E[t^0]$.*
2. *$\delta^C(p) > 0$ if $p \neq 0$.*
3. *$\delta^C(p)$ is a monotonic function of $p$*

See appendix A for the proof. As expected, the manager prefers a more heterogeneous team if she expects to successfully enable the reallocation of tasks.[19] A poor information environment, though, increases the probability that the manager makes bad decisions. As a consequence, the manager will choose a more homogeneous group to minimize the impact of misinformation. An overly-homogeneous team, though, reduces the benefits of task reallocation. In a firm setting, if the information environment depends on manager expertise, our proposition states that a poorly-informed manager would prefer a more homogeneous team than an expert one in a centralized organization.

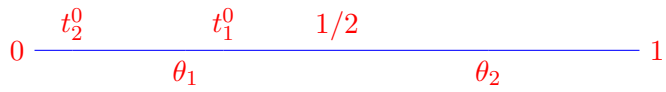
[18] Notice $\delta(\theta_1, \theta_2) \in [0, \frac{1}{2}]$. The division by two is only for numerical tractability and it does not affect the results. Moreover, if we assume symmetric positions relative to the ex-ante expected task, we get: $\delta(\theta_1, \theta_2) = E[t^0] - \theta_1 = \theta_2 - E[t^0]$.

[19] Intuitively, the symmetry around the ex-ante expected task realization is natural since we assume a symmetric distribution and a worker's action on one side of the mean is a mirror of a equidistant worker's action on the other side.

### 3.2 Decentralized organization and incentive conflict

The manager's objective is unchanged in the decentralized organization. She must choose a team that minimizes the expected distance between workers' specialization and tasks. However, workers now decide whether to reallocate the tasks, which may improve the reallocation of tasks due to workers having perfect information.[20] Critically, the workers' preferences are not perfectly aligned with the manager's preferences in this case. Because unanimity is required to reallocate tasks in the decentralized organization, either worker can unilaterally guarantee the status quo task assignment. We can therefore identify instances as in Figure 2 where the manager would like to exchange the tasks but one of the workers will not.

Figure 2: Main Incentive Problem in a Decentralized Organization




In this example, worker $\theta_1$ minimizes her cost with her assigned task and will vote to not switch tasks. As a result no exchange takes place, though both other group members would have preferred reallocation. The reallocation of tasks in this case also maximizes the joint profits for the entire group.

**Assumption 2** *There is no monetary transfer among workers.*[21]

Figure 3 highlights two symmetric areas where the manager would like to exchange tasks and one of the workers does not. The shaded triangle on the bottom left is the area where the worker in position $\theta_1$ does not want to exchange tasks. The shaded triangle in the top right is the area where the worker in position $\theta_2$ does not want to exchange tasks. Those areas are the graphical representation of the potential expected incentive conflict between the managers and the workers in a decentralized organization given $(\theta_1, \theta_2)$. The shaded area considers the cases in which both workers decide to reallocate tasks.[22] The two downward-sloping diagonals in Figure 3 determining the area where workers reallocate tasks are parallel and they cross the 45 degree line exactly on the positions selected by the manager. If we assume that the manager chooses a more homogeneous team, those parallel lines get closer and the areas representing the incentive conflict grow larger. A manager can reduce the areas of conflict by choosing a more heterogeneous team, expanding the parallel lines outward. As a result, the members of the team exchange tasks more often. Since the manager affects the final results of the workers only through the positions selected, the optimal positions are independent of the level of information

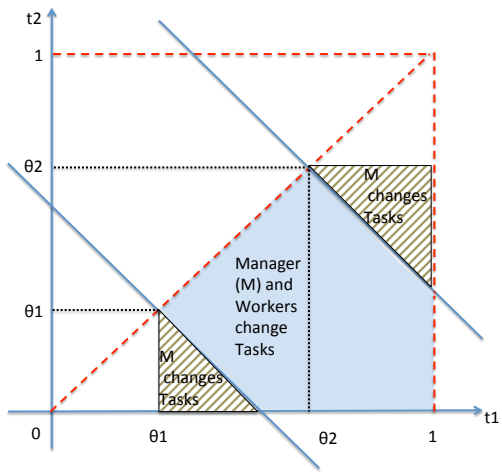
[20] Unlike in a centralized organization, initial task assignment plays an important role in the decentralized organization since both workers may want the same task. This may depend on experience, knowledge, rank or luck (e.g. project arrival). For simplicity, we assume tasks are randomly assigned. While other assignment rules may be interesting to study, they are beyond the scope of this paper.

[21] See Garicano and Santos [2004] and Fuchs and Garicano [2010] for market-based solutions to efficient matching. We focus here on organizational solutions where monetary transfers between members of the team are unlikely. For instance, when those transfers carry a reputational cost.

[22] The shaded area plus the two triangular areas pointed out previously denotes the cases where a manager with perfect information ($p = 1$) decides to reallocate tasks.

$p$. At the extremes, with a perfectly heterogeneous or homogeneous teams there is no conflict at all. In the decentralized organization, the optimal team composition is symmetric around the expected task and the distance between positions selected is constant for any value of $p$. The manager chooses a more heterogeneous team in a decentralized organization than in a centralized organization for all $p$.

Figure 3: Reallocation Regions in a Decentralized Organization




**Proposition 3** *For any $p$, if $t_i^0 \sim \mathcal{U}(0,1)$ for $i = 1,2$, there is a unique $(\theta_1^D(p), \theta_2^D(p))$ in a decentralized organization, such that:*

- *$(\theta_1^D(p), \theta_2^D(p))$ are symmetric with respect to $E[t^0]$.*
- *$\delta^D(p)$ is constant $\forall\ p \in [0,1]$.*
- *$\delta^D(p) > \delta^C(p)\ \forall\ p \in [0,1]$.*

### 3.3 Optimal organizational structure

In this section, we integrate team selection into the manager's organizational structure decision to compare the expected profits generated by both solutions based on the level of information:

**Proposition 4** *If $t_i^0 \sim \mathcal{U}(0,1)$ for $i = 1,2$, there exists a level of information $p^*$ such that:*

- *If $p \geq p^*$, the manager prefers a centralized organization with $(\theta_1^*, \theta_2^*) = (\theta_1^C(p), \theta_2^C(p))$.*
- *If $p < p^*$, the manager prefers a decentralized organization with $(\theta_1^*, \theta_2^*) = (\theta_1^D(p), \theta_2^D(p))$.*

Proposition 4 states that the manager prefers to have the right to reallocate tasks among her workers when the level of information is "good enough." On the other hand, when the manager's information is poor, she prefers to delegate task reallocation rights to the workers. This result is not surprising and has been pointed out before in the literature. For instance, Dessein [2002] shows a similar result without team selection driven by the communication technology between the principal and the agents. However, we related this finding with the optimal team

composition.

# 4 The experiment

Using a controlled laboratory experiment, we test the model's trade-off between the manager's information and her potential incentive conflict with her workers' decisions in order to respond effectively to randomly drawn tasks.

## 4.1 Experimental Design

We implement a hybrid between/within design where subjects were randomly assigned a role of Manager ($M$), Worker 1 ($W_1$), or Worker 2 ($W_2$) in three-person groups. Roles were denoted Participant A, Participant B1, and Participant B2 and the experiment was presented as one of decision-making instead of one of organizational decisions to avoid framing effects. In the experiment we consider a uniform distribution of the tasks over the support $[0, 100]$. We use four different treatments, each capturing a different level of information. Specifically, the probability $p$ took one of the following fixed values in each treatment: $[0.2, 0.5, 0.8, 0.9]$. The body of experimental work on the control premium (among other topics) demonstrates that people are much more likely to sub optimally retain control than to sub optimally cede control. Thus, we focus on values of $p$ below 0.82. Our design allows us to examine the behavior of subjects as they approach the information threshold in three environments that call for decentralization, and one in which centralization is optimal.

Each session was broken into three blocks of several rounds each. The first two allow the manager to familiarize herself with team selection in a centralized or decentralized environment, after which she enters a third block in which she decides both the team composition and now the organizational structure as well. This provides a stronger test of the model by giving subjects experience and feedback in both organizational structures before they must choose the organizational structure themselves.

Blocks 1 and 2 lasted 10 rounds each and were either Centralized or Decentralized (counterbalanced for each value of $p$). It was announced that groups would be fixed for each block with random rematching between blocks. The timing was as in the model. At the beginning of each round, subjects were reminded the value of $p$ for the session and the role they were assigned. Then, managers chose the type of workers $\theta_1$ and $\theta_2$ by assigning each a "placement" between 0 and 100. Once the placement decision was made, the positions of $W_1$ and $W_2$ were fixed for the remainder of the round. Once both workers had been placed, the position of the tasks assigned to each worker were revealed. Workers saw both task positions with certainty, and were told which task had been matched to them. Managers saw each task position independently with the probability $p$ for that session. Once the tasks were revealed or not to all group members, subjects completed a "switch" task. This task determined whether the workers would switch tasks or not. Subjects knew that workers and tasks could not be repositioned between 0 and

100, they could only switch which task was assigned to which worker. In the Centralized environment, the manager made the switch decision unilaterally, whether she saw one, both, or neither task position. In the Decentralized environment, workers voted over whether to switch. Only an unanimous vote to switch would result in a switch. If only one worker voted to switch, the tasks remained as initially assigned. After the switch tasks, payoffs were realized for all the subjects.

Payoffs in experimental currency (ECU) for group members were determined as shown in the equations below. It was possible, though improbable, for subjects to earn negative payoffs in a round. To minimize this risk, subjects received their total earnings collected over all rounds of the session and were reminded of this fact.

$$\pi_{W_i} = 50 - |T_i - W_i| \tag{1}$$

$$\pi_M = 50 - 0.5 \sum_i |T_i - W_i| \tag{2}$$

Where task $T_i$ is matched with worker $W_i$ at the end of the round. These formulas were explained to subjects with several examples, and subjects were given a calculation screen during the instructions with which to familiarize themselves with the payoffs (see the appendix B for experimental materials including instructions and screenshots). The experimenter walked through an example at this time, with and without switching tasks. Once all subjects had some time to experiment with the payoff calculator, the experimenter made the following scripted comments to help ensure subjects knew how their decisions affected their payoffs: "What these payoff functions tell you is simply that you maximize your payoffs when you minimize the distance between each B participant and that participant's final marker. Note also that the A participant increases his or her payoff by minimizing the distance between each B participant and that participant's marker. Nothing in the payoff function depends on the B participants being close to each other or far apart from each other."

