Organizing for strategy making:

An information aggregation view

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Abstract

This study examines the process of strategic decision making within organizations by analyzing four commonly used information aggregation structures: individual decision making, delegation to experts, voting, and averaging of opinions. Using a formal mathematical model, we investigate how the performance of each of these structures is contingent upon the breadth of knowledge within the firm and changes in the environment. Our model builds on work done in the Carnegie tradition and in other decision-theoretic disciplines. We use the model to explore when delegation is preferable to the more “crowdlike” structures of voting and averaging. We show that delegation is the most effective only when there is diversity of expertise, when accurate delegation is possible, and when there is a good fit between the firm’s knowledge and the knowledge required by the environment. Otherwise, depending on the knowledge breadth of the firm, voting or averaging may be the most effective structure. Finally, we use our model to shed light on which structures are more robust to radical environmental change and also to answer calls for a better understanding of the microfoundations of strategy.

Keywords: organizational structure, decision making, knowledge, environmental change, microfoundations of strategy
1 Introduction

By most accounts, strategy involves making important decisions. Yet the more important a decision, the less likely it is to be made by a single individual (i.e., the proverbial strategist) rather than multiple individuals, since multiple individuals can add checks and balances and bring valuable specialized knowledge (Bower 1970, Kogut and Zander 1992). Examples of organizational structures that use multiple individuals to engage in strategic decision making include boards of directors, top management teams, and finance committees. However, even decision structures that involve multiple individuals with different opinions must arrive at a single, organization-level decision. Hence individuals’ opinions must be aggregated, and this fact makes the process of information aggregation important for strategy.

How organizations aggregate information, which is also known as the structure of decision making, was proclaimed by the Carnegie tradition as one of its central concerns (Cyert and March 1963:19–22). In fact, Simon (1947/1997:18–19) defines the basic construct of “organization” in terms of information aggregation: “the pattern of communications and relations among a group of human beings, including the processes for making and implementing decisions.” Despite this deep concern with structure and information aggregation, a recent article by Gavetti, Levinthal, and Ocasio (2007:528) notes that structure is one of the “forgotten pillars” of the Carnegie tradition. Other literatures that share an information processing sensibility—such as the resource allocation process (Bower 1970), organization design (Thompson 1967, Burton and Obel 2004), and the microfoundations literature (Abell et al. 2008)—have also discussed the lack of research on the topic (Miller et al. 2009).

Information aggregation is not only of theoretical concern; it has important managerial implications. Imagine the case of three founders of a startup firm deciding on whether or not to acquire a competitor. How should their different opinions on the value of the target be aggregated? Should they vote on whether to acquire or not, should they delegate the decision to one member, or should they average their differing valuations and make a decision based on that average? Would the answer depend on the expertise of the decision makers (e.g., if they were three MBAs versus if they were an accountant, an MBA, and a scientist)? Would the
answer depend on the degree of environmental uncertainty (as when, e.g., the target produces a promising but unproved technology versus a commodity)? Because truly important decisions are usually made by a group and not by a lone individual (Tindale et al. 2003:381), situations like the one described in this case pervade strategic decision making from small startups to large governments.

This paper furthers our understanding of information aggregation in organizations by developing a stylized but realistic model of how different information aggregation structures perform under different environments and with different decision makers who have heterogeneous knowledge. Our model uses decision theory to address questions that are central to the process of strategic decision making.

1.1 Antecedents of Our Work

Recent years have seen the resurgence of interest in formal models of decision making in the management field, very much in the spirit of classic works in the Carnegie tradition (e.g., Cohen et al. 1972, March 1991). This new work can be broadly classified into two types: alternative generation and alternative evaluation (Knudsen and Levinthal 2007). The idea behind this classification is that boundedly rational firms use different processes to identify potential projects they can pursue (the alternative generation phase) and to choose which specific project(s) to pursue from within that choice set (the alternative evaluation phase). Most of the management work on the structure of decision making has focused on the alternative generation phase, which is commonly viewed as the process of organizational search and modeled using NK and other simulation methods (Seshadri and Shapira 2003, Rivkin and Siggelkow 2003, Ethiraj and Levinthal 2004, Siggelkow and Rivkin 2005, Gavetti, Levinthal, and Rivkin 2005, Fang, Lee, and Schilling 2010).

In this paper we seek to extend and augment the few existing studies on alternative evaluation in strategy by building on work of Knudsen and Levinthal (2007), Christensen and Knudsen (2010), and Csaszar (2009a,b). Our study differs from these works in three ways. First, previous studies generally focus on voting committees (à la Sah and Stiglitz 1986), whereas we add structures that use mechanisms based on averaging and delegation. Second, we ex-
plore a different set of conditions—namely, the roles of heterogeneous individual knowledge and changes in the external environment. Finally, we focus on a different outcome measure; that is, we work more in the tradition of strategy and look at overall performance instead of at errors of omission and commission.

Models of information aggregation and alternative evaluation have been studied by a number of disciplines other than management. These studies have roots in classical works on group decision-making (Aristotle c.330 BCE/1984, Condorcet 1785/1994, Laplace 1814/1995)\(^1\) and have appeared in social psychology, economics, and other disciplines. Work on group decision making in social psychology has used decision theory to analyze formally the different aggregation mechanisms (for a recent survey, see Tindale et al. 2003), including work on the effect of correlation among experts’ opinions (Clemen and Winkler 1985), and on the manipulability of group decisions (Davis 1992). In economics, research has focused on comparing hierarchy and polyarchy (Sah and Stiglitz 1986), on studying the efficiency of decentralized computation in hierarchies (Radner 1993), and on characterizing the performance of hierarchies in the context of “management by exception” (Garicano 2000). Research on information aggregation has also appeared in political science (Ladha 1992, Hammond 1994), forecasting (Kaplan et al. 1950, Timmermann 2006), and artificial intelligence (Breiman 1996).

