Organizational Structure as a Determinant of Performance: Evidence from Mutual Funds[1]

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Abstract

This paper develops and tests a model of how organizational structure influences organizational performance. Organizational structure, conceptualized as the decision-making structure among a group of individuals, is shown to affect the number of initiatives pursued by organizations, and the omission and commission errors (Type I and II errors, respectively) made by organizations. The empirical setting is over 150,000 stock-picking decisions made by 609 mutual funds. Mutual funds offer an ideal and rare setting to test the theory, since there are detailed records on the projects they face, the decisions they make, and the outcomes of these decisions. The study's independent variable, organizational structure, is coded based on fund management descriptions made by Morningstar, and estimates of the omission and commission errors are computed by a novel technique that uses bootstrapping to create measures that are comparable across funds. The findings suggest that organizational structure has relevant and predictable effects on a wide range of organizations. In particular, the paper shows empirically that increasing the consensus threshold required by a committee in charge of selecting projects leads to more omission errors, fewer commission errors, and fewer approved projects. Applications include designing organizations that achieve a given mix of exploration and exploitation as well as predicting the consequences of centralization and decentralization. This work constitutes the first large-sample empirical test of the model by Sah and Stiglitz (1986).

Keywords: organization design, omission and commission errors, exploration/exploitation, centralization and decentralization, decision making

1   Introduction

There is a long-standing concern that the strategy literature needs a better understanding of the relationship between organizational structure and performance. This concern goes back at least to Cyert and March (1963:21), who posed the following questions when motivating their theoretical enterprise: "What happens to information as it is processed through the organization? What predictable screening biases are there in an organization?" Yet with few exceptions, questions of this sort remain largely unexplored in the strategy literature (Rumelt et al., 1994:42). The lack of knowledge about how decision-making structure affects organizational performance surfaces repeatedly in different areas of management. For example, in the context of ambidextrous organizations, Raisch and Birkinshaw (2008:380) note that "far less research has traditionally been devoted to *how* organizations achieve organizational ambidexterity," and in the context of R&D organization, Argyres and Silverman (2004:929) show surprise "that so little research has addressed the issue of how internal R&D organization affects the directions and impact of technological innovation by multidivisional firms." These observations are congruent with the view that organization design—the field specifically devoted to studying the links between environment, organizational structure, and organizational outcomes—is in many respects an emerging field despite its long history (Daft and Lewin, 1993; Zenger and Hesterly, 1997; Foss, 2003).

This paper contributes to a better understanding of the relationship between organizational structure and organizational performance by providing the first large-sample empirical test of the theory developed by Sah and Stiglitz (1986). Among other predictions, this theory establishes a causal link between the structure of a decision-making committee and the number of omission and commission errors the committee will make. Errors of omission and commission (which are equivalent, respectively, to Type I and II errors in statistics) correspond to missing good choices (omissions) and pursuing bad choices (commissions). Specifically, Sah and Stiglitz's (1986) theory predicts that committees with a high consensus level (e.g., requiring unanimous approval) will make relatively few commission errors but many omission errors. In contrast, committees with a low consensus level (e.g., requiring the approval of just one of its members) will exhibit the opposite behavior: they will make few omission errors but many commission errors. Additionally, the theory predicts that the higher the consensus level, the fewer projects that will be pursued

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by the committee. This paper finds empirical support for these three predictions of the Sah and Stiglitz model.

The Sah and Stiglitz model makes predictions regarding *organizational* performance (e.g., expected omission and commission errors of a given organization design). Yet in many cases, by using a contingency or "fit"-type of logic, one may extend the reach of their model to infer predictions regarding *competitive* performance (e.g., profitability in the face of competition). For instance, all other things being equal, if in a given competitive situation omission errors are costlier than commission errors, then a firm whose organizational design produces fewer omission errors will be more profitable than one whose design produces more omission errors.

From a practical standpoint, empirically validating Sah and Stiglitz's theory is relevant because it has performance implications for committees, a widespread decision-making structure. Moreover, committees are used in many settings relevant to strategic decision making, such as boards of directors, top management teams, finance committees, and investment teams.

From a theoretical standpoint, confirming the Sah and Stiglitz model is of special interest to organization design, as their theory provides a parsimonious mechanism to explain how micro decisions (individual choices) are aggregated by an organizational architecture into macro behaviors (organization-level performance). In fact, by separating performance into omission and commission errors and then linking structural choices to the occurrence of these errors, Sah and Stiglitz's model sheds light on such organization design issues as the implications of centralization and decentralization and how organizations can pursue exploration and exploitation.

It is especially important to test the Sah and Stiglitz model because it has spawned a large number of descendants.[1] Thus, all these works rely critically on the untested validity of its predecessor. Despite there being many ways in which the work of Sah and Stiglitz can illuminate managerial phenomena, few of the references have come from the management field. The occasional exceptions include work on mergers and acquisitions (Gulati and Higgins, 2003; Puranam et al., 2006), venture capital (Lerner, 1994), technological choices (Garud et al., 1997), the implications of alternative evaluation on search (Knudsen and Levinthal, 2007), and analyzing the errors of more complex organizational structures (?Christensen and Knudsen, 2010). Perhaps the lack of empirical validation explains why few of the references to the work of Sah and Stiglitz have come from the, largely

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[1]At the time of this writing, over 180 citations according to ISI Web of Science.

empirical, management field.

Sah and Stiglitz's theory is so simple—it is based solely on the probabilities that different voting rules have of vetoing projects—that one may be tempted to suppose their predictions are obviously true in organizations resembling those in the theory. But without empirical validation it is not obvious whether Sah and Stiglitz's terse description of organizations has predictive value. For example, it could be that their idea of looking at organizations as veto mechanisms greatly oversimplifies the communication capacity of individuals or the information aggregation rules actually used by organizations. Alternatively, it could be that the process described by Sah and Stiglitz does operate in organizations but that its effects are minuscule when compared with other concurrent effects, such as groupthink (Janis, 1972), herding (Bikhchandani et al., 1992), power (Pfeffer, 1992), decision biases (Kahneman and Tversky, 1979), or massive inaccuracies in managerial decision making (Starbuck and Mezias, 1996). In sum, determining the falsifiability of Sah and Stiglitz's theory is an empirical question. Science progresses by theory building and theory testing, but Sah and Stiglitz's theory-building effort has until now lacked an accompanying theory-testing effort.

This paper tests Sah and Stiglitz's model by using data on the decision-making structure and on the omission and commission errors of mutual funds. One could argue that Sah and Stiglitz's theory has not yet been tested empirically because collecting information on organizational structure and errors (particularly omissions) is difficult. Luckily, mutual funds offer a rare opportunity to observe all the required information: mutual funds' decision-making structure (which squarely maps into the committees described by Sah and Stiglitz) is observable from analysts' reports; and omission and commission errors can be measured by looking at the investment universe of each fund, the assets that each fund decides to buy and not to buy from that investment universe, and the ex post return of each asset.

The current study explores a particular aspect of organization design using a particular setting. Hence, two questions regarding generalizability emerge: how prevalent is the mechanism studied, and how representative is the setting. The mechanism studied—voting—is certainly prevalent, although it is unlikely to occur in such a stylized way as described by Sah and Stiglitz's model. In the real world it is probable that other phenomena (e.g., power, politics, herding) would co-occur. It is interesting that, despite the possibility that any number of factors influence the relationship between structure and organizational performance, the results reported here are consistent with

Sah and Stiglitz's parsimonious characterization. Regarding the second question, on how representative is the mutual funds setting, one characteristic of this setting that suggests that the findings here reported may occur elsewhere is that mutual funds are among the most stringent settings imaginable: stock returns are eminently random (Fama, 1970), so it is hard to imagine that organizational structure could affect any outcome of stock picking. Finding empirical support in this setting therefore suggests empirical support in other, less stringent settings.

The paper is organized as follows: Section 2 describes the mechanism underlying the Sah and Stiglitz model, and Section 3 connects the theory of Sah and Stiglitz to the management literature. Section 4 presents the hypotheses tested, Section 5 describes the empirical setting, and Section 6 presents the results. Finally, Section 7 discusses the broader theoretical and managerial implications of this research.

2 An Overview of the Sah and Stiglitz Model from an Organization Design Perspective

To understand the scope and applicability of Sah and Stiglitz's (1986) model, it is useful to start by describing how it fits within the three fundamental themes of organization design: (i) organizational search or alternative generation (e.g., Rivkin and Siggelkow, 2003; Ethiraj and Levinthal, 2004), (ii) alternative evaluation (e.g., Gavetti and Levinthal, 2000; Knudsen and Levinthal, 2007), and (iii) execution or implementation (e.g., Hrebiniak and Joyce, 1984; Galbraith and Kazanjian, 1986). In light of this characterization, the work of Sah and Stiglitz falls precisely in the category of alternative evaluation.

Sah and Stiglitz (1986, 1988)[2] model how committees screen projects, that is, how effective they are at separating good projects from bad ones. Although originally developed to compare the performance of central planning with that of free markets, Sah and Stiglitz's model can shed light on a broader set of organizational issues because many organizations use committee-like structures. 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

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[2]The paper by Sah and Stiglitz (1988) generalizes Sah and Stiglitz (1986) to committees with arbitrary size and consensus levels. For succinctness, only the earlier paper is cited hereafter.

management teams deciding on which strategic projects to pursue.