Once subjects completed both the placement and switch tasks, results were displayed providing them with information about their decisions in that round and their payoffs. In the Centralized rounds, workers were informed of their final assigned task, task positions, whether the manager switched tasks, and the payoffs of all group members. Each manager was reminded of any task position revealed to her, but workers did not see which task positions had been revealed to the manager. In the Decentralized rounds, the manager was notified whether or not the workers chose to switch tasks; otherwise the information revealed was the same.

Once blocks 1 and 2 concluded, subjects were read instructions for block 3, which we refer to as the Selector stage. Block 3 consisted of 16 rounds that were identical to blocks 1 and 2 with one addition. Prior to making the placement decision, the manager made a new decision to begin each round of block 3 that determined whether that round would be played in the Centralized or Decentralized environment. Specifically, the manager selected whether herself or

the workers would complete the switch task for the round. Once the manager made this choice, she completed the placement decision and the round then mimicked either a round from block 1 or a round from block 2.

### 4.2 Procedure

We conducted this experiment in two locations. Initial sessions were run in the LEEX lab at Universitat Pompeau Fabra, and a second round of sessions were run in the xs/fs lab at Florida State University. Subjects were recruited using ORSEE ([Greiner, 2015]) at FSU and all sessions were run using the zTree software ([Fischbacher, 2007]). FSU sessions consisted of 24 subjects, and each subject received a $10 show-up fee in addition to money accumulated from the game. UPF sessions had 21 or 24 subjects, with each receiving a €5 show-up fee. Sessions lasted just under two hours and average earnings were approximately $24 and €16 ($22) in the U.S. and Spain, respectively (exhange rates were 60 ECU per $1 and 90 ECU per €1).

Instructions were first read aloud that included the value of $p$ for the session (translated to Spanish for UPF by a native speaker also fluent in English), after which subjects were randomly assigned a role of Manager ($M$), Worker 1 ($W_1$), or Worker 2 ($W_2$) in three-person groups. Subjects were only read instructions for each block as it was reached, though they knew there would be three blocks from the beginning. They were also reminded (before block 1 and each subsequent block) that they would play in the same role and face the same value of $p$ for all blocks. During the instructions at the beginning of the session, all subjects were given the chance to familiarize themselves with placement selection and switching decision using the exact same screen they would see during the experiment.

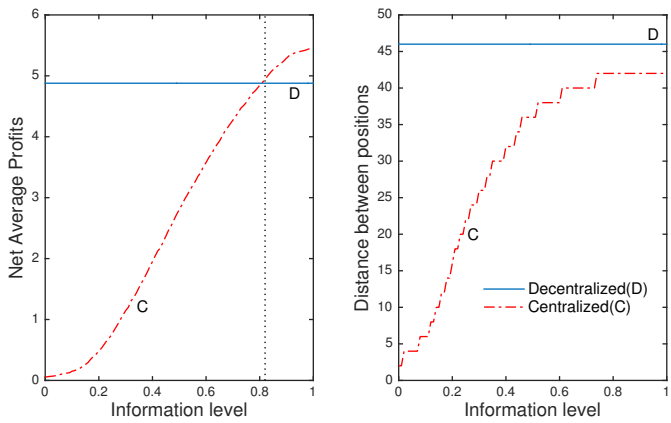
### 4.3 Theoretical predictions

Figure 4 represents a simulation of the main predictions under the previous assumptions of the model given the experimental design. We pursue a Monte-Carlo simulation with 100 managers playing 500 rounds for values of $p \in [0, 1]$. In the left hand panel, we plot the net average payoffs using equations 1 and 2 minus the expected payoffs obtained with a perfectly homogeneous "50-50" team (25 ECU per round). Notice that the value of $p^*$ predicted by the model for this experiment is approximately 0.82. At this value, the participant in the role of the manager is indifferent between the two types of organization. For values above 0.82, the manager prefers a centralized organization; and for values below, the manager prefers to delegate.

**Prediction 1** *In all treatments except the* 90% *treatment, the manager will delegate decision rights to the workers.*

In the right hand panel, we plot the optimal distance between positions for the different levels of $p$. The model predicts the following regarding team selection: In a centralized organization, the manager should select the positions around $(42, 58)$ in the 20% treatment, positions $(35, 65)$ in the 50% treatment, positions $(31, 69)$ in the 80% treatment and positions $(30, 70)$ in the 90%

Figure 4: Payoffs and Team Composition Predictions




*Notes.* The figures summarize our main predictions. It shows the differences, as information quality increases, between expected profits by organizational structure (left hand figure) and team composition (right hand figure).

treatment . In a decentralized organization, the manager should select the position of $(27, 73)$ in all the treatments independently of the level of information. More generally, the predictions with respect to team composition are:

**Prediction 2** *Team composition in a decentralized organization is always more heterogeneous than in a centralized organization for any level of information.*

**Prediction 3** *In a centralized organization, the heterogeneity of the team increases when the accuracy of the manager's information increases.*

**Prediction 4** *In a decentralized organization, the team composition is independent of the accuracy of the manager's information.*

# 5 Experimental Results

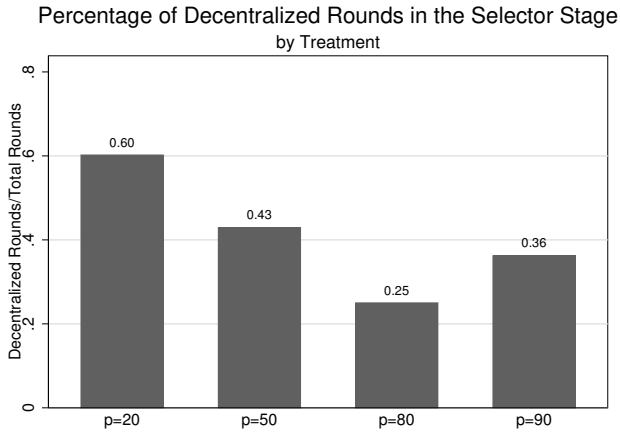
In this section, we use the distance between selected positions as a measure of the team heterogeneity. We are able to use this simplification because in alomost 90% of the cases the positions selected are symmetric around the ex-ante expected task, which takes the value of 50.

## 5.1 Organizational Structure Decisions

Our first prediction is that managers will delegate in the Selector stage in all information conditions except the 90% treatment, since the threshold for centralized control is at $p = 0.82$. Figure 5 plots the percentage of rounds in which managers delegate in the Selector stage by treatment. The rate of decentralization is highest in the 20% treatment and declines as the managers' uncertainty falls. The differences in proportions between treatments are significant (Pearson's chi-squared = 128.99; p=0.000). While managers do not delegate in all rounds below

the threshold, they do so significantly more often when facing poorer information. Interestingly, the rate of delegation in the 90% treatment is statistically indistinguishable from both the 50% and 80% treatments - a result we return to shortly. Remember that uncertainty threshold leading to the first prediction assumes that managers adjust their team composition optimally. However, some managers do not optimally select their team composition as we show in the next section.

Figure 5: Delegation by Treatment




*Notes.* Plot of the percentage of decentralized rounds in the "Selector" stage. We had 30 managers in the 20% and 80% treatments and 29 managers in the 50% and 90% treatments for totals of 480 and 464 rounds respectively.

To further explore the organizational structure decision of the managers, we implement the following logistic regression specification to control for additional factors:

$$Delegate_{ir} = \alpha + \delta_r + \beta_1 50\%_i + \beta_2 80\%_i + \beta_3 90\%_i + \gamma X_i + u_{ir}$$

where $Delegate_{ir}$ is a dummy variable equal to 1 if the manager $i$ delegates in round $r$ and 0 otherwise. $\delta_r$ is a set of round dummies and $50\%_i$, $80\%_i$ and $90\%_i$ are treatment dummies. Finally, $X_i$ are participant controls and $u_{ir}$ captures residual idiosyncratic determinants by participant $i$ in round $r$.[23]

Table 1 shows the regression results for different specifications of the baseline model, and the results are robust to many alternative specifications.[24] Consistent with Figure 5, all treatment coefficients are negative and significant. Moreover, the coefficient for $80\%_i$ roughly double that

[23]The estimated coefficients of $50\%_i$, $80\%_i$ and $90\%_i$ are the mean differences with respect to the omitted 20% treatment. Standard errors are clustered by manager. Our main concern is the between-subjects effect of information quality in the Selector Stage. Adding fixed effects in the regression eliminates the most stable participant types, which reduces effect sizes but preserves significance. As a robustness check, we jointly cluster the standard errors of the coefficient estimates by round and treatment to avoid correlations of the residuals at the session level not captured by the round fixed effects $\delta_r$. Finally, we implement a double clustering, by participant and round-treatment clusters. The main results do not change in any of these alternate specifications. These results are available upon request.

[24]We replicate these results using OLS and probit models. We also see the same results using random effects with bootstrapped standard errors. These are available upon request.

of $50\%_i$ in all specifications (a statistically significant difference), while the coefficient of the $90\%_i$ is between the two. We confirm the convex pattern from Figure 5, that more accurate information leads to higher rates of centralization below the predicted threshold established, but seems to reverse in the 90% treatment. This relationship is robust to including demographic and risk preference controls as well as round dummies.