The aforementioned work on information aggregation in fields other than management offers important insights into information aggregation, but the findings do not translate well to strategic decision making for the following reasons. First, strategic decisions are usually made by small groups, whereas most of the research in the other disciplines has described limit effects (i.e., when the number of decision makers tends to infinity, as in political elections). Second, as shown by the literature on top management teams (Hambrick and Mason 1984), the specialized knowledge of individuals matters to strategic decision making. In contrast, research

\(^1\)Aristotle observed that groups can outperform individuals because, in a group, “some understand one part, and some another, and among them they understand the whole” (Aristotle, c.330 BCE/1984, book III.11). Centuries later, Condorcet (1785/1994) proved that majority voting would tend to select the right choice as the number of voters approached infinity, assuming uncorrelated voters with a modicum of screening ability (see Ladha (1992:632) for a modern demonstration). A few years later, Laplace (1814/1995, chapter IX) suggested that averaging individual opinions could be used to synthesize a highly accurate opinion; the popular press account by Surowiecki (2004) highlights Galton (1907) as a pioneer in the use of averaging to produce more accurate signals. The mechanisms proposed by Condorcet and Laplace—voting and averaging—pervade all subsequent literature on aggregation.
in other disciplines has focused on sources of heterogeneity relevant to each source discipline, such as ability (Sorkin et al. 2001) or perceptual accuracy (Grofman et al. 1983). Third, environmental change plays a central role in most theories of organization, as evidenced by the vast and diverse literatures on topics such as disruptive technological change, organizational ecology, and strategic positioning. Yet environmental change is rarely a concern in the work on information aggregation in other disciplines. (This may be because the organizations they study are typically formed “on demand” to solve a given problem in a given environment and thus need not persist, as firms do, over longer periods of time that entail changes in the environment.) Finally, delegation is the most common decision-making approach used by firms, whereas the other disciplines have focused their attention on more egalitarian forms of decision making (such as voting or averaging). In this paper we view structures that are not usually compared to each other from a unified theoretical perspective and under experimental conditions that are particularly relevant to strategy.

1.2 Aim of This Study

Our central question is this: What is the most appropriate decision-making structure given the organization’s environment and the expertise of its members? In answering this question, we pay attention to the robustness of the different structures with respect to changes in environment and expertise as well as to other contingencies, such as delegation errors and organization designers inaccurately assessing individuals’ expertise. In order to address these issues in a rigorous manner, we develop a parsimonious model of information aggregation that builds on a recent stream of studies in organizational design (Christensen and Knudsen 2010, Csaszar 2009a). Our approach captures the knowledge possessed by the firm and the knowledge required by the environment by modeling individuals, knowledge, and the environment as a stochastic process.

Three novel findings emerge from this analysis. First, the interconnected nature of structure, knowledge, and environment means that each decision-making structure can be the optimal choice under the appropriate set of contingencies. Second, delegation of decision-making authority is effective only when the individual decision makers possess significantly different
types of knowledge, when projects can be assigned to individuals with minimal error, and when there is a good fit between the knowledge of the firm and the knowledge required by the environment. Third, firm performance depends in a nontrivial way on how the opinions of individual members are aggregated. This is true even for means of aggregation that are ostensibly similar, such as averaging estimates and allowing individuals to vote.

The paper is organized as follows: Section 2 explains the model, Section 3 analyzes the model and presents the main results that stem from it, and Section 4 discusses the broader theoretical and managerial implications of this research.

2 Model

The aim of our model is to study how performance depends on organizational structure, on the expertise of the organization’s members, and on the firm’s external environment. We start by providing a brief overview of the model before describing each of its components in detail.

The structures we analyze are in charge of screening a stream of projects—that is, approving good projects and rejecting the rest. Screening projects is a common task performed in many settings; examples include banks choosing which loans to approve, venture capital firms and mutual funds picking investments, movie studios judging scripts, hiring committees selecting candidates, and top management teams deciding on which strategic projects to pursue. The structures we study differ in how they aggregate the opinions of their members to produce organization-level decisions about the projects under review. For the sake of results comparability and model parsimony, we limit our analysis to three structures with three members each (we call these structures Delegation, Voting, and Averaging).\(^2\) For benchmarking purposes we also analyze an organization with a single decision maker (which we call Individual).

The projects screened by the organizations in our model are described by a type and a quality. The project type represents the domain of knowledge, or expertise, involved in accurately assessing the project (e.g., in the venture capital context, project types could correspond to semiconductors, software, Internet, etc.). The project quality represents how much value the

\(^2\)We also explore the effects of varying the number of decision makers as a robustness check (see Section 3.4 and Appendix B).
project will create (e.g., the actual net present value of the project). Project quality is noisily perceived by individuals, and the greater the distance between the individual’s expertise and the type of project being evaluated, the greater the noise in that individual’s perception of the project’s quality (e.g., a software expert will be more accurate at determining the value of a software startup than of a semiconductor startup). Organizational *performance* is defined as the sum of the qualities of the projects approved divided by the total number of projects considered by the organization.

### 2.1 Projects

We define a *project* as a tuple \((q, t)\), where \(q\) denotes the project’s quality and \(t\) its type. We interpret \(q\) as a net present value (NPV); thus we say a project is “good” only if \(q > 0\). For simplicity, we assume that the discount rate is correctly set, that firms do not face liquidity constraints, and that there are no interactions among projects. Under these assumptions, firms maximize their performance by accepting good projects and rejecting bad ones (Damodaran 2010:231). The type \((t)\) of the project is a real number that denotes the specific type of knowledge required to assess the project’s value properly.\(^3\) The actual value of \(t\) is relevant only with respect to the expertise of the individual decision makers, as discussed in Section 2.2.

We define the *project environment* as the range of projects that a firm faces. Consistent with researchers in multiple traditions, we view this environment as a set of problems exogenously posed to the organization (Hannan and Freeman 1977, Carley and Lin 1997). Thus we focus on the evaluation of alternatives, not on their generation (Knudsen and Levinthal 2007). Because projects are described by two parameters, the environment is defined by the ranges that both \(q\) and \(t\) can take. We assume that projects are uniformly distributed in the rectangular interval defined by \([q_l, q_u]\) and \([t_l, t_u]\). Continuing with our example, these bounds could reflect the range of projects a venture capital firm faces in terms of quality (e.g., NPVs from \(-$100 million to $100 million) and types (e.g., from 0 to 10, where 0 represents hardware projects, 10 represents

\(^3\)Our assumption that the project type is a real number can be interpreted in a nonrestrictive manner (à la Hotelling 1929), as simply meaning that it is possible to compute a distance between any two project types and that the values of \(t\) reflect these distances. In other words, we make no assumptions about the dimensionality of the knowledge space and assume only that it is possible to compute distances in that space.
software projects, and intermediate numbers represent mixtures between these two extremes).