Sah and Stiglitz model committees as comprising N decision makers, of which C must approve a project for it to be approved by the committee (C stands for "consensus level"). For example, an organization of three members that approves a project when any member decides to approve it is represented by $N = 3$ and $C = 1$, or simply 3/1; likewise, 2/2 denotes a two-member organization that only approves projects for which there is consensus. An organization consisting of a single individual is denoted 1/1.

The model assumes that individuals are fallible (i.e., individuals perceive reality in a noisy fashion), homogeneous, and uncorrelated (i.e., noises in perception are independent and identically distributed); it also assumes that projects are described by a single number (i.e., a project quality, which is imperfectly perceived). Like all models, this stylized description of organizations leaves many phenomena outside of its scope, such as organizations whose task is different from screening projects, heterogeneity in ability, group dynamics such as herding (Bikhchandani et al., 1992) or groupthink (Janis, 1972), and, more generally, organizational structures different from those describable in terms of N and C. Nonetheless, the model does permit one to focus on some basic mechanisms that are pervasive within organizations: how centralized or decentralized is the decision process of an organization, and how many individuals are involved in it. The following examples illustrate how the model captures these organizational characteristics.

For instance, a 3/3 could represent the decision-making process within a venture capital firm in which the three partners must agree on any investment; it could also represent a three-level hierarchy in which projects received by a low-level employee must escalate up to the CEO for approval. In both examples, all three individuals must concur on the project's viability before it is approved by the organization. In contrast, a 3/1 could represent either of the following decentralized structures: a firm with three research engineers, any one of whom may independently decide to pursue further research on a new technology; or a mutual fund with three autonomous fund managers, any one of whom may authorize the purchase of a security. In these last two examples, it suffices that one of the three individuals likes the project in order for it to be approved.

If the number of decision makers on the committee is fixed, the main predictions of Sah and Stiglitz's model are that, on average, lowering the consensus level leads to: (i) more approved projects, (ii) fewer omission errors, and (iii) more commission errors.

These three predictions can be explained using basic probability theory. The next example illustrates the effect of structure on the number of projects approved—that is, prediction (i) of the model. Imagine two decision makers, each with a 50% chance of approving a project, facing 100 projects to be screened. If unanimity is required (i.e., if both decision makers must agree that a project is good for it to be approved), then they would approve on average 25 projects ($= 100 \times 0.5 \times 0.5$). If instead the approval of just one decision maker is required, then the organization would approve on average 75 projects (conversely to the previous case, now each project is accepted unless both decision makers reject it: $100 - 25 = 75$). Although the examples so far have assumed that decision makers are homogeneous (i.e., in the example the two managers had the same 50% probability of approving a project), the model can be extended to accommodate heterogeneous decision makers. But homogeneity is a reasonable assumption in some settings, as when managers have similar training, and also more generally because, on average, heterogeneous settings behave like homogeneous settings. (For example, a committee whose members have a probability of approval uniformly distributed between 40% and 60% behaves, on average, like a committee whose members have a 50% probability of approval.)

The effect of structure on omission and commission errors (predictions (ii) and (iii)) can be similarly illustrated. Imagine that only 50 of the 100 projects are good and that each decision maker has equal probability of accepting and rejecting good and bad projects (i.e., there is a 25% chance of each decision maker either accepting a good project, accepting a bad project, rejecting a good project, or rejecting a bad project). Then, the unanimous committee (which Sah and Stiglitz call a *hierarchy*) would make on average 6.25 commission errors (i.e., #projects $\times$ probability that both decision makers accept a bad project $= 100 \times 0.25 \times 0.25$), and 43.75 omission errors (i.e., #projects $\times$ probability that any of the decision makers reject a good project $= 100 \times [0.25 + 0.25 - 0.25^2]$). A committee only requiring the approval of one decision maker (which Sah and Stiglitz call a *polyarchy*) exhibits the converse behavior: on average, it would make 6.25 omission errors (i.e., #projects $\times$ probability that both decision makers reject a good project), and 43.75 commission errors (i.e., #projects $\times$ probability that any of the decision makers accept a bad project).[3]

Although not developed for this purpose, the Sah and Stiglitz model can be used to analyze the

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[3]Calculations similar to these—that is, conjunctive (AND) and disjunctive (OR) probabilities—are commonly used in reliability theory (e.g., Rausand and Høyland, 2004). Note that Sah (1991:68) mentions a classic work on reliability (Moore and Shannon, 1956/1993) as an antecedent of the Sah and Stiglitz (1986) model.

effects of centralization and decentralization in organizations. The applicability of their model to these effects stems from the facts that "decision makers generally base their actions on estimates formulated at other points in the organization" (Cyert and March, 1963:85) and that, in centralized organizations, these estimates must "flow up" through more decision makers (before reaching the final decision maker) than in decentralized organizations (Robbins, 1990:6). Thus, the information flow in centralized organizations resembles that of hierarchies whereas the information flow in decentralized organizations resembles that of polyarchies. In sum, the Sah and Stiglitz framework captures the dynamic of information passing through more filters in centralized than in decentralized organizations.

Appendix A generalizes the examples given here by developing a model that makes the same qualitative predictions but under more general assumptions (regarding number of decision makers, consensus level, individual screening abilities, and types of incoming projects). The model in the appendix does not present new theory, but it does serve as a concise summary of the work of Sah and Stiglitz that is useful for the purposes of this paper.

3 Theoretical Motivation

What are the effects of organizational structure on organizational performance? This is among the fundamental questions in the fields of strategy (Rumelt et al., 1994:42) and organization theory (Thompson, 1967), so it is no surprise that it has been addressed extensively from several perspectives since old (even biblical; Van Fleet and Bedeian, 1977:357) times. Therefore, rather than attempting the impossible task of summarizing these literatures, this section presents a broad overview with an emphasis on highlighting the main differences and similarities between current and previous approaches. The review focuses mainly on organizational structures whose building blocks are individuals (as in Cyert and March, 1963), not business divisions (as in Chandler, 1962). The focus on this kind of structures is consistent with the Carnegie-tradition understanding of organizational structure as "the pattern of communications and relations among a group of human beings, including the processes for making and implementing decisions" (Simon, 1947/1997:18–19).

This section is organized in terms of three main disciplines that share an interest in how organizational structure affects performance: organization design, organizational economics, and signal

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detection theory.

3.1 Organization Design

Important early attempts at understanding the relationship between structure and performance are present in the work of Chandler (1962) and Barnard (1938). Their work, like most ensuing efforts in organization design, took an information processing perspective. For instance, Chandler (1962:69–70) cites memos from Du Pont's reorganization in 1919 that were explicit about the role of information processing: "The most efficient results are obtained at least expense when we coordinate related effort and segregate unrelated effort." Similarly, Barnard (1938:215) mentions that "the function of executives is to serve as channels of communication so far as communication must pass though central positions."

Influenced by Barnard, Simon (1947/1997) developed a more formal understanding of organizations as information processing devices composed of boundedly rational individuals. Under this view, organizational structure plays a central role, as it defines how information flows and is aggregated inside organizations, allowing organizations to accomplish goals that would be otherwise unattainable by any of its individual members. Led by Simon (1947/1997), Cyert and March (1963) gave organizational structure a central place in the Carnegie tradition. However, with one exception (Cohen et al., 1972), this tradition devoted most of its energies to decision making in the *absence* of concerns about organizational structure. In fact, organizational structure has recently been called a "forgotten pillar" of this tradition (Gavetti et al., 2007:525).

The work of Sah and Stiglitz (1986) is consistent with the information processing perspective that permeates the organization design literature: it views the role of organizational structure as a means to aggregate the information coming from boundedly rational, fallible individuals. Yet in addition to being consistent with organization design, it extends the information processing approach by offering a new set of predictions about structure and types of projects approved. By providing empirical support for Sah and Stiglitz's model, this paper aims to pave the way for these predictions to be used fruitfully in organization design.

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3.2 Organizational Economics

Several models in organizational economics have studied the effect of structure on performance. In broad terms, the organizational economics literature on structure can be divided into two strands: incentives[4] and information processing. The current paper is directly related to this latter strand.

The information processing strand of the organizational literature has dealt mainly with the selection of projects and the efficiency aspects of project implementation. Early works along these lines include Williamson (1967) on optimal hierarchy size and Marschak and Radner (1972) on optimal decision making by teams. More recent work has studied efficiency measures of hierarchies (e.g., Radner, 1992; Bolton and Dewatripont, 1994; Van Zandt, 1999); the optimal organization of production as a function of environmental uncertainty (Cremer, 1980); the acquisition of knowledge by hierarchies with heterogeneous agents (Geanakoplos and Milgrom, 1991; Garicano, 2000); the extent to which hierarchies can accommodate coordination and specialization (Hart and Moore, 2005); and the relative performance of such common organizational forms as the M-form and the U-form (Harris and Raviv, 2002; Qian et al., 2006).

Sah and Stiglitz (1986) contribute to organizational economics by introducing two new elements: modeling communication patterns as sequential or parallel circuits, and measuring performance as omission and commission errors. The literature that has descended from the work of Sah and Stiglitz has been primarily theoretical and focused on voting (see the introduction of Christensen and Knudsen (2010) for a review), so the application of their model to organization design issues remains largely unexplored.