In Panel B, we attempt to separate the direct effect of information quality on the manager's decision from the indirect effect of prior decisions. The decision to delegate is not affected by earnings from the previous round, but it is affected by the manager's previous decisions. Models 5 and 7 show that for every one unit change in the team heterogeneity, the log odds to delegate increase. The original treatment effects on the probability to delegate remained almost unchanged in model 5. This provides initial evidence of a weak relationship between team heterogeneity and the level of information, which we return to in the next section. Model 6 shows that the organizational structure decision in the previous round has a positive and significant effect on current decentralization that reduces the magnitude of the direct treatment effect.[25] Finally, in the two rightmost columns, we divide the sample between the first eight rounds played in the Selector stage (model 8) and the last eight (model 9). Model 8 shows that the direct effect is higher initially, compared to model 7, while the indirect effect is lessened. It also depends weakly but significantly on the payoffs on the previos rounds. The opposite relationships appear in model 9, which suggests that managers successfully learn from their experience.[26]

The evidence explored so far shows that in making their delegation decisions, managers respond to the level of information. As level of information increases, managers tend to centralize more often until they reach the predicted threshold of the model where this pattern seems to reverse. We also find evidence that managers are learning as they depend more heavily on their previously organizational structure decisions on the later rounds of the Selector We return to the organizational structure decisions after we better understand their team selection behavior.

[25]Model 7 in Table 1 includes the lags of the team heterogeneity, delegation decision and payoffs. While it may raise some concerns about multicollinearity, we observe that all the correlations (Pearson's Correlation Test and Spearman's Rank Test) between these variables are positive but modest ($corr < 0.13$) in the Selector stage for managers. Moreover, the correlation between delegating and profits is not significant. In other words, there is sufficient variation across observations in the Selector Stage to obtain unbiased estimates.

[26]We find no gender differences in delegation, but delegating is positively and significantly correlated with risk seeking. We also see slightly more delegation in the U.S. sessions than those run in Spain, with significantly more only in the 50% treatment. These results are available upon request.

Table 1: Organizational Structure Decision: Probability to Delegate in Selector Stage

| | Panel A: Full Sample | | | Panel B: Including Lags | | | | Rounds 1-8 | Rounds 9-16 |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $50\%_i$ | -0.701** | -0.889** | -0.892** | -0.851** | -0.868** | -0.497** | -0.529** | -0.698*** | -0.375 |
| | (0.35) | (0.35) | (0.35) | (0.35) | (0.34) | (0.25) | (0.24) | (0.25) | (0.27) |
| $80\%_i$ | -1.513*** | -1.754*** | -1.759*** | -1.766*** | -1.813*** | -1.185*** | -1.256*** | -1.402*** | -1.141*** |
| | (0.40) | (0.39) | (0.39) | (0.40) | (0.39) | (0.28) | (0.27) | (0.28) | (0.30) |
| $90\%_i$ | -0.981*** | -1.386*** | -1.390*** | -1.416*** | -1.410*** | -0.931*** | -0.962*** | -1.116*** | -0.851*** |
| | (0.38) | (0.44) | (0.44) | (0.45) | (0.44) | (0.30) | (0.30) | (0.32) | (0.31) |
| $Payoff_{ir-1}$ | | | | 0.007 | | | 0.006 | 0.015** | -0.000 |
| | | | | (0.00) | | | (0.01) | (0.01) | (0.01) |
| $Team.Heterogeneity_{ir-1}$ | | | | | 0.020*** | | 0.018*** | 0.018*** | 0.018*** |
| | | | | | (0.01) | | (0.00) | (0.01) | (0.01) |
| $Delegation_{ir-1}$ | | | | | | 2.020*** | 2.001*** | 1.827*** | 2.151*** |
| | | | | | | (0.26) | (0.26) | (0.28) | (0.28) |
| *Constant* | 0.414* | -1.203** | -1.226** | -1.327** | -1.974*** | -1.768*** | -2.639*** | -2.798*** | -2.611*** |
| | (0.25) | (0.53) | (0.55) | (0.57) | (0.61) | (0.48) | (0.52) | (0.56) | (0.53) |
| *RoundDummies* | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $Controls_i$ | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N. obs. | 1888 | 1888 | 1888 | 1770 | 1770 | 1770 | 1770 | 826 | 944 |
| N. clusters | 118 | 118 | 118 | 118 | 118 | 118 | 118 | 118 | 118 |
| Pseudo R2 | 0.051 | 0.091 | 0.093 | 0.094 | 0.112 | 0.229 | 0.242 | 0.228 | 0.258 |
| **Est. margin (mean)**: | | | | | | | | | |
| 20% | 60.2 | 64.6 | 64.7 | 64.6 | 64.6 | 54.9 | 55.6 | 57.8 | 53.9 |
| 50% | 42.9 | 42.9 | 42.9 | 43.8 | 43.4 | 42.6 | 42.5 | 40.5 | 44.5 |
| 80% | 25.0 | 24.0 | 23.9 | 23.8 | 23.0 | 27.1 | 26.3 | 25.2 | 27.2 |
| 90% | 36.2 | 31.3 | 31.3 | 30.7 | 30.9 | 32.4 | 32.4 | 30.9 | 33.3 |

*Notes.* * p< 0.1; ** p<0.05; *** p<0.01. Logit regressions with standard errors clustered by subject. $Treatment(p = k)_i$ is a dummy variable taking value 1 if the manager knows each of the tasks with a probability $k$. $Decentralization_{ir}$ is a dummy variable taking value 1 if the manager $i$ delegates in round $r$, $Payoffs_{ir}$ are the payoffs per round in experimental currency obtained by subject $i$ in round $r$ and $Team.Heterogeneity_{ir}$ is the distance between positions selected by the subject $i$ on round $r$. The controls by subject we are considering are the Eckel-Grossman risk aversion test, a cognitive reflection test, a dummy variable taking value 1 if Male, a dummy variable taking value 1 if the session was run in US and and a variable capturing different intervals of age.

## 5.2 Team Composition

A brief overview of the data shows that the average distance between positions in the centralized and decentralized stages are 30.23 and 29.22, respectively. On aggregate, then, we see no clear or statistically significant difference. In the selector stage, the average distance between positions in the centralized rounds becomes 29.71 and 32.61 in the decentralized rounds (Mann-Whitney two-tail test, $p < 0.01$). This direction is in line with prediction 2, though not as large as predicted by the model. It also provides initial evidence that subjects may be learning to play more optimally with experience, at least in the decentralized rounds.[27] However, a pairwise test is suggestive but not conclusive given the repeated decisions made by each manager. We next explore more robust tests of the relationship between team composition, delegation and the manager's level of task uncertainty.

Figure 6 plots the percentage of decentralized rounds by the distance between positions in the Selector Stage. We use the frequency of observed heterogeneity to weight each observation, represented by marker diameter. Approximately 63% of the sample is captured by the clusters shown in bold.[28] These clusters also contain 68% of the total number of decentralized rounds during the Selector Stage. The correlation shown by the linear trendline is approximately 0.1 and it is significant at the 5% level.[29] At the same time, we see a concentration of perfectly homogeneous teams, which appears to a varying degree among all treatments, as shown in Figure 7. Figure 7 shows the frequencies of the distances between positions in the different stages of the game by treatment and organizational structure. The frequency of rounds with perfectly homogeneous teams decreases in most of the cases when we compare the Centralized and Decentralized stages with the centralized and decentralized rounds in the Selector stage.[30] This points again to some type of learning process, where agents start to play more heterogenous teams more often on the Selector stage. The existence of perfectly homogeneous teams is important because in those situations the theory predicts that the agent should be indifferent between a centralized or decentralized organizational structure. As we discussed in more detail in section 6, this behavior is concentrated in just a few playersis and is one of the main reasons why we observe deviations from the predicted patterns in the model.

Beyond the perfectly homogeneous teams, we observe that the distributions of distance

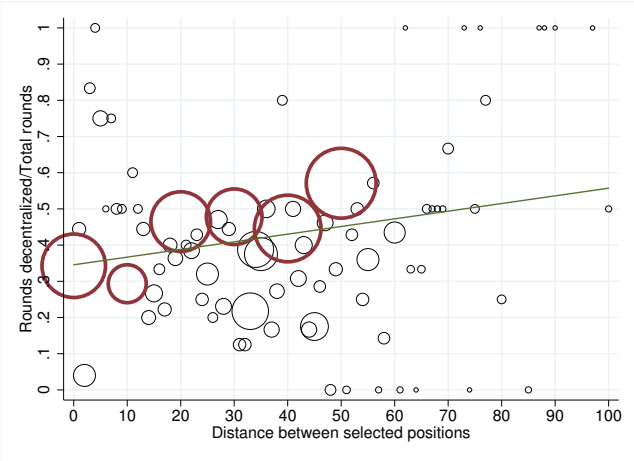
[27] We use the distance between positions as a measure of team heterogeneity. It is also informative about the positions selected since positions are symmetric in a vast majority of cases.

[28] The bold markers represent 6 different values of the distance between positions: 0, 10, 20, 30, 40 and 50.

[29] We obtained a similar result using a Spearman rank correlation test.

[30] They only increase on the centralized rounds on the 20% treatment and remain in the same level on the 90% treatment for both cases.

Figure 6: Delegation and team heterogeneity




*Notes.* Plot of the percentage of decentralized rounds in the Selector Stage (y-axis) by distance between worker positions (x-axis), along with a linear fit. The observations are weighted by the frequency of each chosen distance. The bold bubbles represent 63% of all rounds played on the Selector Stage.

between positions are concentrated close to the optimum distance predicted by the model.[31] Moreover, comparing the frequencies in the Centralized and Decentralized stages (solid bars) with those on the Selector stages (hollow bars) of Figure 7, we observes a movement towards the optimal distances predicted by the model. In the 20% treatment, the selected distances move towards 40 and 50 in the decentralized rounds of the Selector stage, where the optimal distance is 46. Selected distances move towards zero in the centralized rounds on the Selector stage, where the optimal distance is 16. in the 50% treatment, there is movement towards values between 30 and 50. However, in the centralized stage (optimum distance of 30) they come mostly from more heterogenous teams while they come from more homogeneous teams on the decentralized stage (optimum distance, again, of 46). In the 80% treatment, we see a shift towards more heterogeneous teams with the highest concentration on distances of 40 and 50 in both centralized (optimum distance, 38) and decentralized (optimum, 46) rounds, with higher frequencies in decentralized rounds. In the 90% treatment, there is movement towards values between 30 and 40 for the centralized rounds (optimum distance, 40) and to 50 in the decentralized rounds (optimum distance, 46).