2.2 Individuals

As with projects, we model individuals as having a type, which we call an expertise. For any given project, the difference between a project’s type and the expertise of the individual assessing that project affects the level of noise in the individual’s perception of project quality. For example, if a software expert is called upon to evaluate a project that involves mostly software, then her perception will likely be more accurate in this case than the perception of a hardware expert. We model noisy perception as a signal plus noise, where the signal is the actual quality of the project \( q \) and the standard deviation of the noise is proportional to the distance between project type and individual expertise. Mathematically, if an individual of expertise \( e \) is called to assess the quality of project \((q, t)\), then she will perceive the quality of this project as

\[
q' = q + \tilde{n}, \text{ where } \tilde{n} \sim N(0, |t - e|).
\]  

We thus denote the perceived quality as \( q' \).\(^4\) Modeling perception as signal plus noise is consistent with prior models (e.g., Gavetti and Levinthal 2000, Knudsen and Levinthal 2007) and with empirical work on managerial perceptions (Mezias and Starbuck 2003). Heterogeneity in expertise is a common assumption in literatures on, for example, top management teams (Hambrick and Mason 1984), information economics (Radner 1993), and organizational learning (Liang et al. 1995).

2.3 Structures

In the spirit of Simon’s (1947/1997:18–19) definition of organization as “the pattern of communications and relations among a group of human beings, including the processes for making and implementing decisions,” we model organizational structure as the mechanism that aggregates

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\(^4\)The noise term in equation (1) implies that if expertise equals project type then perception is completely accurate. One might argue that this standard of perfection is too high, even for an expert with \( t = e \). It is possible to relax this assumption by adding a baseline error rate, so that no individual can achieve perfect perception. Doing so does not result in any qualitative change to our results, as we discuss in Section 3.4 and Appendix B.
individual perceptions into a group-level decision regarding each project reviewed.

The four structures we study are graphically summarized in Figure 1. Each of these structures (except for the first) consists of three individuals with expertise levels $e_L$, $e_M$, and $e_H$ such that $e_L \leq e_M \leq e_H$. To ease presentation of results and to simplify our discussion of the homogeneity or heterogeneity of expertise, we express the three expertise levels in terms of two parameters, $e_M$ (the expertise of the intermediate individual) and $\beta$ (the breadth of knowledge in the organization) such that $e_L = e_M - \beta$ and $e_H = e_M + \beta$. We discuss an alternate distribution of expertise in Section 3.4. The following paragraphs describe how each of the four structures operates.

**Individual** (Figure 1a). This is the simplest possible structure; it involves only one manager, with expertise $e_M$, who is in charge of either accepting or rejecting projects. If he perceives a project to have a positive quality (i.e., $q' > 0$) then he approves the project; otherwise, he rejects it. We use this as a benchmark against which the other, more complex structures are compared. This structure is representative of settings where decisions are made by a single individual; examples include many small and entrepreneurial firms as well as firms with a particularly powerful manager.

**Delegation** (Figure 1b). In this structure, projects are delegated to the manager whose expertise is closest to the type of the project being screened (e.g., if a project type $t = 0.4$ is assessed by a structure with experts $e_L = 0$, $e_M = 0.5$, and $e_H = 1$, then the project would be assigned to $e_M$). Hence the assigned expert accepts the project if she perceives it as a good one and rejects it otherwise. We initially assume that the project is assigned to the manager whose expertise is closest to the project’s type. Later we relax that assumption by exploring the case of imperfect delegation, as may occur when the determination of project types or individual expertise is subject to error. The Delegation structure is representative of such settings as engineering and consulting firms, where the evaluation of a project is usually assigned to the partner with the most relevant experience, or movie studios where a producer or executive might specialize in a certain movie genre and review all scripts that are pitched in that genre.

**Voting** (Figure 1c). Under this structure, each of the three managers evaluates the project and the organization makes a decision based on the vote of the majority (i.e., if two or more of
Figure 1: Graphical description of each of the structures analyzed. The input to each structure is a project \((q, t)\).
the individuals perceive the project to have a positive quality then the project is approved, and otherwise it is rejected). This structure is representative of boards of directors, partnerships such as venture capital firms, and egalitarian top management teams.

**Averaging** (Figure 1d). This structure is similar to the previous one; however, instead of counting votes, the structure averages the actual perceptions of the three individuals. If the average of the three perceived qualities is positive, then the organization accepts the project and otherwise rejects it. This structure could represent cases where committees try to fine-tune their decisions to incorporate more fully the assessments of members. For example, if two managers have a mildly negative view of a project but the third manager has an extremely positive perception of it, this structure would yield acceptance of the project. One question this research tries to answer is why this structure, which arguably takes into account more information than does Voting (continuous perceptions rather than yes/no votes) is not observed more often within organizations. It is, however, often used outside business organizations in attempts to harness the “wisdom of crowds.” Examples include averaging scores from movie critics (e.g., metacritic.com) and creating a consensus earnings forecast based on estimates from multiple financial analysts (e.g., First Call).

### 2.4 Performance

We define organizational performance as the expected quality of the projects accepted by a given structure employing a given set of experts under a given external environment. We use the definitions presented previously to derive mathematically the organizational performance of each structure. Here we show how to derive this metric for the Individual structure; the metrics for the other structures can be similarly derived and are summarized in Appendix A.

Given equation (1), the probability that an individual with expertise $e$ approves a project of quality $q$ and type $t$ is

$$P(\text{approving a given project}) = S_{\text{ind}}(q, t; e) = 1 - \Phi(0, |t - e|) - q, \tag{2}$$
where $\Phi(\mu, \sigma)\big|_x$ is the cumulative distribution function of an $N(\mu, \sigma)$ evaluated at $x$.\footnote{See Csaszar (2009a) for details.} In agreement with the previous literature (e.g., Sah and Stiglitz 1986), we call this probability the “screening function of the organization.”

The previous probability is defined for a single $(q, t)$ project. Hence, in order to obtain a performance metric for an environment of several projects it is necessary to compute expected values over the range of $q$-values and $t$-values that define that environment:

$$
E(\text{quality of approved projects}) = \left(\frac{1}{\bar{t} - t}\right) \left(\frac{1}{\bar{q} - q}\right) \int_? \int_? q S_{\text{ind}}(q, t; e) \, dq \, dt. \quad (3)
$$

We call this expected value the organization’s performance in a given environment.\footnote{We choose this measure of performance because if project quality ($q$) is understood as an NPV, then equation (3) corresponds to the average NPV the firm receives per screened project.} Note that if decision making is random and if the range of $q$-values is centered on zero, then the value of performance will be equal to zero. Because equations (2) and (3) cannot be solved analytically, we analyze the model numerically.