3.3 Signal Detection Theory

Almost without connection to the previous literatures, a rich body of work that addresses many of the same questions has been developed in social psychology, under the label of signal detection theory, and in the closely related theory of social decision schemes.

Signal detection theory (Peterson et al., 1954; Green and Swets, 1966; Macmillan and Creelman,

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[4]The incentives strand has dealt mainly with project implementation or execution. Topics studied include the relationship between the manager's incentives and the range of projects implemented by the firm (Rotemberg and Saloner, 1994); the interplay between organizational structure and formal authority (Aghion and Tirole, 1997); and the types of projects that are better served by managers who persuade employees instead of resorting to authority (Van den Steen, 2009).

2004) provides a mathematical framework to analyze perception and decision making by fallible individuals. This theory conceptualizes decision makers as trying to detect a signal in a noisy environment, and it provides a set of models, measures, and experiments to assess how good decision makers are at detecting those signals under different settings. This theory was first used to measure the sensory acuity of military personnel (i.e., radar operators) and was later adapted to study myriad discrimination problems in cognitive processes (e.g., medical diagnosis, weather forecasting, quality control).[5] Given the generality of signal detection theory, many problems of choice can be seen as special cases of it. Of particular interest to this paper is that some problems of managerial decision making have been analyzed from a signal detection perspective: Puranam et al. (2006) use the theory to study M&As, and Garud et al. (1997) use it to study technological innovation.

One of the contributions of signal detection theory is representing the omission and commission errors of different decision makers via a "receiver operating characteristic curve" (Figure 1 is akin to that representation). Although signal detection theory and the Sah and Stiglitz model both pay explicit attention to omission and commission errors and to their costs, one difference between these approaches is that, whereas Sah and Stiglitz study the performance of committees, signal detection theory studies the performance of individuals.

The theory of social decision schemes (Davis, 1973, 1992) is similar to the work of Sah and Stiglitz on committees in that it presents mathematical models of group decision making (although performance is not measured as omission and commission errors). This literature has produced empirical results (Stoner, 1961; Stasser and Titus, 1985; Hinsz et al., 1997); however, because the experiments have primarily been conducted in the laboratory using small groups that meet for brief times, reported results may not be generalizable to more complex organizations (Argote and Greve, 2007:344).

In sum, an empirically validated version of the Sah and Stiglitz model can serve to combine the strengths of both signal detection theory (i.e., its focus on omission and commission errors) and social decision schemes (its focus on groups), thereby bringing closer to organization design the rich bodies of work on group decision making that are based in social psychology.

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[5]The updated bibliography on the 1988 reprint edition of the classic book on the subject (Green and Swets, 1966) lists more than a thousand studies published on the subject during the period 1967–1988 alone.

Although the reviewed literatures have provided many important insights regarding the impact of structure on performance, the field of organizations lacks an empirically validated theory that—starting from structure at the level of individuals—is able to predict organization-level measures of performance that are relevant to firm strategy. If empirically validated, Sah and Stiglitz's model would offer such a theory. The contribution of this paper is to test this theory empirically for the first time.

4   Hypotheses

The independent variable of the study is organizational structure, which from the data set used can reliably be coded into three, nonoverlapping categories: (i) mutual funds managed by one individual (in terms of the model outlined in Section 2, this corresponds to $N = 1$ and $C = 1$); (ii) mutual funds managed by more than one individual, with each individual operating independently from the others (in terms of the model, $N > 1$ and $C = 1$); and (iii) mutual funds managed by more than one individual and where decisions are made unanimously (in terms of the model, $N > 1$ and $C = N$). For brevity, these structures will be referred to (respectively) as individual, decentralized, and centralized. Because of data limitations to be discussed later, the data set does not contain structures featuring intermediate levels of consensus (i.e., N/C with $1 < C < N$, such as $N = 7$ and $C = 6$).

The dependent variables of the study are the three outcomes predicted by the model: number of approved projects, omission errors, and commission errors. Because the model predicts that these three outcomes are most different for centralized versus decentralized structures, the hypotheses are stated as comparisons between those two structures. It would be possible to formulate six further hypotheses comparing individual managers to centralized structures and individual managers to decentralized structures; however, in order to avoid a litany of hypotheses, these comparisons are discussed in the results section without being formally enumerated here.

The three hypotheses are equivalent to the three properties of Sah and Stiglitz's model described in Section 2. These three hypotheses encompass all the mechanisms exposed in Sah and Stiglitz (1986, 1988) regarding committees with exogenously given screening functions.

Hypothesis 1 *Decentralized organizations accept more projects than centralized organizations.*

Hypothesis 2 *Decentralized organizations make fewer omission errors than centralized organizations.*

Hypothesis 3 *Decentralized organizations make more commission errors than centralized organizations.*

5 Empirical Setting and Approach

5.1 Empirical Challenge

Before delving into the specifics of the data set and statistical methods, it is important to understand the structure of the empirical problem. To test the hypotheses, all of the following must be observed: (i) organizations making decisions about projects, (ii) a measure of the quality of each project decided upon, (iii) the decision that each organization made with respect to every project it faced, and (iv) the organizational structure of each organization. Item (i) exists in many settings (e.g., firms deciding whom to hire, where to expand, what to sell). Item (ii) is also readily available in settings where the ex post value of the project is visible and can proxy for the project's true quality. In the venture capital context, for example, it could be a function of the IPO value of a startup in which a venture capitalist considered investing; in the R&D context, it could be the number of citations accrued by a patent after a firm had the opportunity to buy it.

Yet items (iii) and (iv) are serious hurdles for the empirical researcher. First, there is typically no track record of the projects an organization considered but decided not to pursue (e.g., all the firms a venture capitalist screened but did not invest in). Second, organizational structure is not available from public databases. Organizational charts are sometimes available, but they give no indication of whether a given decision-making process is centralized or decentralized (e.g., by looking at an organizational chart it is not possible to know the decision process used to set the direction of R&D, perform M&As, or decide on IT investments).

Mutual funds offer a rare window into the implications of organization design on organizational performance because, in this setting, the four necessary ingredients are observable: (i) managing a mutual fund is essentially about making decisions (i.e., deciding what to buy and what to sell); (ii) the ex post return of each investment is a good measure of the quality of each decision;[6] (iii) regula-

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[6]Stock returns are exogenously given (in most plausible cases they do not depend on anything a fund manager

tions require funds to disclose their holdings periodically, which allows the researcher to distinguish between accepted "projects" (i.e., stocks that were bought) and those that the fund rejected (stocks that were not bought); and (iv) organizational structure is observable from descriptions of the fund management prepared by Morningstar. Additionally, there are thousands of mutual funds, and the typical fund makes dozens of decisions per quarter. All these considerations make mutual funds an exceptional vehicle for studying the effects of organization design on organizational performance; indeed, mutual funds would make a good aspirant for the "fruit fly" of organization design.

Despite these virtues of mutual funds as an empirical setting, there is a strong tradition in the finance literature that maintains organizational structure should not be a determinant of fund performance. In a nutshell, the efficient market hypothesis (EMH; Fama, 1970) purports that all available information is already reflected in asset prices, rendering future returns unpredictable. If that is true, then organizational structure should not predict mutual fund performance. However, two caveats apply. First, the EMH's performance measure is financial return, not omission and commission errors.[7] Second, the EMH is no longer viewed as invulnerable, since a vast literature on market anomalies (e.g., Goetzmann and Ibbotson, 1994; Chevalier and Ellison, 1999; Cohen et al., 2008) has emerged in the last 20 years.

Because the variance explained by market anomalies is small (e.g., the typical R^2 of an anomaly is less than 1%), any variance explained by organizational structure is not expected to be large. A further implication is that any explanatory power the model has will likely increase in settings where the link between cause and effect is more deterministic. Since stock picking is arguably one of the most random task environments possible, it follows that mutual funds make for a stringent testing arena and that the results of this paper serve as conservative estimates.

5.2 Independent Variable: Mutual Fund Organizational Structure

A mutual fund is a type of investment that pools money from many investors to buy a portfolio of different securities such as stocks, bonds, money market instruments, or other securities. Mutual funds in the United States are regulated by the US Securities and Exchange Commission (SEC);

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can do) and thus provide a good match for Sah and Stiglitz's model, which treats quality as exogenously given.

[7] A surprising result of this paper is that the organizational structure of a fund can affect its omission and commission errors in such a way that financial return is not affected—a result that supports the apparently contradictory predictions of both Sah and Stiglitz (1986) and Fama (1970).