To further analyze the team compositions selected by the managers we use linear regressions with standard error clustered by manager, reported in Table 2.[32] Panel A confirms that there is

[31]Subjects tend to focus on round numbers for the distance between positions. In particular those that are multiple of 5 and 10. The optimum distances between positions predicted by the model are 16, 30, 38 and 40 in the centralized rounds for the 20, 50, 80 and 90% treatments respectively and 46 for all treatments in the decentralized rounds.

[32]These regression results are not intended to argue a causal relationship necessarily, as managers may have

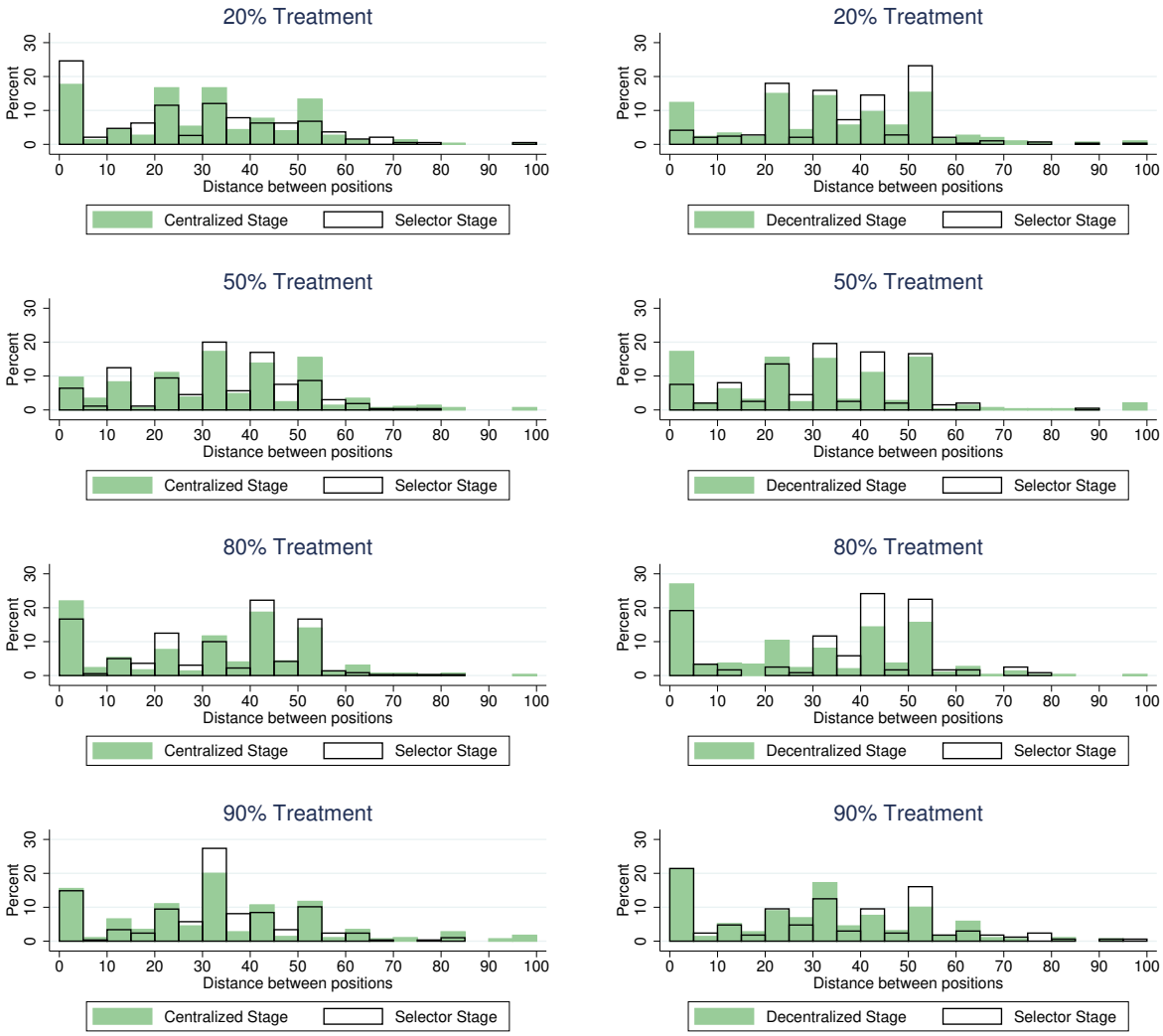
a strong relationship between delegation and team heterogeneity. Interestingly, the treatments have no direct effect on team heterogeneity once we control for the organizational structure. In Panel B we see that all lagged variables are positively and significantly related to team heterogeneity even when we consider them together. Notice that the lagged heterogeneity in model 5 removes the significant effect of delegation in the current round, while the lagged delegation decision in model 6 is significant but does not reduce the significance of the current delegation decision. This suggests that the prior team heterogeneity impacts current heterogeneity more than current delegation, while delegation itself has an additive effect over time.

From Table 1, we know that there is a relationship between the delegation choice and both the lagged delegation decision and lagged team heterogeneity. As a consequence, the observed relationship between heterogeneity and delegation in Table 2 is not unexpected. Comparing results from Table 1 and Table 2 highlights different drivers of these two decisions. Beyond the fact that both decisions depend on the lagged decision of the individuals, the decision to delegate depends on the treatments while for team heterogeneity it is not true. Finally, the last two columns split the selector stage in two halves. As in Table 1, we see evidence of learning. Model 8 suggest that agents are relying more on payoffs and their previous team heterogeneity decision since they may not have settled on their preferred organizational structure. Once they have determined their preferred structure, they do not rely further on prior payoffs but rather on their prior delegation decision (Model 9). The evidence presented here generally supports prediction 2: managers are choosing more heterogeneous teams in decentralized groups. This allows them to minimize the potential for incentive conflict and encourages more frequent switching of tasks between workers.[33]

determined their team heterogeneity based on intended organization structure or vice versa. What we do show is that the two decisions are clearly related.

[33]The dynamic nature of the experimental setting creates the dependence of workers' decisions on their history of play, which represents a challenge to simple interpretation of our coefficients. For a more conservative view, we regress each manager's average distance between positions in the Selector stage on the total number of delegated rounds chosen. The correlation between these two variables is positive and significant, with the impact of delegating one round more associated with an increase in worker heterogeneity of 0.86. When we split the Selector stage in half, we see that the relationship grows over time. As before, treatment has no impact on team heterogeneity.

Figure 7: Team heterogeneity distribution by treatment




(a) Selector Stage: Full Sample

(b) Selector Stage: By Treatment

*Notes.* Panels on the left hand side of the figure plot the frequencies of the distance between positions observed in the centralized rounds of the Centralized and Selector stages, by treatment. Panels on the right hand side of the figure plot the frequencies of position distance observed in the decentralized rounds of the Decentralized and Selector stages, by treatment.

Table 2: Team Selection: Distance between worker positions in Selector Stage

| | Panel A: Full Sample | | | Panel B: Including Lags | | | | Rounds 1-8 | Rounds 9-16 |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $Delegate_{ir}$ | 3.712** | 3.943** | 3.945** | 4.220** | 1.010 | 3.195** | 0.040 | 0.405 | -0.389 |
| | (1.84) | (1.96) | (1.98) | (1.96) | (0.98) | (1.52) | (0.99) | (1.40) | (1.31) |
| $50\%_i$ | | 1.035 | 1.035 | 1.009 | 0.476 | 1.488 | 0.727 | 0.912 | 0.670 |
| | | (3.30) | (3.31) | (3.26) | (1.46) | (3.31) | (1.44) | (1.72) | (1.57) |
| $80\%_i$ | | 1.642 | 1.642 | 1.803 | 0.900 | 2.731 | 1.210 | 1.605 | 0.866 |
| | | (3.67) | (3.69) | (3.66) | (1.66) | (3.74) | (1.65) | (1.89) | (1.80) |
| $90\%_i$ | | -0.423 | -0.423 | -0.616 | -0.242 | 0.266 | -0.066 | -1.026 | 0.671 |
| | | (3.81) | (3.82) | (3.81) | (1.75) | (3.91) | (1.72) | (2.09) | (1.86) |
| $Payoff_{ir-1}$ | | | | 0.139*** | | | 0.076*** | 0.107*** | 0.049 |
| | | | | (0.04) | | | (0.03) | (0.04) | (0.04) |
| $Heterogeneity_{ir-1}$ | | | | | 0.571*** | | 0.565*** | 0.530*** | 0.596*** |
| | | | | | (0.05) | | (0.05) | (0.06) | (0.05) |
| $Delegated_{ir-1}$ | | | | | | 2.699* | 2.098** | 1.320 | 2.813** |
| | | | | | | (1.40) | (0.95) | (1.34) | (1.32) |
| Constant | 35.575*** | 35.011*** | 36.748*** | 30.334*** | 12.853*** | 33.193*** | 11.007*** | 12.337*** | 10.772*** |
| | (5.22) | (5.61) | (5.65) | (5.88) | (3.55) | (5.77) | (3.55) | (3.95) | (3.38) |
| $RoundDummies$ | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $Controls_i$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N. obs. | 1888 | 1888 | 1888 | 1770 | 1770 | 1770 | 1770 | 826 | 944 |
| N. clusters | 118 | 118 | 118 | 118 | 118 | 118 | 118 | 118 | 118 |
| Pseudo R2 | 0.067 | 0.069 | 0.072 | 0.082 | 0.372 | 0.076 | 0.377 | 0.347 | 0.408 |

*Notes.* * p< 0.1; ** p<0.05; *** p<0.01. OLS estimation with standard errors clustered by subject. $k\%_i$ are treatment dummy variables. $Delegate_{ir}$ is a dummy variable taking value 1 if the manager $i$ delegates in round $r$, $Payoffs_{ir}$ are the payoffs per round in experimental currency obtained by subject $i$ in round $r$ and $Heterogeneity_{ir}$ is the distance between positions selected by the subject $i$ on round $r$. The controls we consider are the Eckel-Grossman risk aversion test(higher numbers indicate more risk seeking), a cognitive reflection test (higher scores indicate greater cognitive reflection), a dummy variable taking value 1 if Male, a dummy variable taking value 1 if the session was run in US and and a variable capturing different intervals of age.