### 3 Results

In this section we use the model to explore the relationship between organizational structure, individual expertise, and the external environment. We do this in two stages. First, we study the effect of employee expertise (i.e., the “knowledge of the organization”) on the performance of each structure for a given environment. Studying firms that differ with regard to the expertise of their employees serves to elucidate the performance effects of knowledge diversity. Second, we investigate how changes in the project environment (i.e., the type of projects that constitute the stream of projects) affect the performance of each structure. Studying the effect of different project environments can shed light on how robust a structure is when faced with an unexpected change in the environment (e.g., a radical technological change).

We use graphical plots to convey the main results of the analysis in an intuitive yet precise way. Each plot shows how performance (on the $y$-axis) varies as a function of knowledge breadth ($\beta$, on the $x$-axis) for a fixed range of project types $[\bar{t}, T]$ and project qualities $[\bar{q}, \bar{q}]$. 
Thus, to compare organizations within a given environment we look at one plot, and to compare across environments we look at two or more plots.

To explore the model in a way that is amenable to analysis yet representative of its behavior under a broad range of realistic conditions, we present results for a carefully chosen set of scenarios. We focus on these scenarios after extensively exploring the model and verifying that the results (a) capture the fundamentals of the model’s behavior and (b) are qualitatively robust with respect to the exact value of the inputs (robustness checks are described in Section 3.4 and Appendix B). In other words, analyzing the model under these values is sufficient for enabling the reader to extrapolate results to other plausible scenarios.

In general, two regularities allow us to keep the number of scenarios presented to a minimum. First, the effect of varying the range of project qualities \([q, \overline{q}]\) is straightforward: as the quality of the portfolio increases, the performance of all the structures increases monotonically and without affecting the performance ranking of the structures. In the limit (when project qualities become extremely positive or extremely negative), all structures perform identically (accepting or rejecting all projects, respectively). Thus, to understand the behavior of the model, it is enough to study it under one range of qualities (in the ensuing analyses we use \(q \sim [-5, 5]\)). This leads to the second regularity: because the noise in individual perception is a function of the difference between project type and expertise (by equation (1), which shows that noise is proportional to \(|t - e|\)), to understand the behavior of the model it is enough to vary one of the elements of the difference while keeping the other fixed; in most of our analyses, we vary the expertise while keeping the range of project types fixed.

Within each plotted scenario (defined by a range of project types \(t\) and qualities \(q\)), we explore the behavior of the different structures while varying the degree of expertise heterogeneity within each structure. As mentioned previously, in most of our analyses the respective expertise of the three managers employed by Delegation, Voting, and Averaging are parameterized by the expertise \(e_M\) of the middle manager and knowledge breadth \(\beta\) such that \(e_L = e_M - \beta\) and \(e_H = e_M + \beta\). In the first scenario analyzed, we set the expertise of the middle manager at exactly the center of the range of project types (i.e., \(e_M = \frac{t - \overline{t}}{2}\)). This choice of \(e_M\) minimizes the expected perception errors of that manager. This assumption is relaxed later, but we con-
sider this choice of $e_M$ a reasonable starting point because mechanisms such as competition or learning could allow firms to discover that this is an optimal position for $e_M$. We vary knowledge breadth $\beta$ from zero (i.e., all individuals are identical) to the value at which the three experts are maximally different but still remain within the range of the project types (e.g., if $t \sim U[0, 10]$ and $e_M = 5$, then $\beta_{\text{max}} = 5$ since this value leads to $e_L = 0$ and $e_H = 10$).

We structure the analysis as follows. First, we familiarize the reader with the inner workings of each structure by focusing on a base case. This first step helps uncover the basic mechanisms that relate knowledge breadth ($\beta$) to performance for each structure. Second, we explore the effect of shifting the range of project types while keeping the expertise of the individuals fixed. Third, we explore what happens to the performance of Delegation when we relax the assumption of perfect assignment of projects. Finally, we describe the robustness of the findings. More general implications of the model are discussed in Section 4.

3.1 Base Case

Figure 2 shows the performance of the four structures as a function of knowledge breadth $\beta$ in a single environment ($q \sim U[-5, 5]$ and $t \sim U[0, 10]$) and under the assumption that the middle manager is located at the middle of the project types being considered ($e_M = 5$). A first look at this figure reveals several nontrivial relationships, including noticeable differences between Averaging and Voting in addition to the strong performance of Delegation as knowledge breadth increases. The following paragraphs delve into the mechanisms explaining these and other differences in performance across structures.

A baseline observation from Figure 2, which also holds for all subsequent figures, is that the performance of the Individual structure is flat with respect to knowledge breadth. This follows directly from the definition of this structure, in which $\beta$ does not play any role—this structure involves only one individual, whose expertise is $e_M$. Because this structure is so simple (in terms of both structure and performance) and because it serves as a building block of all the other structures, it makes a natural benchmark against which to compare the performance of those other structures. This figure shows that the Individual structure is the poorest performer (with one exception in the lower right of the figure, which we discuss later). Thus, in our model,
going from organizations of one individual to organizations of three individuals is almost always associated with a positive effect on performance.

*Averaging versus Voting.* Perhaps the most striking observation from Figure 2 is that, although Voting and Averaging are intuitively similar, the relationship between performance and knowledge in these two structures is quite different. The performance of Averaging peaks when its managers are the most similar (i.e., with no knowledge breadth or \( \beta = 0 \)), and it decreases rapidly as knowledge breadth increases. In contrast, the Voting structure is less sensitive to knowledge breadth and exhibits a nonmonotonic behavior: performance peaks at a moderate level of \( \beta \) before declining slightly. The performance difference between Voting and Averaging is particularly interesting in that everybody we informally surveyed beforehand believed that any difference between the performance of the two structures would be to the advantage of Averaging, which takes more information into account (Averaging combines individual perceptions whereas Voting combines votes, which are nothing more than discretized versions of those individual perceptions). Moreover, this pro-Averaging argument seemed consistent with the well-known concept of applied statistics that running a statistical procedure (e.g., a regression) on continuous variables, rather than on binary versions of them, produces better estimates.
But these a priori arguments proved to be deceptive.