Electronic copy available at: https://ssrn.com/abstract=1281559

Structure (N/C)	Excerpts from Morningstar's mutual fund description
1/1	"Ron Baron has been at the helm since the fund's inception ... He's the driving force behind this portfolio ... buys companies he thinks can ..." (BPTRX)
2/1	"Managers Scott Glasser and Peter Hable each run 50% of the portfolio ..." (CSGWX)
3/1	"Three management firms select 10 stocks apiece for this fund's portfolio." (SFVAX)
5/1	"[the fund] divvies up assets among five subadvisors, and each picks eight to 15 stocks according to his own investing style." (MSSFX)
2/2	"Teresa McRoberts and Patrick Kelly became comanagers of this fund in late September 2004 ... They don't pay too much attention to traditional valuation metrics such as ..." (ACAAX)
7/7	"All investment decisions are vetted by the entire seven-person team ... Management populates the fund with 30–50 stocks ..." (CBMDX)

Table 1: Examples of how organizational structure is coded from Morningstar's fund descriptions (the ticker symbol of each fund is given in parentheses).

among other requirements, the SEC requires funds to report their portfolio holdings at the end of the last trading day of every quarter (Form 13F) and also to identify periodically their fund managers (Form 487). Mutual funds are heavily scrutinized not only by the SEC but also by institutional investors and investment research firms.

Morningstar, one of the leading investment research firms, offers information about mutual funds to investors and financial advisors. Using public sources and periodically meeting with fund managers, Morningstar's analysts produce a one-page report—densely packed with statistics and analysis—for each fund they track. For the present study, the most important element of these profiles is a section entitled "Governance and Management," which presents a short biography of the managers and describes how they manage the portfolio. This section of the report contains enough information to code organizational structure as modeled in this paper (in terms of number of managers, N, and level of consensus required, C). To understand how the coding was done, consider the excerpts shown in Table 1, which illustrate typical descriptions. In order to increase consistency, four rules were followed for the coding.

1. If the description mentions managers' names then N is set to the number of people mentioned as manager or co-manager, with the exception of people who are described explicitly as having a secondary role (e.g., if a manager is described as subordinate, performing administrative tasks, not participating in the day-to-day management, or recently promoted but retaining

his/her analyst tasks).

2. If the description is explicit about the number of "sleeves" or subadvisors, or if it describes how managers split their portfolios, then N is set to the number of divisions of the portfolio and C is set to 1 (since this is a decentralized fund).

3. If two or more managers are mentioned but nothing is said about how they coordinate (e.g., they are addressed as a plurality, as in "they invest in ..."), then it is assumed that the fund employs a consensus ($N = C$) decision procedure. This is reasonable, as this is the default structure of co-managed funds, and because if managers work separately, they have no incentive to being reported as working in tandem (managers want to create their own reputation).

4. If no specific manager names are mentioned (e.g., the description only mentions a generic "the management"), or if the description states that the fund is run by an algorithm (some funds that track indices operate like this), then the fund is left unclassified.

Less than 4% of the funds fell in the unclassified group, and less than 1% of the funds had a consensus level other than 1 or N. These two classes of funds were eliminated from the data set.

Because fund descriptions do not include such nuances as the relative sizes of each sleeve of a decentralized fund, the organizational structure of the subadvisor of each sleeve, or the share of power each manager has in a centralized fund, the funds were aggregated into three broader categories: 1/1 (managed by an individual), $N/1$ (decentralized), and N/N (centralized). This decision ensures against overinterpreting the results.

All the funds were coded both by the author and by one research assistant. The percentage of agreement between both categorizations was 96%. The results presented here use the author's categorization, but all the results are robust to using the other categorization.

5.3   Dependent Variables: Omission and Commission Errors

The main intuition behind the measures of omission and commission error developed in this paper is as follows: In hindsight, a commission error occurred whenever a fund bought an asset that turned out to have a poor performance (i.e., whose ex post return fell below a given benchmark);

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similarly, an omission error occurred whenever a fund failed to buy an asset that turned out to have a good performance.[8] To observe these errors, two types of data are required: the list of assets that a fund did and did not buy, and the returns of these assets. Good data sources exist for both elements.

In order to make the discussion more precise, some notation is useful. For a given mutual fund F at time t, let $A = \{a_1, a_2, \ldots, a_n\}$ be the set of assets that F bought during time period t (subscript t is omitted for convenience). The best available information on mutual fund holdings is reported quarterly, so hereafter the unit of time is one quarter. Let $U = \{u_1, u_2, \ldots, u_M\}$ represent the assets in which F can invest, or F's investment universe at time t. The number of assets bought by F at period t is n, and the number of assets in its investment universe at time t is M. By definition, the assets bought by a fund are a subset of the fund's investment universe, $A \subseteq U$.

Asset returns are measured as holding period returns; that is, $r(a)$ represents the total return of asset a from the end of period t to the end of period $t+1$ (this measure accounts for changes in price as well as for any income from dividends). The study uses a *per fund benchmark*, defined as the average return of the assets in the fund's investment universe at time t; thus, $b = \frac{1}{M} \sum_{i=1}^{M} r(u_i)$. An asset is catalogued as "good" if its return in a given period equals or exceeds the benchmark b. The subset of good assets that the fund bought during period t is denoted $A^+ = \{a | a \in A$ and $r(a) \geq b\}$, and its cardinality is denoted n^+. Similarly, the bad assets bought consist of $A^- = \{a | a \in A$ and $r(a) < b\}$ with cardinality n^-.

At first sight, several measures might capture the commission error of a fund. Two possibilities are the number of bad assets bought, n^-, and the total negative return, $\text{TNR} = -\sum_{\{a \in A^-\}} r(a)$ (the initial minus sign makes the measure increase in the proper direction). Yet a problem now arises in that—because different funds invest in a different number of assets and in different investment universes—these raw metrics are not comparable across funds and thus are unsuitable for the purposes of this study.

One way of solving the comparability problem is to convert these raw error measures into probabilistic measures that account for the specifics of each situation. An example will help clarify this point. Imagine you want to find out who is better at games of chance, someone who flipped

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[8]Omission and commission errors can also be measured with respect to sell decisions. This case is discussed in Section 6.3.

a coin 100 times and got 60 Heads or someone who threw a die 200 times and got 40 Sixes. If a probability distribution is placed on the outcomes ($\Pr\{\text{Head}\} = \frac{1}{2}$ and $\Pr\{\text{Six}\} = \frac{1}{6}$), then it doesn't matter that each one played a different game; in both cases it is possible to compute a statistic (in this case, a chi-squared) and then compare the players in terms of how unlikely their results were.

A first approach to creating probability-adjusted measures of a fund's errors is to use the hypergeometric distribution. This distribution, whose probability mass function is $f(r; M, R, m) = \binom{R}{r}\binom{M-R}{m-r}/\binom{M}{m}$, is typically illustrated in terms of the probability of getting exactly r red marbles after drawing m marbles (without replacement) from an urn containing M marbles of which R are red. Thus, replacing "marble" with "stock" and "red" with "bad" yields a function that computes the probability of getting a given number of bad stocks and that is already adjusted for portfolio size, for universe size, and for the number of bad stocks in the investment universe. A nice feature of this approach is that it removes the effect of the environment from the error measures. For example, an economy-wide shock that has a positive effect on one type of fund, but a negative effect on another, would not distort the measures of error. In other words, that the negatively affected fund draws stocks from a "tougher" urn than does the positively affected fund is controlled for by the hypergeometric distribution.

5.4 Using the Bootstrap to Compute a Better Measure of Omission and Commission Errors

The hypergeometric approach just illustrated can be further improved by using the bootstrap, a important recent development in statistics (Efron, 1979; Efron and Tibshirani, 1993). One limitation of the hypergeometric approach is that it weighs all bad decisions equally, regardless of the size of the errors (i.e., a stock that slightly underperformed the benchmark is counted the same as a stock whose price collapsed). The bootstrap allows one to model a probability distribution that takes into account the size of the errors.[9]

The bootstrap consists of creating an arbitrarily good approximation of a population via Monte Carlo simulations and then using this new population to compute the exact value of a statistic. In

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[9]Distinguishing between large and small errors is a natural property to expect from a measure of errors—especially since models that conceptualize perception as signal plus noise (such as Sah and Stiglitz's or signal detection theory) would predict that blunders are less likely to occur than slight errors.

this case, the population to be estimated is the set of all possible portfolios of a given size that can be drawn from a given investment universe. An example will clarify how the bootstrap can be used to measure commission errors. Suppose the returns of the assets in the investment universe of fund F are $\{-5\%, -2\%, -1\%, 1\%, 3\%, 4\%\}$, the benchmark is $b = 0$, and the fund bought the three assets that ended up returning $\{-2\%, -1\%, 4\%\}$. Hence F's total negative return is 3% (TNR $= -[-2\% + -1\%]$). To assess how large or small this number is, it must be compared to the TNRs of the population of funds that can draw three stocks from the same investment universe as F. In this example, 20 ($= \binom{6}{3}$) other portfolios could have been bought, but in realistic cases the space of possible portfolios cannot be explored exhaustively;[10] hence the method relies on randomly sampling the space of possible portfolios. With the exception of some well-known pathological cases (Davison and Hinkley, 1997, Sec. 2.6), a statistic computed via bootstrap converges to the real statistic as the number of random draws increases. For the data used in this paper, each fund "competes" against 100,000 simulated portfolios, and the standard error introduced by the bootstrap procedure is less than 0.003.

Once the population of portfolios comparable to a fund F is created, the measure of commission error is simply a measure of the deviance of F's error with respect to the commission errors of that population. Given the central limit theorem and the large number of simulations, the normal distribution is a good approximation for the TNRs of the population. Errors are therefore reported in terms of standardized scores; the higher the score, the higher the error.