### 5.3 On track vs Lost Managers

As in any experiment, differences in subject behaviors generate a broad range of results that we need to further examine. Moreover, the source of those deviations from the expected behavior could be very different from one participant to the next. However, the evidence we present thus far suggests that the managers are learning and getting closer to the optimal team compositions, particularly in the later rounds of the Selector stage. To explore further, we classify managers according to how closely their selected team compositions come to the optimal positions in this stage. We divide managers into either "on track" or "lost" using a median split of their average distance from optimal teams. Specifically, we separate the "on track" managers from the others using the sum of the distance between their selected positions and the optimal positions predicted by the model over the final eight rounds of the Selector stage - $\sum_{i=8}^{16} |\theta_1 - \theta_1^*| + |\theta_2 - \theta_2^*|$. This measure is calculated separately by treatment and type of organizational structure. A manager is considered "on track" if their measure is below the median of the category under analysis.[34] This classification is independent of whether each manager chose to delegate or not.

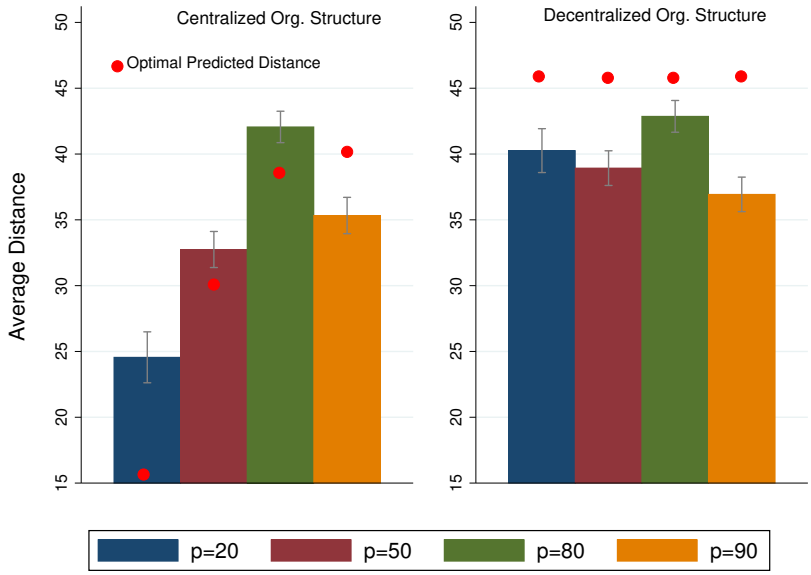
#### 5.3.1 Team Composition

Figure 8 shows the average distance between selected positions - ($|\theta_1 - \theta_2$) - per round in the Selector stage for the "on track" managers. The left hand panel shows that the "on track" managers in the centralized organizations are increasing their team heterogeneity as task uncertainty falls. The differences are statistically significant at 5% level for the first three treatments, moving from 24.5 to 32.7 to 42.1 on average respectively. There is a reduction in the 90% treatment to 35.3, which is statistically lower than in the 80% treatment but higher than in the 20% and 50% treatments. In the right panel, we see that the "on track" managers in decentralized groups choose average distances between 37 and 40 across all treatments. The average selected team in the 80% treatment is statistically more heterogeneous than in the other treatments, and the average selected team is more homogeneous in the 90% treatment.[35]

[34] The median distance in the 20%, 50%, 80% and 90% treatment for the centralized organizations are 216, 125, 96 and 170, respectively. For the decentralized organizations, they are 174, 144, 122, and 195 respectively. There is not a clear correlation between the median and average distance per round in the Selector stage depicted in Figure 8. It is also important to mention that we have 240 observations/rounds for each treatment.

[35] If we instead make our classification conditional on the organizational structure decision, we obtain very similar results but the selected positions are closer to the optimal positions. Figure 13 in the appendix C does just that. Conditional to the organizational structure decison, the number of observations in each group depends on how many times managers selected centralized or decentralized organizations in the Selector stage in each treatment. However, we prefer to show here the unconditional analysis given the timing of the game and the backward induction nature of the theoretical solution.

Figure 8: Distance between selected positions: On track managers




*Notes.* Plot of the average distance between positions per round in the Selector stage for all the managers considered "on track". The red dots are the optimal distances between positions predicted by the model for each treatment. The left hand panel shows data from a centralized organizational structure, while the right hand panel shows data from a decentralized organizational structure.

More importantly, figure 8 provides evidence that is qualitatively consistent with the main predictions of our model. First, average distances between selected positions are more heterogeneous in the decentralized than in the centralized organizations.[36] Second, we observe that the selected team compositions are sensitive to the level of uncertainty in the centralized groups but not in decentralized groups. Interestingly, these managers slightly over-shoot the optimal distance in centralized rounds, while under-shooting in the decentralized groups. One possible explanation is that the managers are trying to find the optimal team composition while they are learning the optimal organizational structure, and as a consequence they end up on average in a team composition in between the optimal positions of these two types of organizational structure.[37] This evidence is consistent with learning models based on trial and error.[38]. We will revisit these issues in section 6. Next we explore the degree to which "on track" managers approximate the model's predicted organizational decisions before examining how much better off they are in payoffs than their "lost" counterparts.

[36]They are not significantly different in the 80 and 90% treatments. However, the distance between the optimal positions predicted by the model in the centralized and decentralized organizations in these two treatments are lower than in the other two treatments.

[37]This pattern does not hold for the centralized groups in the 90% treatment, but once again this is the treatment where the optimal positions in centralized and decentralized organization are the closest.

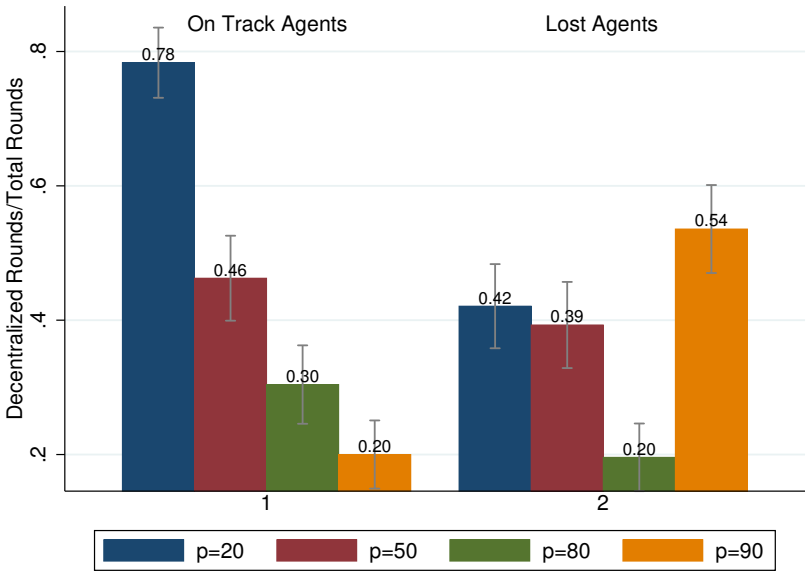
[38]Experience-weighted attraction learning, learning direction theories or reinforcement learning models

### 5.3.2 Organizational Structure

In this subsection, we compare the delegation decisions of the "on track" and "lost" managers by treatment. We again define managers as "on track" and "lost" using the team composition criteria from the previous section.

The left hand panel of Figure 9 shows that "on track" managers centralize in 80% (192/240) of the rounds in the Selector stage for the 20% treatment. The number of delegated rounds decreases rapidly as the level of information improves up to the point where they only delegate in 20% (48/240) of the rounds for the 90% treatment. On the other hand, we do not observe a clear pattern by the lost managers, whose behavior helps us to explain some of the deviations we see from the model's predictions, especially for the extreme treatments. While we still do not observed all managers decentralizing below the informational threshold predicted by the model or decentralizing above it, but "on track" managers do centralize more as the level of information increases.[39]

Figure 9: Delegation by Treatment: On track vs Lost managers



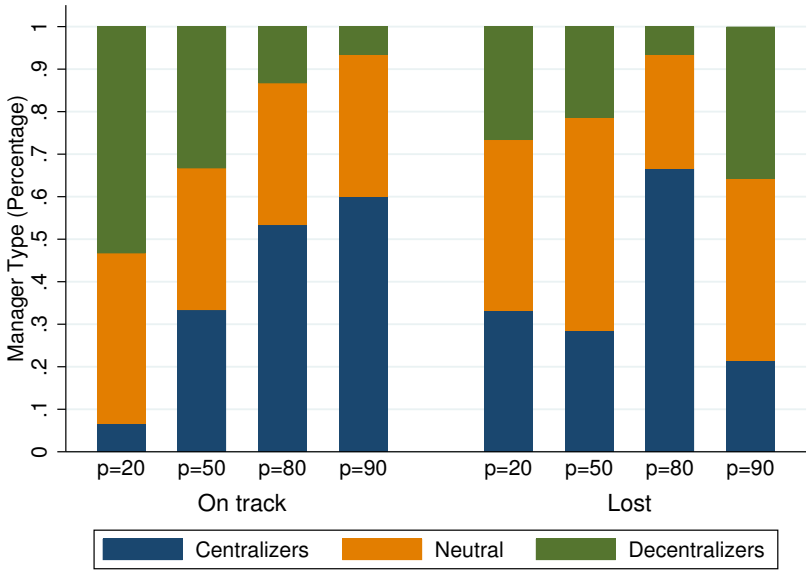

*Notes.* Plot of the percentage of decentralized rounds in the ?Selector? stage by treatment dividing the managers in two groups: on track managers and lost managers in terms of their selected team compositions.