The logic explaining the counterintuitive difference between Voting and Averaging is that Averaging overweights perceptions of the less suitably informed individuals. For example, if experts $e_L = 0$, $e_M = 5$, and $e_H = 10$ review a project of type $t = 10$ and quality $q = 1$, then expert $e_L$ would likely perceive it with substantial error while $e_H$ would accurately perceive it as having $q = 1$. Given how close the project’s $q$ is to 0, whether the organization accepts or rejects the project depends almost entirely on whether $e_L$ produces a noisy estimate that is very high (leading to acceptance) or very low (leading to rejection). Thus, under Averaging, the perception of the least-suited individual can throw the organization-level decision completely off balance. In contrast, Voting has the property that, no matter how mistaken is the perception of any individual, her effect on the final decision is capped: she can only affect the vote count by one vote.

The only case where Averaging surpasses Voting is when knowledge breadth is close to zero (i.e., $\beta < 1$ in Figure 2). In this case, all the individuals are similarly qualified to evaluate the project, so no individual has undue power to throw the averaging process off balance. When individuals are identical and thus unequal noise ceases to be an issue, the additional information carried in the continuous signals of Averaging (versus the discrete signals of Voting) has a positive effect. In other words, when $\beta$ is low, the continuous signal used by Averaging does not come at a significant cost and the informational advantage of these signals becomes observable.7 An intriguing implication of the possibility that Averaging may underperform Voting is that groups should not necessarily use all the information at their disposal. Sometimes, less information is better (i.e., discrete votes instead of full-fledged perceptions).

An application of the previous comparison is that if the organization designer is unsure about the actual expertise of the organization’s members then he may be better-off choosing Voting rather than Averaging. In the opposite case, an organization designer who can perfectly choose the expertise of its members may be better-off employing members of identical expertise and preferring Averaging rather than Voting. An instance of this advantageous use of Aver-

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7In statistical terms, continuous signals have an informational advantage over discrete signals because they allow for errors to be cancelled out more efficiently or, equivalently, because they have a greater asymptotic accuracy (Casella and Berger 2002:470).
aging could be in Olympic competitions, where scores are usually computed by averaging the scores of the judges (rather than by counting votes); the organizers of the games can arguably choose many judges that have similar expertise (e.g., ex-Olympians). In most other settings—conspicuously in business and government—where perfect calibration to a well-defined task is unlikely to occur or hard to assess, the organization designer might better employ Voting. In sum, Voting structures are robust to miscalibrated members. This characteristic may explain why voting is so prevalent in settings that face a variety of environments and high member turnover, such as boards of directors and legislative bodies.

**Delegation.** We now explore the behavior of Delegation, whose performance (as shown in Figure 2) also exhibits a distinct path—in this case, an inverted-U shape. We describe the performance of Delegation in three steps. Initially, under knowledge homogeneity ($\beta = 0$), Delegation performs identically to the Individual structure because any individual receiving a delegated project is identical to the only member of the Individual structure. Then, as $\beta$ increases, so does the performance of Delegation. As the decision makers become spread over a larger portion of the knowledge range, it becomes more likely that the expertise of the manager receiving the delegated project is close to the type of the project. Finally, the relationship between performance and $\beta$ peaks at an intermediate level of $\beta$. To understand why the maximal performance of Delegation occurs there, imagine three goalkeepers jointly trying to cover a goal that is 6 meters wide. Simple arithmetic shows that, if the goalkeepers position themselves 0, 3, and 6 meters from the left post then, in the worst-case scenario, a goalkeeper will be 1.5 meters from the ball when it crosses the goal line. However, if the goalkeepers locate at positions 1, 3, and 5, then one of them will be at most 1 meter from the ball. A similar reasoning explains why, under Delegation, the optimal knowledge breadth is less than the maximal $\beta$ (i.e., the value of $\beta$ that would locate experts at the corners of the range of project types).

**Comparing structures.** An interesting perspective emerges from reading Figure 2 normatively: consistent with the main tenet of contingency theory (Lawrence and Lorsch 1967), there is no “best” organizational structure. In fact, Delegation, Voting, and Averaging each can be the best performer depending on the distribution of knowledge breadth ($\beta$). We address
these across-structure comparisons in greater detail in Section 4.1, after describing additional contingencies in Sections 3.2 and 3.3 below.

3.2 Changing Environment

Here we explore how these structures perform when the environment changes. Specifically, in this section we explore the case of a shift in the type of projects reviewed by the firm while the expertise of its members remains fixed. This type of change is akin to the effect of a radical new technology, such as the shift from analog to digital photography (Tripsas and Gavetti 2000). For example, at Polaroid during this transformation, expertise related to hiring software engineers became more important while expertise related to hiring chemists became less important. At the same time, because of organizational inertia and the unexpected nature of the change, an incumbent firm like Polaroid could not adapt its expertise instantly and so remained stuck with its previous set of experts, who had been selected based on the older, analog environment. The analyses in this section shed light on what structures and levels of knowledge breadth are better able to cope with radical environmental changes. In other words, we now study how structure and knowledge breadth can protect firms that cannot instantly change their managers every time the environment varies.

The panels in Figure 3 show four snapshots of performance as the environment gradually varies from the base case ($t \sim U[0, 10]$ in the first panel) to a radically different environment ($t \sim U[15, 25]$ in last panel). A first observation from this figure is that the overall performance of the structures (i.e., the ranges on the $y$-axes) decreases as we move from panel (a) to panel (d). This happens because, as we advance through the panels, the project types begin to drift away from the expertise of the firm, which remains fixed (at $e_L = 5 - \beta$, $e_M = 5$, and $e_H = 5 + \beta$). Thus, for example, in the last panel, experts centered around $e_M = 5$ must screen projects with types between 15 and 25, which leads to large evaluation errors and a consequent effect on performance.

Another observation from Figure 3 is that, at each step, Averaging increasingly trumps Delegation as the best performer at low and middle levels of expertise breadth (i.e., in the first panel Averaging dominates until $\beta = 1$, whereas in the last panel Averaging dominates over
Figure 3: Four snapshots of performance as a function of knowledge breadth ($\beta$ on the x-axes) and the range of project types (in each panel).
the entire range of $\beta$). The rationale is that, as the environment shifts farther and farther away from the decision makers within the firm, the errors made by the Averaging decision makers in evaluating projects become increasingly similar in their distributions (when the shift is extreme, the three decision makers become nearly homogeneous in their expertise relative to the types of the projects under consideration). This convergence improves the relative performance of Averaging even if the decision makers are homogeneously low in their ability to evaluate the project. Hence, a group could make comparatively good decisions even if none of its members had the appropriate expertise to make a good decision individually.