The omission error can be defined analogously to the commission error. Instead of measuring TNR, in this case one measures the total unbought positive returns (TUPR)—that is, the sum of the good assets that belong to the investment universe of fund F but were *not* bought in the current period. Mathematically, TUPR $= \sum_{\{a \in U \text{ and } a \notin A\}} r(a)$. Following the previous example, the TUPR of fund F is 4% ($= 1\% + 3\%$). As before, the bootstrap is then used to compute a probability-adjusted measure that is expressed as a standardized score.

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[10]The average fund in the dataset buys 16 stocks from a universe of 195, which creates a space of $\binom{195}{16} \approx 10^{23}$ possible portfolios.

5.5   Data Preparation and Limitations of the Data Set

The content and format of Morningstar's one-page mutual fund reports have changed repeatedly over the years, and in 2007 it started including a "Governance and Management" section with enough information to code organizational structure for a large sample of funds. This implies that the data on organizational structure for December 2007 are available only as a snapshot. Therefore, whereas the dependent variables are computed using errors from 2004Q4 to 2007Q1, funds that changed their organizational structure after 2004Q4 but before December 2007 are partially misclassified in the analysis. Fortunately, changes in the organizational structure of funds are rare. There are no official statistics, but a good estimate of change in the organizational structure of mutual funds can be gathered from Morningstar (2008). In addition to 500 fund reports, Morningstar (2008:29) also includes a brief description of all the management changes that took place in these funds during 2007. Of the 500 reported funds, 32 experienced some sort of management change (the most typical change is replacement of a manager), and only four funds experienced a change in organizational structure as coded in this paper. This amounts to a 0.8% yearly probability of such change.

In December 2007, Morningstar kept organizational descriptions for 1687 funds. To increase comparability, only funds that were primarily devoted to stocks (not other asset classes, such as bonds or options) were selected. Thus, funds were chosen if their asset composition (according to the CRSP data set "Mutual Fund Profiles and Monthly Asset Data") was at least 60% stocks in the time period under study. This narrowed the list down to 1087 funds. The CRSP data sets "Portfolio Holding Information" and "Monthly Stocks" were then used to choose only those funds for which CRSP reported the returns of the individual stocks owned by the fund for at least 50% of its portfolio value. This reduced the list to 642 funds. This drop is primarily explained by CRSP's tracking only the returns of stocks traded on NYSE, NASDAQ, and AMEX (while many funds invest in international stocks) and to a lesser extent by observations missing from the CRSP portfolio holdings data set. Finally, funds for which the Morningstar description did not allow an organizational structure to be inferred were dropped, leaving the final count at 609 funds owned by 154 different parent firms. Collectively, for the ten quarters from 2004Q4 to 2007Q1, these funds invested in 5833 distinct stocks (as identified by their CUSIP number), made 153,457 buy decisions,

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and had \$1.6 trillion under management at the end of the period. The range of dates used is due to data limitations: before 2004Q4 the CRSP holdings database is sparse; and by December 2007, CRSP had not yet uploaded the holdings information for the quarters after 2007Q1.

The stocks that a fund bought during the quarter ending at date t were determined by looking at the stocks added to the portfolio since the last reported quarterly holdings. The quarterly holdings were gathered from the CRSP data set "Portfolio Holdings Information," itself a compilation of the Forms 13F that mutual funds submit to the SEC. An intrinsic limitation of the data is that, if a stock is bought and sold during the same quarter, then that buy decision is unobserved. However, this would pose a problem only if the error measures of the unobserved and observed trades differed in a way that depended on organizational structure. There are no reasons to believe a priori that this might be the case.

The returns used to determine whether an investment was a good or a bad one were the quarterly returns of each stock from the end of quarter t to the end of quarter $t + 1$; these returns were gathered from the CRSP dataset "Monthly Stocks" using the field "holding period return," which adjusts for stock splits and dividends. Because the exact date at which assets are bought is unknown (i.e., the holdings database has quarterly resolution), a further intrinsic limitation of the data set is that it fails to account for the return accrued since a stock is bought until the end of that quarter. Yet this lack of data should affect the results of the study in a conservative way. The reason is that, if managers are able to minimize the errors they make, then this ability should be more noticeable soon after the decision than later, when more unpredictable events may affect the price of their purchase.

The investment universe of a fund at time t was defined as all the stocks available for purchase at time t from the union of all the holdings reported by the fund in a trailing window of seven quarters, including the current quarter (i.e., using the last seven Forms 13F reported by the fund). There are at least three other ways to define the investment universe, but they present conceptual and practical problems that make them less preferable than the trailing-period definition. The first alternative is to use the investment objective, typically reported by each fund in its prospectus; however, this information is imprecise[11] and not always available, so using it to define the investment

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[11]For example, a fund may say that it attempts to track a broad index like the S&P500, but this does not imply that it invests only in stocks that are listed in the index; many of its investments may fall outside it. Another fund may say that it invests in "small caps," a broad category with thousands of stocks, though its investments consistently

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universe would have a subjective quality. A second alternative is to include all the 5833 stocks ever bought by all the funds. This approach was discarded because it is unfair to count the failure to buy stocks that would never be bought by a fund as "omissions" (e.g., a utilities fund does not buy high-tech stocks). A third alternative is to use the union of all the stocks ever bought by the funds that share the same Morningstar investment category. Like the previous alternative, this method creates loose investment universes that lead to a similar (albeit less serious) unfairness problem. In short, letting the deeds of the fund speak for themselves seemed the most appropriate choice. Robustness checks showed that the third alternative definition produced results qualitatively similar to those reported here using the trailing-period definition.

6 Results

Although mutual funds offer a unique window into the effect of structure on performance, actually measuring that effect is relatively challenging. An ideal test would consist of comparing the performance of mutual funds making investments in the same sector, with the same managers, at the same time, and differing only in organizational structure. This situation is unattainable, so the challenge consists of statistically controlling for differences other than organizational structure. Fortunately, the bootstrap (explained in Sections 5.3 and 5.4) and the standard control variables in the mutual funds literature (explained below) can control for these differences.[12]

Each of the three hypotheses was tested using a regression of the form

$$\text{dependent variable}_i = \alpha_0 + \alpha_1 Decentralized_i + \alpha_2 Individual_i$$
$$+ \alpha_3 Beta_i + \alpha_4 \log(ParentSize_i) + \alpha_5 \log(FundSize_i)$$
$$+ \alpha_6 CatLG_i + \alpha_7 CatLB_i + \alpha_8 CatLV_i + \alpha_9 CatMCG_i$$
$$+ \alpha_{10} CatSG_i + \alpha_{11} CatSB_i + \alpha_{12} CatMCB_i + \epsilon_i,$$

where the dependent variable is the logarithm of the number of stocks bought per quarter to test H1, omission error to test H2, and commission error to test H3. The independent variable of the study, organizational structure, was coded as two dummies representing the decentralized and the

fall within a group of fewer than 100 stocks.

[12]For an example of the use of the bootstrap in the mutual fund literature, see Kosowski et al. (2006); for a tutorial presentation, see Burns (2004).

individual structure (the centralized structure is the omitted dummy).

The controls used, which are in line with those used in the mutual fund literature (e.g., Chen et al., 2004), were: (a) $Beta_i$, the risk profile of the fund as measured by its Beta with respect to the S&P500; (b) $\log(ParentSize_i)$, the size of the parent firm (the firm owning the fund) as measured by the logarithm of the number of mutual funds that the parent firm owns (within the universe of 1087 stock mutual funds tracked by Morningstar); (c) $\log(FundSize_i)$, the size of the fund as measured by the logarithm of the net assets managed by the fund (in millions of dollars); and (d) $CatXX_i$, seven investment category dummies as coded by Morningstar (Large Growth, Large Blend, Large Value, Mid-Cap Growth, Small Growth, Small Blend, and Mid-Cap Blend). Roughly 80% of the funds fell into one of these seven categories; the rest were consolidated in an "Other" class that grouped 13 smaller categories and was used as the omitted dummy in the regressions.

The regressions were run on a pooled cross section (and not in a panel) because there is essentially no variation in the structure of the mutual funds during the period analyzed. The number of observations in the regressions is 6,090, since there are 609 funds and each one has data for ten periods. The omission and commission errors were computed as probabilities (see Sections 5.3 and 5.4) that are independent of the specific environment the fund was facing (i.e., actual stocks in the investment universe and its returns), which makes the pooled cross-section specification an appropriate choice.

To avoid a possible source of endogeneity, all the controls were measured at the beginning of the period used to compute the dependent variables (beginning of 2004Q4). To counter the effects of heteroscedasticity—and because observations coming from funds that belong to the same parent firm may not be independent—the standard errors were computed using cluster-robust estimation (Williams, 2000) with clusters defined according to the parent firm. All reported p-values correspond to two-tailed tests; this is a conservative decision because the hypotheses tested are of the form $a < b$, which calls only for running one-tailed tests.