We briefly explore whether we can identify underlying manager types as a result of their organizational structure decisions using our Selector stage data. We classify managers into 3

[39]This pattern may be explained by the learning process of the subjects or, as we discuss in section 6, a similar pattern is obtained if we assume managers select their organizational structure with a fixed team composition in mind. This fixed team composition may be a result of the dynamic nature of the experiment and their histories of play.

different types based on how often they delegate. Once again, we focus on the last 8 rounds but the results are similar if we use all rounds of the Selector stage. For simplicity, we classify a manager as a centralizer (C) if she decides to delegate in at most 1 of the last 8 rounds of the Selector Stage. She is a neutral player (N) if she decided to delegate between 2 and 6 rounds, and any manager delegating in at least 7 of the last 8 rounds is classified as a delegator (D). Figure 10 shows the distribution of agents given this classification, by treatment.[40] This analysis allows us to understand how managers actually change their behavior as the level of information changes. For instance, if we observe an increase of sixteen delegation choices, it could mean that half of the managers are delegating one more round or that one manager has delegated in every round. While the first example could be not taken as definitive proof of a change in behavior, the second is evidence of a change in the behavior of one subject.

Figure 10: Organizational Structure Stability




*Notes.* The percentage of centralizers, decentralizers and neutral players by treatment. We classify a manager as a centralizer (C) if she decides to delegate in at most 1 of the last 8 rounds of the Selector Stage. She is a neutral player (N) if she decided to delegate between 2 and 6 rounds and any manager decentralizing in at least 7 of the last 8 rounds is classified as a delegator (D).

Figure 10 shows that the behavior of many agents are consistent through the last rounds on the Selector stage and the distribution of these type of agents varies across treatments. There is a clear pattern for the "on track" managers moving from more centralization in an environment of poor information (over half in the 20% treatment) to more delegators as the information

[40] Figure 14 in the appendix C replicate this graphic considering the 16 rounds per player in the Selector stage. In this case, we classify a manager as a centralizer (C) if she decides to delegate in at most 2 of the last 16 rounds of the Selector Stage. She is a neutral player (N) if she decided to delegate between 3 and 14 rounds and any manager decentralizing in at least 15 of the last 8 rounds is classified as a delegator (D).

increases (Three fifths of "on track" managers in the 90% treatment). The number of neutral players is almost the same in all the treatments and we observe a substitution from centralizers to delegators as information improves. For the lost managers, there is again no clear pattern. Unlike "on track " managers, there are more neutral players than centralizers or decentralizers in all treatments except for the 80% treatment. In the 80% treatment, we observed a high concentration of centralizers mainly explained by managers selecting perfectly homogeneous teams. When managers position both workers in the same position, the organizational structure decision does not affect the manager's payoffs, so they should be indifferent to delegated or centralized control.

To summarize, managers with team compositions closer to the model's optimal team were able to select more often the right organizational structure. This result is particularly strong in the lowest (20% treatment) and highest (90% treatment) information environments, where 80% of the rounds were played under the appropiate structure.

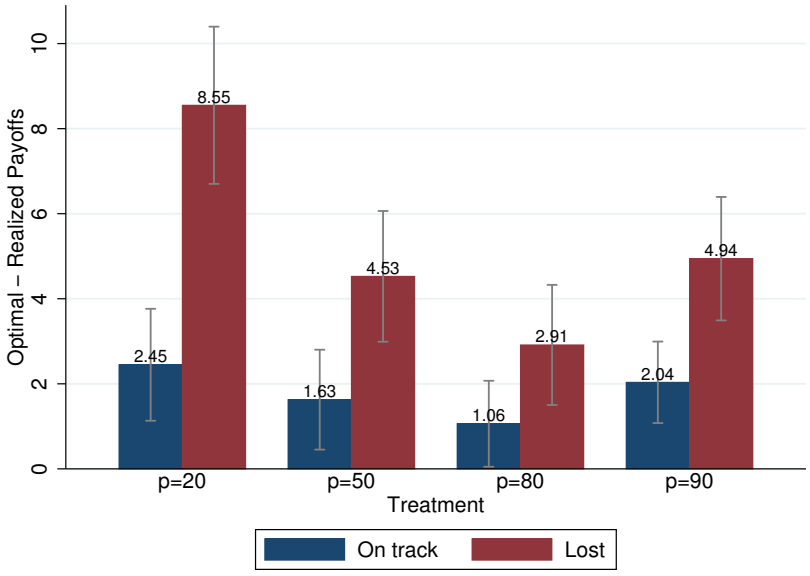
#### 5.3.3 Manager payoffs

The interrelatedness of the organizational structure and team composition decisions make it difficult to disentangle the effect of each on subject payoffs. Comparing average earnings per round does not reveal much, as we see mean manager payoffs by treatment of 24.92, 25.18, 26.63 and 25.86 for the 20%, 50%, 80% and 90% conditions in the Selector stage, respectfully. However, it is more informative to look at counterfactual earnings from decisions in line with theoretical predictions (i.e. how much money they are "leaving on the table"). With known ex-ante optimal decisions and ex-post task realizations, we calculate the payoff each manager would have earned in each round had she played the optimal strategy, and subtract the manager's realized earnings in the round. Using this variable we obtain a pattern mirroring what we see from average profits.

Managers in all treatments under-perform their optimal strategy. Managers leave statistically more profit on the table in the 20% treatment and are statistically closer to their potential profits in the 80% than in other treatments. Figure 11 shows the size of the managers' underperformance by treatment, dividing them into "on track" and "lost" as before. Among "on track" managers, we see no statistically significant difference in underperfomance across treatments, but all are distinguishable from zero. The aggregate differences observed - both in magnitude and pattern of under-performance - are driven mostly by the behavior of the "lost" managers.[41].

[41] If we compare "lost" managers across treatments, we see that the performance of the managers in the 20% is

Figure 11: Underperformance of managers relative to optimal strategy




*Notes.* This figure plots the difference between the counter-factual payoffs that would have been obtained using the optimal strategy minus the actual payoffs realized by managers in the Selector stage, separated by information condition and manager type - "on track" versus "lost" managers.

The underperformance of "on track" managers raises the issue of identifying which decision is driving the sub-optimal results. Specifically, are "on track" managers earning less due to a failure to delegate or an error in team selection?[42] Using the observed outcomes in each round of the Selector stage to compare the hypothetical earnings from playing the optimal decentralized strategy versus the optimal centralized strategy, we see a clear benefit in realized payoffs from delegating in the 20% and 50% condition, but it disappears in the 80% condition and significantly reverse in the 90% condition as predicted by the model.[43] Using the optimal decentralized strategies the average payoffs per round per participant would be around 29 in all treatments. Average payoffs using the optimal centralized strategies (a "second-best" benchmark) are increasing with the quality of information. Therefore, some of the "on track" managers underperformance seen in Figure 11 must be due to their organizational choices.

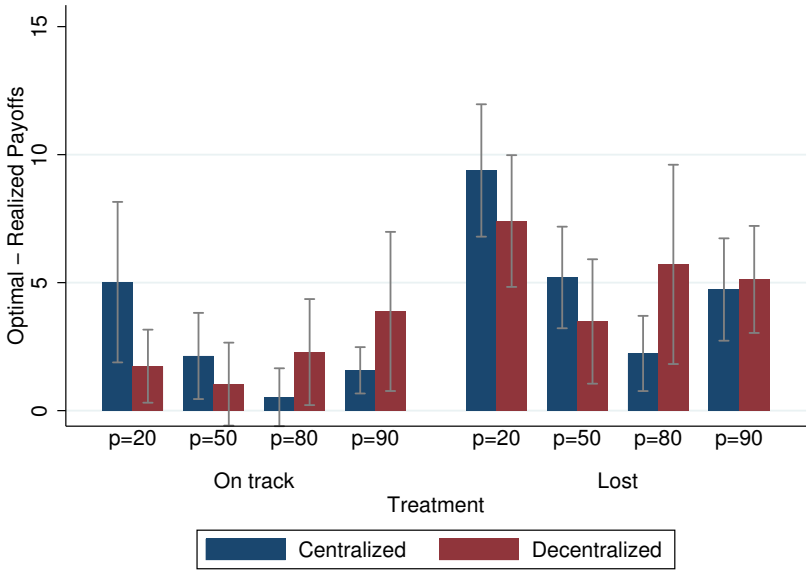
Figure 14 replicates the underperformance results, broken down by the manager decision to delegate or not in the Selector Stage. On average, managers saw the worst performance when they selected the wrong organizational structure given their treatment except in the 80%

significantly worst than in the other treatments. Also, the performance of the managers in the 80% is significantly better than in the 20% and 90% conditions.

[42]Remember that our categorization of "lost" and "on track" managers focuses on their behavior in the last 8 rounds, while our analysis in this section is extended to the whole Selector stage, last 16 rounds.

[43]Figure 15 in the appendix C shows a graphical representation of the of hypothetical earnings using optimal decentralized and centralized strategies given the observed outcomes.

Figure 12: Underperformance of managers relative to optimal strategy




*Notes.* Manager underperformance by treatment, depending on the organizational structure.

condition. The result in the 80% is not surprising since there are no significant differences in potential payoffs from delegating or not. Choosing the wrong delegation decision is particularly costly under the extremes of information accuracy for "on track" managers. The same is true for "lost" managers, but the differences between delegating or not are insignificant in the right-hand columns. This highlights the interaction between uncertainty, misalignment of preferences and organizational structure which are the key to understand the main predictions of the model. The learning process may be affected by the degree of task uncertainty, but also by the size of the potential conflict of interest between the manager and the workers, as dictated by team selection. In the 20% treatment, managers see fewer realized tasks, so they have less information by which to adjust their strategy. There is a higher cost for participants who do not delegate as the level of uncertainty increases, and so the feedback is less powerful in changing organizational structure in the 80% treatment. However, in the 90% treatment, the information is good enough to overcome the expected losses generated by the potential conflict of interest among agents, as a consequence managers fare better under centralized control.