The explanation for the effect of environmental change on Delegation is quite different. Although Delegation loses some terrain against Averaging (and Voting) in the first three panels of Figure 3, Delegation remains the top performer when knowledge breadth ($\beta$) is high. This is because, when $\beta$ is high, the expert who receives the delegated project is better equipped to deal with the new project than is the uneven mix of experts who participate in Averaging or Voting. To make the argument clearer, suppose that experts $e_L = 0$, $e_M = 5$, and $e_H = 10$ are evaluating a project of type $t = 12$, which is slightly above the level of $e_H$’s expertise. Delegation would send the project to $e_H$, whose noisy perception would have a standard deviation of 2 ($\approx |10 - 12|$). Averaging or Voting would additionally use the opinions of the two other experts, whose noisy signals have a much higher standard deviation (of $|0 - 12| = 12$ and $|5 - 12| = 7$) and would thus throw off balance the relatively accurate perception of the other individual rather than cancel out its error. Thus, the Delegation structure performs quite well in a changing environment as long as one of the decision makers possesses expertise that is within or near the range of project types under consideration. As the expertise of the closest decision maker ($e_H$) becomes less helpful in the new environment, the performance of the Delegation structure falls below that of the Averaging structure.

One implication of Figure 3 is that Delegation combined with high breadth of expertise is an organization design that is robust to unexpected shifts in the range of project types—except at the most extreme levels of change (i.e., Figure 3d). Observe that under the extreme change scenario, none of the firm’s original experts ($e$ between 0 and 10) is of much use in the new space ($t$ between 15 and 25). However, a scenario like this is only descriptive of the most
extreme environmental changes. Most changes in the real world probably do not reach these levels. For instance, even after the shift to digital photography, Polaroid’s competencies in camera design and lens technology were still relevant. Therefore, one empirical implication of our model is that Delegation (when knowledge breadth is high) exhibits comparatively higher performance during most periods of radical environmental change.

3.3 Imperfect Delegation

Delegation has an important difference with respect to the other structures: it incorporates a first stage during which the project is allocated to a single decision maker. So far, the model has assumed that projects are perfectly assigned to the expert whose expertise is closest to the type of the received project. But in real life this assignment process can be imperfect. Errors in assignment can occur, for example, if project type or individual expertise are hard to assess, if there is not a reliable process for matching projects to experts, if there are political reasons for not assigning projects to the right experts, or if the right expert is unavailable. Studying the sensitivity of Delegation to errors of assignment is particularly relevant because our analyses so far have identified a wide range of cases where Delegation is the top-performing structure.

To account for possible assignment imperfections in Delegation, we introduce a new parameter, $r$, which denotes the error rate of the assignment process. This parameter can take values between 0 and 1 and affects the delegation process as follows: with probability $r$ the incoming project is assigned to the second-best expert, and with probability $1 - r$ the project is correctly assigned to the first-best expert. For example, if $r = 0.3$ and if experts $e_L = 0$, $e_M = 5$, and $e_H = 10$ face a project of type $t = 6$, then there is a 30% chance of the project being wrongly assigned to expert $e_H$ and a 70% chance of it being correctly assigned to expert $e_M$. A formal definition of firm performance under imperfect delegation is given in Appendix A.

Figure 4 plots the performance of Delegation for different values of assignment error $r$ under the base case environment ($t \sim [0, 10]$). The main observation from this figure is that Delegation is quite sensitive to errors in assignment. For example, if the error rate rises from 0 to 20% (compare lines $r = 0$ and $r = 0.2$ in Figure 4) then the peak performance of Delegation

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8 The results for other environments are qualitatively equivalent.
Figure 4: Performance of Delegation under imperfect assignment, where parameter $r$ denotes the error rate.

falls from roughly 1.20 to 1.14. Comparing Figures 2 and 4 shows that an error rate slightly above 0.2 would make Delegation fall below the peaks for both Averaging (for low $\beta$) and Voting (for high and medium $\beta$). An error rate slightly above 0.6 would render Delegation the worst-performing of the four structures (i.e., even worse than the Individual structure for high levels of $\beta$). Delegation’s sensitivity to assignment errors is an important characteristic to keep in mind when discussing managerial implications.

### 3.4 Robustness Checks

We studied the robustness of our findings with respect to a broad range of parameter values and model specifications. These tests included: (a) varying the number of decision makers; (b) setting the expertise of individuals in a random (rather than a symmetric) fashion; (c) increasing the size of the individuals’ errors; and (d) changing the probability distributions of the individuals’ errors and the project characteristics. In general, our results are qualitatively robust to changes in all of these assumptions. A representative set of the robustness tests is shown in Appendix B.
4 Discussion

This study introduces a mathematical model involving organizational structure, individual expertise, and the external environment. We compare the total performance of four decision-making structures: a Voting body, an Averaging body, a Delegation process, and an Individual decision maker. The results demonstrate that structure, expertise, and environment are tightly interconnected in their effect on organizational performance. Next we discuss practical uses of the model as well as the links between our work and existing theory on crowd-based decision making, organizational adaptation, and the microfoundations and process of strategy.

4.1 Managerial Application

An application of the model consists of recommending a decision-making structure based on given values for the parameters. A concise way to organize model recommendations is by using decision trees. Figure 5 shows one such decision tree, which encapsulates the structure comparison for the base case (Section 3.1) and recommends the most appropriate structure—assuming that the environment is static and that knowledge breadth is given (i.e., managers of the organization cannot be replaced or retrained). The decision tree takes into account four conditions (depicted as boxes), which we describe briefly, starting from the top of the decision tree. The first condition is a cost–benefit one: if the cost of employing three decision makers does not compensate for its benefits, then the Individual structure is preferable (this argument assumes that three decision makers are costlier than one). The second and third conditions relate to knowledge breadth ($\beta$): if $\beta$ is unknown (as when expertise is difficult or costly to assess) then Voting offers a robust performance; if $\beta$ is low then Averaging offers the best performance; and if $\beta$ is high, then which structure is preferable depends on the likelihood of delegation errors. If delegation errors are likely, then Voting is a safe bet; otherwise, Delegation should be used. The figure shows that each of the four structures can be a viable choice under the appropriate set of conditions (i.e., the four structures appear as terminal nodes of the tree), which underscores the contingent nature of organizational design.