Table 2 displays summary statistics and correlations. The correlations show no evidence of multicollinearity, which is reaffirmed by the variance inflation factors—none of which was larger than 1.6, a number well below the customary threshold of 10. Of the 609 funds in the data set, the most common structure is the individual manager (324 funds), followed by the centralized structure (233 funds) and the decentralized structure (52 funds).

		mean	sd	min	max	1	2	3	4
1	Omission error	−0.16	0.48	−2.77	1.09	1.00			
2	Commission error	0.14	0.47	−1.03	2.35	0.33	1.00		
3	Beta	1.15	0.27	−0.09	2.77	0.01	0.05	1.00	
4	log($ParentSize$)	2.14	1.10	0.00	4.68	−0.11	0.06	−0.04	1.00
5	log($FundSize$)	6.17	1.68	−0.24	11.25	0.06	0.08	−0.14	0.32

Table 2: Descriptive statistics and correlations (for the 609 funds in the sample).

6.1 Number of Projects Accepted

To test H1, the number of stocks bought by each fund was analyzed.[13] In order to determine whether the relationship between organizational structure and number of stocks bought is statistically significant, five models were tested (Table 3). Given that the distribution of the number of stocks bought is highly skewed (see, e.g., row 1 in Table 4), its logarithm was used as a dependent variable. In all the models, the decentralized structure ($N/1$) was associated with buying significantly more stocks than the centralized structure (the effect size corresponds to a 30–50% increase, depending on the model and the value of the controls). No significant relationship is present for the structure 1/1, yet the sign of its associated coefficients has the predicted direction in all the models.

The coefficients associated with the controls tell stories that are interesting in themselves. Models A3 to A5 show that funds belonging to larger parent firms buy more stocks—even after the size of the mutual fund and investment category are controlled for. One possible interpretation is that larger parent firms have better support structures, allowing managers to track more stocks. The regressions also show that the more net assets managed by a fund, the more stocks it will invest in; this may reflect that large funds are more likely to run into the liquidity limits of the underlying stocks. That Beta has a positive effect can also be explained in terms of liquidity, as higher-Beta stocks on average correspond to smaller firms. Finally, model A5 shows that there is a significant category effect, which gives additional support to the liquidity explanation because the categories with the largest positive coefficients are those involving small companies (only the categories Small Growth and Small Blend were statistically significant, with respective coefficients

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[13]As a robustness check, also the number of stocks *sold* by each fund was analyzed. The results were qualitatively the same as those presented here for the number of stocks bought.

	Dependent variable: log(#stocks bought)				
	A1	A2	A3	A4	A5
Decentralized (structure $N/1$)	0.647***	0.630***	0.582***	0.580***	0.544***
	(0.141)	(0.138)	(0.167)	(0.169)	(0.162)
Individual (structure $1/1$)	0.119	0.091	0.041	0.041	0.047
	(0.100)	(0.100)	(0.090)	(0.090)	(0.091)
Beta		0.848***	0.880***	0.883***	0.419+
		(0.236)	(0.245)	(0.253)	(0.250)
$\log(ParentSize)$			0.187**	0.186**	0.210***
			(0.060)	(0.062)	(0.060)
$\log(FundSize)$				0.003	0.013
				(0.027)	(0.025)
Category effects (joint test)					***
Constant	2.215***	1.259***	0.851**	0.832*	0.982*
	(0.097)	(0.273)	(0.325)	(0.399)	(0.414)
Observations	6090	6090	6090	6090	6090
Adjusted R^2	0.030	0.090	0.137	0.135	0.213

Note. Robust standard errors between parenthesis.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests).

Table 3: Results of regression analysis of number of stocks bought.

of 0.55 and 0.91).

Models A1 to A5 were rerun using portfolio size instead of number of stocks bought per quarter, and all the results were qualitatively the same. This increases confidence in the results by showing that what is true for a flow variable (number of stocks bought) is true also for its corresponding stock variable (portfolio size). In all, the large and significant coefficients accompanying the decentralized structure provide ample evidence that decentralized funds accept more projects than do centralized funds (H1).

It is remarkable that this statistically significant relationship between structure and portfolio size has not been reported in the finance literature—probably because researchers in that field have conceptualized organizational structure simply as number of managers (e.g., Chen et al., 2004). Measuring structure as number of managers is roughly equivalent to comparing the average portfolio size of structure N/N and $N/1$ (since both structures have N managers) against the portfolio size of structure $1/1$. Under that averaging, no difference is noticeable. (In particular, from the numbers in Table 4 one can easily calculate that the average portfolio size of N/N and

		N/N Centralized (233 obs.)	1/1 Individual (324 obs.)	N/1 Decentralized (52 obs.)	Total (609 obs.)
		avg (sd) [min, max]	avg (sd) [min, max]	avg (sd) [min, max]	avg (sd) [min, max]
1)	#stocks bought per quarter	15.9 (27.9) [1.2, 280.0]	15.3 (16.7) [1.3, 131.2]	26.1 (27.2) [3.4, 148.2]	16.5 (22.7) [1.2, 280.0]
2)	#stocks in portfolio	91.5 (105.9) [18.6, 1220.3]	138.6 (293.7) [20.3, 3455.2]	171.1 (168.3) [25.6, 990.9]	123.3 (230.6) [18.6, 3455.2]

Table 4: Descriptive statistics—number of stocks per organizational structure.

$N/1$ is 131.3; and this is not statistically different from the portfolio size of structure 1/1, which is 138.6.) In other words, if structure is measured in the wrong way, then the relationship between structure and portfolio size is rendered invisible even though that relation is actually quite strong.

6.2 Omission and Commission Errors

Figure 1 displays the average omission and commission error made by each organizational structure. The axes of the figure correspond to the standardized measures previously described (computed via bootstrap). The figure looks exactly as Sah and Stiglitz's model would predict, with the centralized fund at the lower right (minimizing commission errors), the decentralized fund at the upper left (minimizing omission errors), and the individual manager in between.

All five models in Table 5 support H2 by showing that a decentralized fund makes significantly fewer omissions than a centralized one. The magnitude of the coefficients associated with the decentralized structure is sizable, as it can be shown that decreasing an error by 0.15 points of the standardized score is associated with a 13% increase in annual performance (relative to current performance; e.g., a 10% annual return would become 11.3%).[14] As in the previous set of regressions, the coefficients accompanying the individual manager have the correct sign but are not statistically significant.

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[14]To compute the effect on a fund's annual return, a simulation was run using parameters representative of the average fund. This fund buys 16 stocks from a universe of 195 stocks each quarter; the stock's returns are drawn from a $N(0.0339, 0.2042)$ distribution; the portfolio turnover is one year; and the effect due to superior stock-picking is only effective (this is a conservative assumption) in the quarter after the stock was bought.
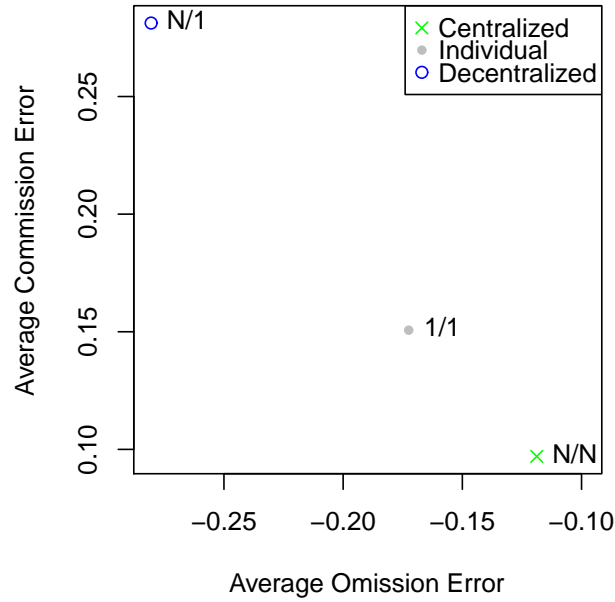
Figure 1: Average (centroids) omission and commission errors of the three organizational structures.

	Dependent variable: Omission error				
	B1	B2	B3	B4	B5
Decentralized (structure $N/1$)	-0.162^*	-0.162^*	-0.150^*	-0.172^*	-0.161^*
	(0.077)	(0.077)	(0.069)	(0.074)	(0.078)
Individual (structure $1/1$)	-0.054	-0.054	-0.042	-0.044	-0.043
	(0.046)	(0.046)	(0.046)	(0.046)	(0.047)
Beta		0.019	0.011	0.037	0.034
		(0.071)	(0.071)	(0.071)	(0.078)
$\log(ParentSize)$			-0.047^{**}	-0.062^{***}	-0.064^{***}
			(0.016)	(0.017)	(0.018)
$\log(FundSize)$				0.033^{**}	0.035^{**}
				(0.012)	(0.013)
Category effects (joint test)					not sig.
Constant	-0.119^{**}	-0.140	-0.039	-0.235^+	-0.217^+
	(0.039)	(0.089)	(0.100)	(0.127)	(0.130)
Observations	6090	6090	6090	6090	6090
Adjusted R^2	0.005	0.004	0.014	0.024	0.022

Note. Robust standard errors between parenthesis.

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests).

Table 5: Results of regression analysis of omission error.