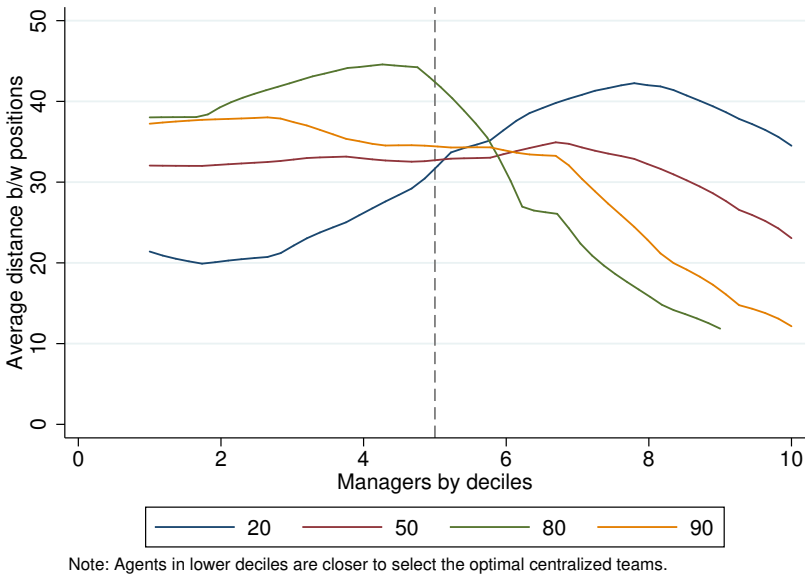
The results for the "on track" managers in the low information environments fit qualitatively with prior findings on the control premium. It is costly when managers insist on having the final say in all decisions affecting their organization when the quality of the information is poor (in our case, selecting a centralized organizational structure). While the experiment was not designed to measure such a control premium, we can derive an incomplete estimate by

comparing the differences in underperformance in the decentralized and centralized rounds with respect to the expected average payoffs under the optimal strategies. Following this protocol we see a control premium that reaches 11.3% of the potential payoffs in the 20% treatment. We obtained qualitatively similar results with the "lost" managers, but their main cause for underperformance is their sub-optimal team compositions.

#### 5.3.4 Robustness

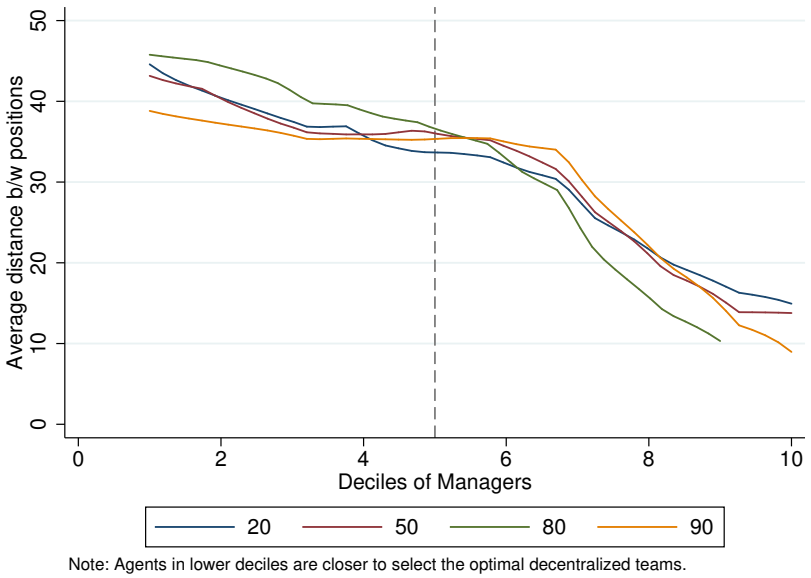
- Important to mention that in the previous subsections we divide the agents as on track and lost (off track?) using the median but in these graphs you can see the team composition selected by each decile of agents.
- Make clear that the patterns are closer to those predicted by the model and the main deviations are on the higher deciles. Those that are by definition further away of the optimal team composition predicted by the model.
- This result is still not perfect but you can see that it is robust.
- In the decentralized case, we should mention that the team compositions follow the same trends in all treatments, whereas in the centralized case the pattern radically change moving towards a reverse order in the treatments. It suggests that the mistakes in the centralized organizations could be more costly?
- Should we do a similar robustness analysis for the percentage of decentralized rounds or payoffs?

Figure 13: Managers and Team Composition: Centralized Organization




*Notes.* Agents in lower deciles are closer to the optimal positions predicted on the centralized organization on that treatment.

Figure 14: Managers and Team Composition: Decentralized Organization




*Notes.* Manager underperformance by treatment, depending on the organizational structure.

# 6 Understanding manager behavior

In the previous section, we have identified two types of managers according their chosen team composition, and then showed that the team selection behavior interacts with the organizational structure decision. All together, this classification explained the large difference in payoffs among managers. But it also raises new questions. Why were some managers less successful in their team selection? Further, what can explain the behavioral deviations we observe with respect to the model predictions? In this subsection we explore some possible explanations.

## 6.1 Deviations from the optimal team selection

### 6.1.1 Perfectly homogeneous 50-50 teams

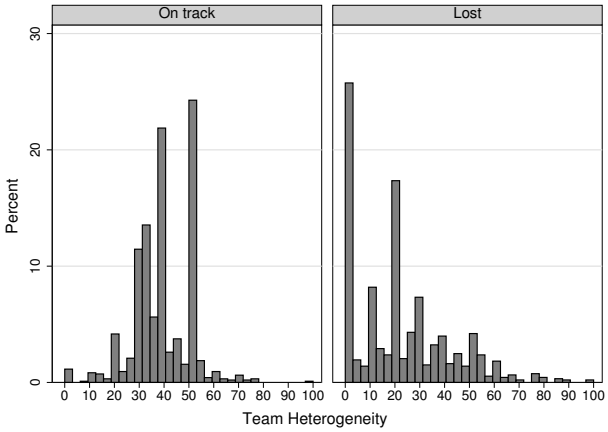
We observe a curiously high number of perfectly homogeneous teams, particularly in the 80% and 90% treatments where agents have more information. These observations explain much of the effect wherein managers reduce team heterogeneity as their information improves, and are remarkably common in both organizational structures.

A notable subset of our "lost" managers selected perfectly homogeneous teams, placing both workers at 50. In total, 22% of all rounds played by lost managers involved these perfectly homogeneous teams, while we see such teams in only 0.1% of rounds for "on track" managers. Figure 15 highlights this disparity more clearly. The modal distances among on track managers are 50 and 34, but the modal distance for lost managers is zero. In looking at individual managers, we find that each treatment contains between one and four managers who choose perfectly homogeneous teams in every round of the experiment in the Selector stage.

### 6.1.2 Learning process: The marginal effect of bad results

The repeated nature of the experiment allows us to identify another possible cause of homogeneous team selection, the individual learning process. We see evidence that agents are learning and, in the particular case of their team selection, they react to the payoffs they receive in the previous rounds. In this section, we show that participants appear to react differently to "bad" outcomes in a round depending if they are "on track" or "lost" managers and depending on the organizational structure. We define "bad" outcomes as those in which payoffs in a round are less than 25 ECU, as that is the average payoff that a participant would receive if she takes the most conservative route of always chooses a homogeneous team at 50-50. Our sample focuses in

Figure 15: Team heterogeneity distribution: "On track" vs "Lost" managers




*Notes.* This graph shows the frequencies of the team heterogeneity selected by the "on track" and "lost" managers on the Selector stage. Team heterogeneity is measured as the difference between the selected positions.

the first two stages where participants could only select their team composition.[44] To explore this effect we regress team heterogeneity on lagged heterogeneity, lagged bad outcomes, and an interaction term.[45]

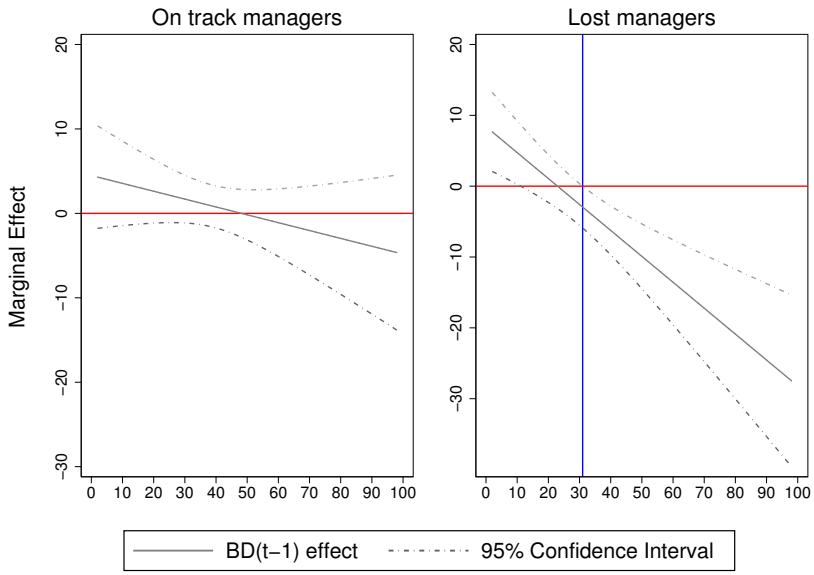
Figure 16 plots the marginal effects of bad outcomes by distance between positions separately for "on track" and "lost" managers in the centralized organization. In both cases we see a negative slope, which implies that managers with too heterogeneous teams tend to respond to bad outcomes selecting more homogeneous teams and managers with too homogenenous teams tend to respond to bad outcomes selecting more heterogeneous teams. However, these effects are only significant at the 5% for the "lost" managers below a distance between positions of 12 and above 31, which is consistent with their average selected distance among positions of 31.8.[46] Clearly, "lost" managers react more than their "on track" counterparts to bad results in the centralized organizations. It seems that "on track" managers have developed more stable strategies for team selection that better withstand bad short term outcomes. By contrast, the strong reaction of "lost" managers facing bad outcomes caused them to reflexively narrow the gap between their workers, preventing them from reaching optimal team composition, as it is evident from Figure 15.

[44] We focus on the cases when the distance between positions is not equal to zero in round $t-1$. However, the results using the full sample do not change, since those playing perfectly homogenoeus team remain using this strategy in most rounds without reacting too much to changes on payoffs per round.

[45] Full results omitted for space consideration, but available upon request

[46] This average omits perfectly homogeneous teams. If we include them the average is just 24.7. On the other hand, those average are 38.7 and 35.6, respectively, for the "on track" managers.