Similar decision trees can be constructed for the three remaining combinations that stem
Figure 5: Decision tree that recommends the best structure as a function of knowledge breadth ($\beta$) and delegation errors ($r$), and assuming a static environment.

from considering knowledge breadth as given or controllable and the environment as stable or changing. We do not present these trees here for the sake of brevity (in any case, they can be inferred from the Results section).

4.2 Delegation or “The Wisdom of Crowds”?

The “wisdom of crowds” (Surowiecki 2004) and related concepts such as prediction markets (Wolfers and Zitzewitz 2004) have received significant coverage in the practitioner literature. The general tone of this coverage is that choices made by crowds are superior to the results of traditional, delegative decision making in firms. For example, a recent article in the Wall Street Journal (Murray 2010) postulates that crowdlike decision making will cause “the end of management.” Yet, casual observation indicates that delegation is probably the most prevalent form of decision making in firms. Are firms wrong to choose delegation in favor of crowds?

The model developed in this paper sheds light on when decisions made within the firm should be made with crowdlike decision processes versus delegation. Delegation outperforms crowdlike structures (Voting or Averaging) when the projects assessed by the firm are well
matched by the delegated individual’s expertise (in terms of the model, when \( \beta \) is moderate or high), when significant environmental shocks are unlikely to make existing firm expertise obsolete, and when assignment errors are relatively rare (\( r \) is low). Otherwise, one of the crowdlike structures is preferable. We conjecture that the conditions under which Delegation outperforms the other structures have been prevalent throughout business history, so that (in the sense of organizational evolution) Delegation has become the default decision structure for firms. A further managerial implication is that crowdlike mechanisms should be considered in settings that deviate from the pro-Delegation conditions just listed.

A related question is why, when firms do use a crowdlike mechanism, it is usually by means of Voting and only rarely by means of Averaging. Prior work has suggested that the Averaging structure can be costly: the process of arriving at a specific number can be more time-consuming and more cognitively demanding than the “thumbs up–thumbs down” approach of Voting or Delegation’s division of labor (Hastie and Kameda 2005). This higher cost may be one reason that few firms use Averaging structures, and our modeling effort suggests two additional reasons. First, it may be challenging to ensure that all decision makers are similar in terms of expertise, either because doing so is costly or because organizations (and their members) will change over time. Second, Averaging is more susceptible than Voting to agency concerns, since Averaging would overweight an outlier opinion even if that opinion were based on personal preferences and not on facts. In contrast, Voting is less susceptible to this bias because the negative effect of a dishonest individual is capped at one vote.

4.3 Structure and Environmental Change

A long-standing question in management is how firms can use organizational structure to cope with environmental change. Some of the early structures that have been suggested in this regard are Organic (Woodward 1965), Prospector (Miles and Snow 1978), and Adhocracy (Mintzberg 1979). Our work here suggests that there is no single correct structure to deal with environmental change and that the proper choice depends on internal and external contingencies—namely, the knowledge possessed by the organization’s members and the knowledge required by the environment. Specifically, for a firm that possesses the appropriate
knowledge, Delegation makes the most sense. This finding aligns with work on technological change, which suggests that firms could adapt more successfully by placing authority in the hands of, for example, scientists with directly relevant knowledge instead of executives who may be wedded to existing business models (Tripsas and Gavetti 2000, Christensen and Bower 1996, Eggers and Kaplan 2009). However, if the firm does not possess the knowledge relevant to the new environment (either because the firm is extremely homogeneous or because the shift is radical), then it would be more advantageous for the firm to employ Voting or Averaging.

4.4 Information Aggregation and the Microfoundations of Strategy

Several calls have been made to better understand the processes by which organizations make decisions. Here we briefly summarize these calls and show how our model provides at least a partial answer to them. We group these calls into three types. A first type seeks a better understanding of the strategic decision-making process. For example, Rumelt, Schendel, and Teece (1994:527) ask “How does the policy process matter?” as one of the five questions that motivated their conference and book entitled Fundamental Issues in Strategy. Along the lines of this current paper, they describe the policy process as the outcome of information aggregation by several individuals and point out that no research so far has explored “the link between the policy process and the quality of the decision.” Similar calls have been made by Maritan and Schendel (1997:259) and Bower (1997:27).

A second type of call has emerged from within the Carnegie tradition and highlights the organizational aspects of decision making. For instance, Gavetti et al. (2007:528) and Argote and Greve (2007:344) remark that, although one of the goals of the Carnegie tradition was to create behaviorally plausible models of organizational decision making, research on decision making in this tradition—with only a few notable exceptions (e.g., Cohen et al. 1972)—has been remarkably nonorganizational, making this one of the least-explored elements of this tradition. A third type of call has come from research on the microfoundations of strategy (Abell et al. 2008). These authors point out that most theories that offer to explain organizational capabilities do so via reasoning that applies only to the level of macro constructs, neglecting that macro behavior must be the outcome of micro processes.
These calls share the goal of building micro-to-macro links between the process by which decisions are made and the effect of these processes on organizational performance. The three calls also share the view that organizations should no longer be seen as black boxes but rather as involving processes with a finer-grained set of elements such as individuals and decisions. We view our paper as an attempt to address these three types of calls. By developing a model of how different organizational structures aggregate the opinions of heterogeneous individuals, we contribute to understanding the strategic decision process and the role of organizational structure in aggregating information, as well as to fleshing out one micro-to-macro process characteristic of organizations.

4.5 Future Work

The research presented here can be extended in several directions. Possible avenues for empirical work include: (a) testing the model’s predictions (e.g., test the hypotheses implicit in the decision tree of Figure 5); (b) developing ethnographic studies to understand better how real organizations use and misuse the mechanisms proposed here; and (c) measuring the effect sizes associated with the model’s parameters, as well as the variance explained by information aggregation versus other firm- and industry-level characteristics.