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	Dependent variable: Commission error				
	C1	C2	C3	C4	C5
Decentralized (structure $N/1$)	0.184**	0.183**	0.177*	0.164*	0.146*
	(0.068)	(0.067)	(0.071)	(0.075)	(0.073)
Individual (structure $1/1$)	0.054	0.051	0.045	0.044	0.045
	(0.044)	(0.044)	(0.042)	(0.041)	(0.041)
Beta		0.079	0.083	0.098	0.082
		(0.079)	(0.080)	(0.088)	(0.103)
$\log(ParentSize)$			0.023	0.014	0.014
			(0.019)	(0.018)	(0.018)
$\log(FundSize)$				0.019	0.018
				(0.014)	(0.014)
Category effects (joint test)					not sig.
Constant	0.097**	0.008	-0.042	-0.156	-0.183
	(0.033)	(0.103)	(0.118)	(0.178)	(0.207)
Observations	6090	6090	6090	6090	6090
Adjusted R^2	0.008	0.008	0.010	0.012	0.013

Note. Robust standard errors between parenthesis.

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed tests).

Table 6: Results of regression analysis of commission error.

Among the controls, parent size and net assets appear to be significant determinants of omission errors. That funds owned by larger firms make fewer omissions indicates that the ability to avoid missing investment opportunities may reside partly in routines that are more likely to exist in larger firms, as might be research support services, fund manager training, or knowledge sharing among managers of different funds. Conversely, the finding that funds managing more assets make more omission errors may be due in part to large funds having little incentive to exploit small, yet profitable investment opportunities because their relative contribution to the fund's overall profitability would be tiny.

All the models in Table 6 support H3 by showing that a decentralized fund makes significantly more commission errors than does a centralized one. As before, the coefficients for the individual manager have the predicted sign but are not significant. Parent size and net assets, which were significant controls in the regressions of omission error, are not significant predictors of commission error; this may mean that small funds devote comparatively more resources to minimizing commission (rather than omission) errors.

Two controls that are typically significant in studies of investment performance—the fund's Beta and its investment category—are not significant predictors of either omission or commission errors. The reason is that the bootstrap mechanism used to compute the errors already controls for these parameters: each fund is compared in standardized terms against a large number of funds that draw stocks from the same investment universe and so, on average, have the same Beta and investment category as the focal fund.

6.3 Ruling Out Alternative Hypotheses

Mutual funds offer the best available setting to test the Sah and Stiglitz model's predictions because this setting offers observability of structure and omissions, a large number of observations, and cross-sectional variance in structure. At the same time, the setting is not perfect because there is essentially no variation of structure over time. This means that, when making causal interpretations, close attention must be paid to possible endogeneity and unobserved heterogeneity issues. The following logic shows how difficult it is to construct alternative hypotheses that might bias the results in the same direction as predicted by the Sah and Stiglitz model.

The controls used in the regressions (for parent and firm size, risk profile, and the investment category dummies) serve to rule out simple alternative hypotheses such as relating a type of error to an investment strategy. More importantly, the bootstrap (described in Sections 5.3 and 5.4)—by controlling for the specific environment faced by each fund—takes care of a large set of possible issues, such as the effect that economy-wide shocks could have on different funds.

Unobserved heterogeneity seems unlikely for two reasons. First, any unobserved heterogeneity explanation due to a deliberate preference of managers for omission or commission seems implausible because mutual fund managers are primarily concerned with surpassing a benchmark, not with *how* this benchmark is surpassed, and omission and commission errors contribute equally to the performance of the fund vis-à-vis the benchmark. Omission and commission errors are equally costly for mutual funds. After all, failing to buy a stock that would have contributed $1 to returns is no more or less costly than buying a stock that subtracted $1 from returns; in both cases there is a loss of $1 with respect to a competing fund that did not make the same error.

Second, most imaginable unobserved characteristics should affect both buy and sell decisions. Yet it turns out that structure affects only the buy decisions. (In regressions for the omission

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and commission errors on the sell decisions, available from the author on request, none of the structure coefficients was significant.) This is consistent with a mechanism that surfaced during informal interviews with fund managers. They revealed that, although the purchase of stocks is quite deliberative, the sale of stocks is a semi-automatic process that is often guided by stop-loss orders or tax and liquidity considerations.

Another issue that may bias the results would be incorrect imputation of organizational structure. It could be argued that some of the funds that are coded as being managed by one individual are really managed by either a hierarchy (N/N) or a polyarchy ($N/1$) but that these details do not appear in the Morningstar report from which structure is coded. Yet if that were the case then it would bias the conclusions *against* the hypothesized results—namely, it would be harder for funds coded as hierarchy and polyarchy to be statistically different from the mass of funds coded as individually managed. In other words, Morningstar reports that were imprecise in this way would bias the results in a conservative fashion.

7   Discussion

This study has used mutual funds as a rich data source to explore how organizational structure affects organizational performance. In perfect accordance with predictions of the Sah and Stiglitz model of fallible decision making, decentralized structures accept more projects (H1), make fewer omission errors (H2), and make more commission errors (H3) than do centralized structures. This section places these results in perspective.

7.1   Mutual Funds and Organizational Structure

Two questions come to mind regarding the organization design of mutual funds: Is there an optimal organizational structure for mutual funds? And why is the individual manager the most common structure? (Note that 53.2% of the funds in the data set used this structure.)

As mentioned previously, omission and commission errors are equally costly for a mutual fund concerned only with maximizing returns. Hence, the structure this hypothetical fund should choose is the one that minimizes the sum of both errors. Strikingly, the sum of the omission and commission errors (measured as standardized scores) for each of the three structures is statistically

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indistinguishable from zero (i.e., if the coordinates of the points on Figure 1 are added, the results are $-0.28 + 0.28 = 0.00$, $-0.17 + 0.15 = -0.02$, and $-0.12 + 0.10 = -0.02$ for structures $N/1$, $1/1$, and N/N, respectively). Given this equivalency in overall errors, it seems natural that most funds choose the least expensive structure. The existence of funds with structures different from $1/1$ may speak to other concerns, such as securing continuity against manager turnover, offering promotion opportunities to junior employees, or creating a differentiated product.

There is a special beauty to the fact that, in the mutual fund setting, the overall error of each structure is not different from the overall error of picking stocks at random: The unpredictability of returns stated by the efficient market hypothesis holds when looking at the overall error, even if each error measured independently is partly predictable. This equivalency in the cost of errors is also beneficial (and perhaps essential) for the purposes of the empirical test carried out in this paper, for otherwise it is likely that mutual funds would all flock to the structure minimizing the relevant error and thereby drain the data set of variation in the independent variable.

Thus, the mutual fund setting has a particular characteristic that does not generalize to other domains: in the structure–errors–performance chain of causation, structure affects errors (i.e., *organizational* performance) but errors (as long as they cost the same and add up to the same overall error) do not affect *competitive* performance. In most other settings (in which the two errors have different costs), errors should affect competitive performance. Generalizing results to such other domains is discussed next.

7.2 Generalizability to Other Domains

This paper's proof of the hypotheses derived from Sah and Stiglitz (1986) serves as a foundation on which to guide structure recommendations. The key observation in this context is realizing that different organizations face different costs for omission and commission errors. For example, juries are more concerned with commission errors (i.e., to avoid convicting the innocent); the typical IT department also is presumably more concerned with minimizing commission errors (e.g., not leaking sensitive information) than with minimizing omission errors (e.g., implementing every good IT innovation); and a well-funded R&D lab in an industry characterized by first-mover advantages is more likely to be concerned with avoiding omission errors. Thus, this paper supports the following recommendations for organizations aiming to choose the best structure given the environment

it faces. If the omission error is the costlier error, then the organization is better served by a polyarchical ($N/1$) structure; if the commission error is costlier, the organization is better served by a hierarchical (N/N) structure.[15]

This research also speaks to the unexplored question of what are the processes that link organizational structure to exploration and exploitation (Siggelkow and Levinthal, 2003:650; Argyres and Silverman, 2004:929; Raisch and Birkinshaw, 2008:380). A relevant observation in addressing this question is that omission and commission errors are another way of looking at exploration and exploitation (Garud, Nayyar, and Shapira, 1997:33; Garicano and Posner, 2005:157). The logic of this argument is that, on the one hand, firms in unstable or fermenting environments must try to avoid omissions because these curtail the extent of exploration of new high-fitness positions. Illustrations of this behavior are Bill Gates saying that "the real sin is if we [Microsoft's R&D] miss something" (Hawn, 2004) and Andy Grove's quip, "miss the moment [for change in a high-tech firm such as Intel] and you start to decline" (Stratford, 1993). On the other hand, firms facing stable or incrementally changing environments try to avoid commission errors, since these could disrupt their currently efficient exploitative operations. Examples of these phenomena include Procter & Gamble, where new product proposals are often reviewed more than 40 times before reaching the CEO (Herbold, 2002:74), and IBM's mainframe-era inspired "non-concur policy," which enabled any department to veto projects initiated anywhere in the firm (Gerstner, 2003:192–199). Hence, given that (i) it has been shown here how organizational structure can influence the omission and commission errors made by organizations and (ii) previous research has shown that these errors control the degree to which organizations can explore and exploit, this paper exposes a mechanism by which organizational structure can influence exploration and exploitation.