Figure 16: Marginal Effect of a Bad Result ($\pi_A \leq 25$) on Team Heterogenoeity: Centralized Rounds

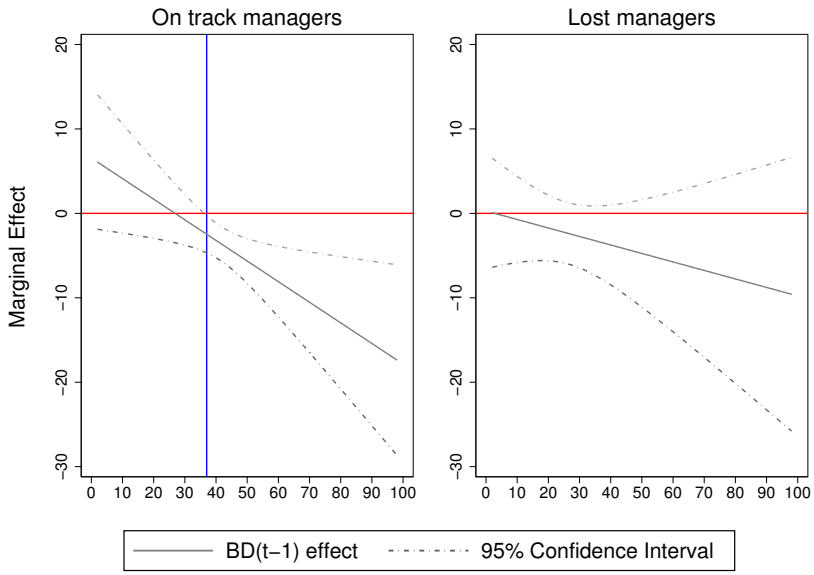



*Notes.* Plot of marginal effects of earning less than 25 ECU (y-axis) by distance between positions (x-axis) for "on track" and "lost" managers in the centralized stage with 95% confidence bounds. The vertical line indicates ranges over which the effect is significant at the 5% level.

Figure 17 replicates this analysis for the decentralized stage. We see the same negative trend in marginal effects for both type of agents. However, the "on track" managers are now more reactive, and only their marginal effects are significant for distances between positions above 37. Interestingly, in the decentralized organizations the model predicts a unique optimal level of team heterogeneity equal to 46. Beyond the fact that on tracks agents select more homogeneous team than expected by the model, they are in the right direction. On the other hand, "lost" managers do not seem to be following a clear pattern, though their muted negative reactions cause them to have more homogeneous teams as a result of bad outcomes.

What exactly is causing managers to reduce heterogeneity in response to bad outcomes? One explanation is that we are observing something akin to loss aversion (Kahneman and Tversky [1979]; Kőszegi and Rabin [2006]). However, the exhibited behavior is also largely consistent with certain learning theories. For instance: Selten's learning direction theory (Selten and Stoecker [1986]; Selten and Buchta [1999]), reinforcement learning (Erev and Roth [1998]), experienced-weighting atraction learning models (Camerer and Hua Ho [1999]) or bayesian learning when agents face small samples (Rabin [2002]). While understanding the learning process of agents facing this type of dynamic games in controlled environments is a very important question, it is beyond the scope of the present paper. We can, though, suggest that "on track"

Figure 17: Marginal Effect of a Bad Result ($\pi_A \leq 25$) on Team Heterogeneity: Decentralized Rounds




*Notes.* Plot of marginal effects of earning less than 25 ECU (y-axis) by distance between positions (x-axis) for "on track" and "lost" managers in the decentralized stage with 95% confidence bounds. The vertical blue line separates the areas in the graph where we have significance effects from the areas where we do not.

and "lost" managers are using different learning strategies. In this section, we provide an explanation that is consistent with this observed behavior and data, though we cannot claim that it is the only interpretation.

## 6.2 Deviations from the optimal organizational structure

In this section we revisit our finding that delegation slowly rises as uncertainty grows, instead of the step function predicted by the model. We show here that such behavior is consistent with managers playing as if they have fixed team composition.

Given the challenge of the decision environment, it may be that managers try to simplify their problem by fixing their team composition and then deciding their organizational structure. We examine this possibility by adjusting the model to capture cases where managers select their organizational structure under exogenously determined team heterogeneity.[47] This model represents situations that effectively limit the personnel options of a manager. The optimal allocation of decision rights under fixed team composition will give us an alternative benchmark with which to compare the experimental results. The timing of the decisions in the game

[47] With exogenously determined team composition, the model approximates a linear version of Alonso, Dessein and Matouschek [2008] without communication.

remains largely unchanged, except that instead of selecting their team at the outset, they see their exogenously chosen team.

Solving the model by backward induction, we obtain predictions for cost minimization in centralized and decentralized teams (see the appendix A for details). We focus on symmetric positions assuming tasks are uniformly distributed and compare the expected cost in both organizational structures. This comparison creates two distinct regions – One region where the decentralized organization dominates the centralized organization and second region where the opposite occurs.

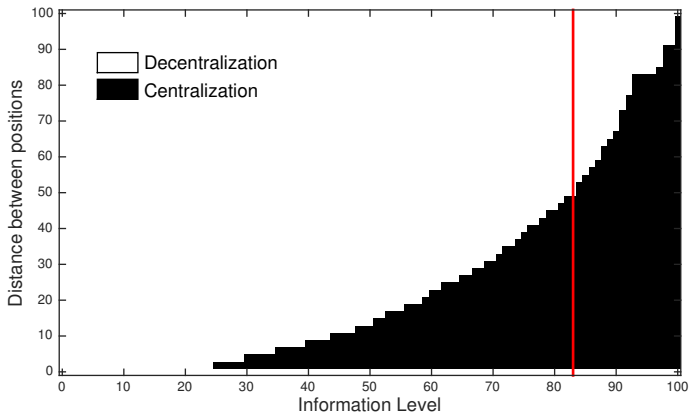
To illustrate, we simulate 100 managers playing according to the model predictions over 500 rounds each, with uniformly drawn tasks. We apply the reallocation rules for each organizational structure on a grid determined by the possible team compositions and level of uncertainty.[48] We then estimate the average profit per round at each point on the grid and compare centralized and decentralized teams.

Figure 18 identifies the regions on this grid where the simulated managers strictly prefer delegation. Unlike the case where a manager can choose her team composition, we do not see a constant threshold level of uncertainty determining which organizational structure is payoff maximizing. Instead we observe a convex frontier that separates the region where the decentralized and centralized organizations dominate, which is in line with our results in Figure 5 and Figure 9, where delegation falls gradually in conjunction with reduced uncertainty. This suggest that some participants may play as if they have some fixed positions in mind. It is also consistent with the experimental finding that the positions selected are not reactive to the treatment directly and adjust incrementally through prior realized payoffs.

While this analysis falls short of being conclusive, it suggests that further studies of exogenously selected teams would be worthwhile. In particular, our data may more closely approximate decisions by managers of low-skilled labor or those with other forms of hiring constraints.

[48] We focus on symmetric positions around the mean ($\theta_i + \theta_j = 100$ and $\theta_i - 50 = 50 - \theta_j$) covering all combinations from $(0, 100)$ to $(100, 0)$ with a 0.01 difference in each position by observation. We vary the level of information covering all values from 0 to 1 in 0.01 increments. This gives a grid with dimensions $101 \times 101$.

Figure 18: Dominant Organizational Structure: Simulation




*Notes.* The figure identifies the organizational structure with the higher average profits from a Monte Carlo simulation with 100 repetitions of 500 rounds. On the y-axis we have the team composition represented by the distance between selected positions (for symmetric positions around the ex-ante expected task). On the x-axis we identify the level of task uncertainty faced by managers. As groups become more homogeneous and manager uncertainty is reduced, centralized organizations gradually become payoff dominant.

# 7 Conclusion

The change in Jack Dorsey's management strategy with Square highlights the interrelatedness of personnel decisions and delegation. It also shows how difficult managerial decisions can be when multiple facets must be considered at once. Given the prevalence of managers who control both hiring and delegation, it is critical to understand this link.

To begin exploring this connection, we developed and experimentally tested a model of managerial decision making in which managers chose their team's personnel and decision structure in concert. As in organizations outside the lab, we see substantial heterogeneity in managerial decisions. Managers tend to retain control of reallocation when delegation is in their best interest. We know from Fehr, Herz and Wilkening [2013] that this often leads managers to over-exert in other areas to make up the loss, which actually exacerbates the harm of centralized control. We do find some reassuring evidence: Although our managers delegate less than the model predicts, we see them respond to worsening task uncertainty by delegating more, in line with the model using fixed team composition. We also see more diverse teams selected in decentralized versus centralized teams, as they should. In fact, when we focus on those managers who choose team compositions closer to optimal than the median, we see strong convergence towards the models predictions.

However, we find that managers who struggle with team selection may be hampered by over-

reacting to bad outcomes, and better feedback actually *exacerbates* the problem. As uncertainty is reduced, the effect becomes more evident. While more research is needed to fully identify the mechanism, the behavior we see is certainly consistent with loss averse managers. To make decisions in this challenging environment, managers may rely on fixed teams to simplify their responsibility. Our simulations of fixed-position teams are consistent with this approach.

Our model is best seen as a first step in better understanding the complexities of managerial and organizational economics. We theoretically capture two important characteristics of managerial decision making and the data suggest that many of the tensions in the model have real impact on behavior. The experimental study also highlights just how difficult it can be to handle two such critical decisions. Our data suggest that choosing the right team is critical, and even reduces the harm of choosing a suboptimal organizational structure. Many of the managers in our study do not appear learn with experience. In the experiment, this cost them a noticeable amount in payoff reduction. Outside the lab, we may even see worse results for many managers: most people unable to effectively manage these tasks may not keep their job or receive a second chance.

The behavior of managers within an organization is a vital, though nuanced, topic of research. Our results highlight important ways in which personnel decisions interact with other managerial issues such as delegation. From here, we can begin to incrementally examine many additional - and equally important - elements of managerial decision making.

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