Possible avenues for theoretical work include: (i) studying other information aggregation structures, such as more complex network structures or dynamic structures that reflect the characteristics of incoming project (e.g., if the project type is close to an expert then use Delegation and otherwise Voting); (ii) predicting other performance metrics, such as errors of omission and commission or the speed of decision making; and (iii) studying organizational processes other than alternative selection, such as alternative generation or organizational learning. We believe that models of information aggregation, such as the one presented in this study, hold great promise for the study of organizations because they are fully aligned with the main tenets of behavioral theory of the firm: that an organization’s main task is to process information (March and Simon 1958/1993) and that organizational structure determines how information is aggregated (Simon 1947/1997).
4.6 Conclusion

In this study we have sought to investigate formally the process of strategic decision making within organizations by analyzing four commonly used information aggregation structures. Our study constitutes a step toward better understanding the links between information aggregation and the process of strategy by uncovering complex interdependencies between organizational structure, individual expertise, and environmental change. From a practical standpoint, our results shed light on which structure to use when. Some of the questions we have addressed are: when to use delegation of authority versus crowdlike mechanisms; how structure can be used to cope with radical environmental change; and when organizational decision making is better-off using less (rather than more) information from its members. From a theoretical standpoint, we address several calls to enrich our understanding of organizations by describing a mechanism that can predict organization-level performance based on micro-level assumptions. Overall, our results underscore the critical role of information aggregation in strategy.
References


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A Appendix: Screening Function of Each Structure

The respective screening functions for each of the four structures are detailed here (these equations are the equivalents of equation (2)). The performance of each structure can be computed by evaluating equation (3) with the corresponding screening function. A detailed log that includes the derivation of the metrics is available from the authors, as is simulation code that verifies these derivations are correct.

A.1 Individual
\[ S_{\text{ind}}(q, t; e) = 1 - \Phi(0, |t - e|) \]

A.2 Delegation
\[
S_{\text{del}}(q, t; e_L, e_M, e_H) = \begin{cases} 
S_{\text{ind}}(q, t; e_L) & \text{if } t < \frac{e_M + e_L}{2} \\
S_{\text{ind}}(q, t; e_M) & \text{if } \frac{e_M + e_L}{2} \leq t \leq \frac{e_M + e_H}{2} \\
S_{\text{ind}}(q, t; e_H) & \text{if } t > \frac{e_M + e_H}{2}
\end{cases}
\]

A.2’ Imperfect Delegation
\[
S_{\text{del}'}(q, t, r; e_L, e_M, e_H) = \begin{cases} 
(1 - r)S_{\text{ind}}(q, t; e_L) + rS_{\text{ind}}(q, t; e_M) & \text{if } t < \frac{e_M + e_L}{2} \\
(1 - r)S_{\text{ind}}(q, t; e_M) + rS_{\text{ind}}(q, t; e_L) & \text{if } \frac{e_M + e_L}{2} \leq t \leq e_M \\
(1 - r)S_{\text{ind}}(q, t; e_M) + rS_{\text{ind}}(q, t; e_H) & \text{if } e_M < t \leq \frac{e_M + e_H}{2} \\
(1 - r)S_{\text{ind}}(q, t; e_H) + rS_{\text{ind}}(q, t; e_M) & \text{if } t > \frac{e_M + e_H}{2}
\end{cases}
\]

A.3 Voting

where,
\[
P(v_L, v_M, v_H) = \prod_{i \in \{L,M,H\}} \left[ \begin{array}{ll}
S_{\text{ind}}(q, t; e_i) & \text{if } v_i = A \text{ (individual } i \text{ accepts)} \\
1 - S_{\text{ind}}(q, t; e_i) & \text{if } v_i = R \text{ (individual } i \text{ rejects)}
\end{array} \right]
\]

A.4 Averaging
\[ S_{\text{avg}}(q, t; e_L, e_M, e_H) = 1 - \Phi \left( 0, \frac{1}{3} \sqrt{(t - e_L)^2 + (t - e_M)^2 + (t - e_H)^2} \right) \]
B Appendix: Robustness Analysis

Here we present figures corresponding to the robustness checks mentioned in Section 3.4. Each figure is discussed separately, and the overall conclusion is that the results presented in the body of the paper are qualitatively robust under a broad range of model specifications. The figures illustrate how the main findings of the paper do not depend on the exact number of decision makers employed, the exact location of the decision makers, or the base error rate of the individuals. In other tests, not shown here, we also establish the model’s robustness with respect to the exact probability distributions used (i.e., we used different combinations of uniform, normal, and logistic distributions for the individual errors and distribution of projects).

Varying the number of decision makers. Figure 6 plots the performance of structures with \( N = 5 \) and \( N = 7 \) decision makers (left and right panels, respectively). We used these values of \( N \) because strategic decision making within firms rarely involves higher numbers of individuals. The larger structures operate analogously to those described in Section 2—for instance, with \( N = 5 \), Delegation, Voting, and Averaging involve five (instead of three) individuals. Comparing the results of the base case (Figure 2) with the two panels in Figure 6 reveals that, as the number of decision makers increases, the performance of all the structures also increases. Moreover, the ordering relationship among the different structures’ performance is unchanged.

Randomly locating the experts. Figure 7 plots the performance of structures in which the experts are not located symmetrically (previously, \( e_M - e_L = e_H - e_M = \beta \)). Now, the position of each of the three individuals is randomly picked from the range \( [e_M - \beta, e_M + \beta] \) (where \( e_M \) is no longer the position of the middle expert and is now just the middle of the firm’s

![Figure 6: Varying the number of decision makers (N).](image-url)
expertise range). Again, the ordering of the lines is the same as in the base case (Figure 2). The performance of the Individual structure is now decreasing in $\beta$ because its expertise is no longer ideally positioned at $e_M$.

Figure 7: Randomly locating the decision makers within the range $[e_M - \beta, e_M + \beta]$.

Adding a base error rate to the individual perceptions. Equation (1) assumes that the standard deviation of the individuals’ perceptions is proportional to $|t - e|$. In this robustness check we explore the case of individuals whose standard deviation does not reach zero even if their expertise perfectly matches the type of the project screened. We therefore add a constant $k$ to the standard deviation of the individuals’ perceptions (i.e., the noise in equation (1) becomes $\tilde{n} \sim N(0, |t - e| + k))$. Figure 8 plots the base case when $k = 0.5$ and $k = 1$ (left and right panels, respectively). The figure shows that, although overall performance decreases (compare the range in the $y$-axes), the ordering relationship among the different structures’ performance remains unchanged.

Figure 8: Adding a base error rate ($k$) to the individuals’ perceptions.