A core debate in strategy and organization design has concerned the direction of causality in the relationship between strategy and structure. On the one hand, there is Chandler's (1962) famous dictum that "structure follows strategy." On the other hand, several authors have argued in favor of a reverse, complementary logic—in other words, that structure may also influence strategy (see, e.g., Burton and Kuhn, 1979:4; Burgelman, 1983:61; Pettigrew, 1987:665). The current paper describes clear mechanisms for both directions of the causality arrow. If strategy is understood

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[15]It is possible to make finer-grained structure recommendations (i.e., recommending a specific N and C) by feeding into the model information about the situation in question (e.g., cost of each of the errors, cost of each decision maker).

as the pool of all the projects pursued by the organization (akin to Mintzberg's (1978) concept of emergent strategy), then structure influences the types of project that end up in that pool (e.g., hierarchy decreases commission errors) and thus structure influences strategy. On the other hand, if strategy is understood as a deliberate plan (i.e., in a Chandlerian way), then the role of organization becomes subordinate to strategy (e.g., a firm that wants to reduce commission errors decides to use a hierarchical structure) and so strategy influences structure.

7.3   Further Work

Further research could employ alternative settings (or perhaps alternative experiments) to explore the predictions of the model that cannot be tested using the current data set. Some questions open to empirical examination involve the omission and commission errors associated with structures other than those studied here as well as how committee decision making interacts with other organizational dynamics, such as power. Another line of inquiry, very much in the spirit of contingency theory, could explore whether firms that exhibit a better structure–environment fit achieve a higher performance or exhibit a higher rate of survival. For example, in industries requiring more conservative decision making (i.e., where commissions are costlier than omissions), one would expect the performance of firms using higher consensus levels to surpass that of those using lower levels.

In more general terms, this paper also suggests that decomposing performance into omission and commission errors can reveal phenomena otherwise unobservable when using standard performance measures. Hence, future research on organizations may benefit from including omission and commission errors as alternative measures of performance.

7.4   Conclusions

From a theoretical point of view, this research presents a mechanism by which micro decisions are aggregated into macro behaviors and links to important questions of strategy research—for example, "Do organizations have predictable biases?" (Cyert and March, 1963:21), "What do we know about the relationships between organizational size (or other stable characteristics) and behavior?" (Rumelt et al., 1994:42), and What is the relationship between decision making and decision outcomes? (Zajac and Bazerman, 1991:37).

From a practical standpoint, this research sheds light on how the structure of organizations can

be modified to compensate for the shortcomings of individuals, and it allows several managerial concerns to be addressed: What type of organization is required in order to avoid exceeding a given error level? Is it true that hierarchy hampers innovation? What organizational structures can lead to more innovation? In regard to this last question, an important area of application is enabling established organizations to exhibit traits usually associated with entrepreneurial ventures. The 9/11 Commission Report contains an eloquent call for this sort of transformation: "imagination is not a gift usually associated with bureaucracies [...] it is therefore crucial to find a way of routinizing, even bureaucratizing, the exercise of imagination" (National Commission on Terrorist Attacks upon the United States, 2004:344).

Maritan and Schendel (1997:259) observe that "there has been surprisingly little work that has explicitly examined the link between the processes by which strategic decisions are made and their influence on strategy." This paper aims to illuminate that topic by advancing a small step toward understanding how organizational structure aggregates individual decisions into strategic outcomes.

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A Appendix: Model

This appendix develops a model similar to the one presented by Sah and Stiglitz (1986, 1988). The model enables one to derive rigorously all the hypotheses tested in this paper. The aim is to present a synthesis of results relevant for organization design.

The projects faced by the organization are assumed to have a true value that is imperfectly perceived, as a signal plus noise, by the members of the organization. For simplicity, all the members of the organization have the same ability to screen projects; in other words, their screening generates independent draws from the same noise distribution. Finally, the model assumes that each of the two types of error the organization can make (missing a good project or approving a bad one; also known as omission and commission errors, or Type I and II errors,[16] respectively) has a given cost (respectively c_{OE} and c_{CE}).

Mathematically, the model is described as follows. An individual approves a project if her perception of its quality is above a benchmark b. Thus the probability that an individual approves a project of a given quality q is $p(q) = \Pr\{q + \tilde{n} > b\}$, where $\tilde{n}$ is a random draw from a noise distribution. An organization with N members and consensus level C will approve the project if at least C of its members approve it, which happens with probability

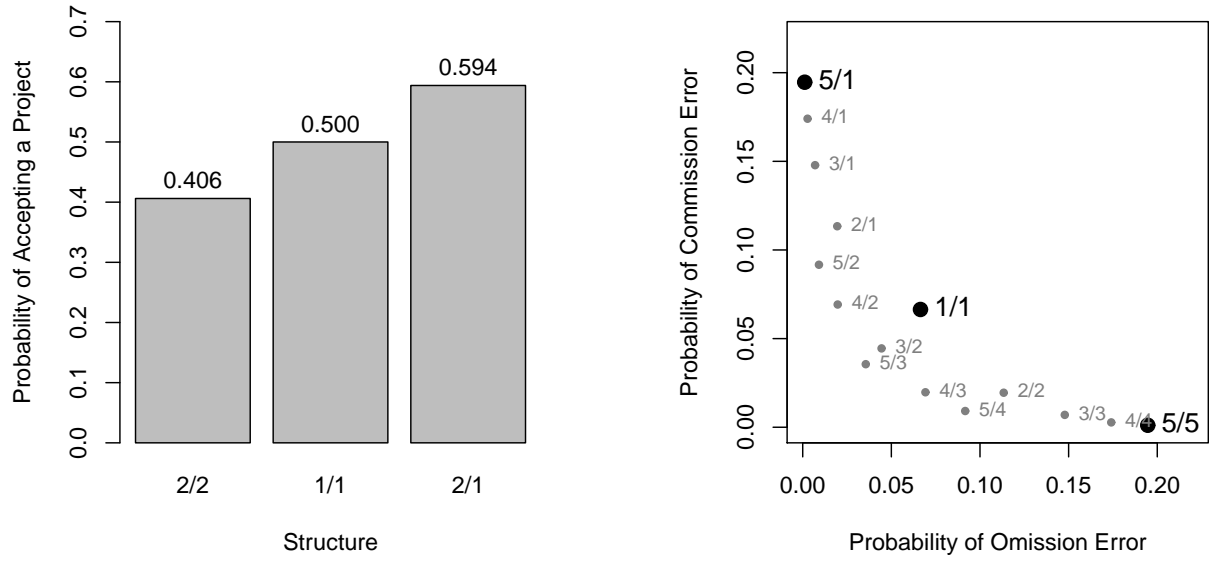$$P(q; N, C) = \sum_{i=C}^{N} \binom{N}{i} p(q)^i \big(1 - p(q)\big)^{C-i}.$$

Based on this formula, several organization-level metrics can be computed.

The probability that an organization will accept a project of an unknown quality is the marginal distribution of $P(q; N, C)$ with respect to q (with probability density function $f_{\tilde{q}}(q)$),

$$P_A(N, C) = \int_{-\infty}^{\infty} f_{\tilde{q}}(q) P(q; N, C) \, \mathrm{d}q. \tag{1}$$

Figure 2a shows the expected probability of accepting a project by three organizational structures (a centralized structure, 2/2; an individual manager, 1/1; and a decentralized structure, 2/1) under

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[16]Some researchers have argued that the labeling should be reversed (i.e., to map omission and commission errors into Type II and I errors, respectively). The convention used depends on what is considered to be the null hypothesis. This paper retains the labeling used by Sah and Stiglitz (1986) and seeks to preclude confusion by speaking mainly of omission and commission errors and less often of Type I and II errors. See footnote 10 in Langlois (1997:91) for more details about this notational issue.

(a) Probability of accepting a project (for all N/C structures of fewer than three members).

(b) Probabilities of omission and commission errors (for all N/C structures of fewer than six members).

Figure 2: Predictions of the model under the assumptions $\tilde{q} \sim U[-3, 3]$, $\tilde{n} \sim N(0, 1)$, and $b = 0$.

the assumptions $\tilde{q} \sim U[-3, 3]$, $\tilde{n} \sim N(0, 1)$, and $b = 0$.

The probability that a given N/C organization will miss a good project (a Type I or omission error) is the probability of rejecting $(1 - P(q; N, C))$ a good project $(q > b)$ weighted by the probability of receiving a project of that quality $(f_{\tilde{q}}(q))$; that is,

$$P_{\text{OE}}(N, C) = \int_{b}^{\infty} f_{\tilde{q}}(q)\big(1 - P(q; N, C)\big)\, \mathrm{d}q. \tag{2}$$

Similarly, the probability of accepting a bad project (a Type II or commission error) is

$$P_{\text{CE}}(N, C) = \int_{-\infty}^{b} f_{\tilde{q}}(q)P(q; N, C)\, \mathrm{d}q. \tag{3}$$

How an organization's structure affects the types of error it makes becomes more evident when plotted on a graph. Figure 2b plots all the organizations with up to five individuals (1/1, 2/1, 2/2, 3/1, 3/2, ...) according to their omission and commission errors and under the same probability distribution assumptions used for Figure 2a. As before, the exact positions of the organizations vary depending on the probability distributions used but their relative ordering (along both dimensions) does not vary.

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According to the model, the optimal organization design for a given setting would be the one that minimizes the overall cost of the errors—i.e., N and C such that $c_{\text{OE}} P_{\text{OE}}(N, C) + c_{\text{CE}} P_{\text{CE}}(N, C)$ is minimized. If appropriate, the wages of the decision makers (e.g., wN) could be added to the previous sum.