Effects of modularity on the organizational performance in presence of conformity

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Abstract

Purpose. This research seeks to explore the intersection between modularity and conformity in organizational contexts. Modularity, a cornerstone of organizational design, pertains to the decomposability of tasks within an organization into subtasks with internal interdependence and external independence. Conformity, on the other hand, is the adjustment of an individual's behavior to match that of others, often driven by a desire to adhere to social norms.

Design/methodology/approach. We employ agent-based modeling and simulation as a technique to model organizations as complex systems. This approach allows us to study the effects of modularity in organizational structures on organizational performance, with a particular emphasis on the role of conformity in this relationship. We treat conformity as exogenously given, which allows us to focus on its effects rather than its emergence.

Findings. The results demonstrate that a concentration of interdependent tasks within fewer departments can boost overall performance. Conformity decreases performance in all organizational structures except for cases when the departments work on highly similar tasks. This decline in performance can also explain why functional organizational structures are still being used in practice even though they are less modular than divisional structures — they feature lower levels of conformity and, thus, face smaller decline. Finally, we find that in highly complex settings, organizational performance can, surprisingly, be improved as complexity within departments increases.

Originality. To the best of our knowledge, this study is the first to explore the modularity in organizational structures in presence of conformity. Distinctively, we adapt the *NKCS* model from evolutionary biology to our study, and perform an exhaustive analysis by examining all possible combinations of parameters that refer to the task allocation within organizations. We thereby contribute a unique perspective to the discourse on organizational theory and behavior.

Keywords: agent-based modeling, decomposability, organizational structure, social norms

1. Introduction

The structure of an organization is one of the most fundamental determinants of its operational performance. According to Daft (2015), organizational structure serves as a roadmap for task allocation, workflows, communication channels, and encompasses vertical and horizontal dimensions of an organization. The vertical dimension involves defining formal roles, reporting relationships, and the number of hierarchy levels. It also includes the grouping of individuals into departments and defining the interrelatedness of these departments. The horizontal dimension ensures effective communication, coordination, and integration of efforts across departments.

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Building upon the foundation of organizational structure, the concept of modularity and decomposability emerges as a central theme in organizational design and operation. Modularity, as defined by Baldwin and Clark (2000), refers to the degree to which an organization's tasks or processes can be segmented into smaller, largely autonomous modules. This structural design principle allows for the independent design, modification, and management of individual components, while maintaining an effective contribution to overall system performance. This decomposition of tasks or sub-processes mitigates systemic complexity and enhances flexibility. Furthermore, Langlois (2002) emphasizes the critical role of modularity in navigating economic and organizational change and fostering innovation. By enabling more efficient coordination of tasks and resources, a modular organization design improves the management of complexity and facilitates organizational evolution in response to a fluctuating business landscape. Thus, modularity in organizational structure presents a strategic design choice with far-reaching implications for an organization's performance and competitive positioning.

However, most research on organizational structures focuses on the underlying tasks and the nature of the problem domain, and pays less attention to the decision making process of individuals working in the organization Anand and Daft (2007). In this study, we analyze the effects of conformity on individual search behavior and, consequently, on organizatinal performance within various organizational structures. Here, the search behavior refers to the agents' problem-solving and decision-making efforts, while conformity, defined by Cialdini et al. (1990), captures the willingness of the agents to match their decisions with those of the group. We treat conformity as independent of the organizational structure and stemming from agents' inner desire rather than the nature of their tasks. We use the agent-based simulations approach (Leitner and Wall, 2015; Wall and Leitner, 2021) and base our model on the *NKCS* framework (Kauffman and Johnsen, 1991). This model represents a complex organizational environment, embodying real-world limitations of individual cognitive capacities, such as bounded rationality. In particular, we model our agents to follow the Social Cognitive Optimization algorithm (Xie et al., 2002) in making their decisions. We study different organizational structures by varying the allocations of tasks to departments, while keeping the overall complexity constant.

We find that the conformity generally decreases organizational performance. However, this decrease is less pronounced for some organizational structures, and conformity can even boost performance in geographic organizational structures. We also find that in highly complex organizations, increasing interdependence within departments can enhance performance, even when this increases overall complexity.

The rest of the paper is structured as follows: Sec. 2 presents the research background and literature review, Sec. 3 formalizes the model used in our simulations, Secs. 4 and 5 present and summarize the results and discuss them, and Sec. 6 concludes the paper.

2. Literature Review

2.1. Organizational structures

The concept of modularity in organization design serves as an efficient strategy for managing complexity and facilitating problem-solving. Simon (1962) stated that decomposable systems or modular organizations allow for division of labor, specialization, and more manageable problem-solving. Langlois (2002) highlighted that, while advantageous to organizations, modular systems are much more difficult to design than comparable interconnected systems. In that sense, a well-decomposed system must pay a fixed cost that an intertwined system does not need to pay. Furthermore, Baldwin and Clark (2000) emphasize that while modularity generally is better for organizations, starting with the modular structure takes away the freedom to choose the design, because firms will need to expend resources to switch back to the intertwined system and the result will generally decrease the performance.

Ethiraj and Levinthal (2004b) stress the importance of proper partitioning in an organization, asserting that an effective modular structure should reflect the problem structure being addressed, which is difficult to observe. Thus, the choices of modules are guesses about the appropriate decompositions. This underscores the importance of informed decisions regarding the organization's structural design without bias towards or against modularity.

Claussen et al. (2015) categorizes non-modular situations in the context of product design into "component complexity" and "interface complexity". This logic can be transferred to the domain of organizations, where component complexity refers to the interdependencies within an individual department of an organization, while interface complexity refers to the interactions between the departments. This distinction is important for our further investigation of the impacts of decomposability and modularity on organizations.

Management literature broadly classifies different task allocation patterns into several organizational structures (Anand and Daft, 2007). Functional structures allocate tasks into departments by function (e.g. Marketing, Finance, Manufacturing etc.), and thus capture cases with high interdependence and low similarity in tasks of departments. Divisional structures allocate tasks in such a way that each department works on a different product, and thus capture cases with low interdependence and higher similarity in tasks of different departments. Management studies also highlight different organizational structures, such as matrix structures, geographic structues, hollow structures (Daft, 2015). Nevertheless, most modeling efforts still focus on the underlying task allocation patterns instead of broad categories to more precisely capture the organizational structures (Zhou, 2013).

2.2. Decomposability and modularity

Modularity in organizational structures presents certain advantages and potential challenges. Aggarwal et al. (2011) emphasized that modularity speeds up the process of finding solutions and makes complexity more manageable, but it can also limit exploration to easily reachable, though not necessarily optimal, solutions. On the other hand, Brusoni et al. (2007) suggests that non-modular systems, while slower, can explore a wider range of possible solutions but may come across less practical or even unworkable options. Ethiraj and Levinthal (2004a) argue that modularity is preferred in situations where rapid adaptation and innovation are valued more than achieving the optimal outcome, because it allows for multiple strategies to be tested in parallel in each module.

Organizations, as complex systems, often exhibit not fully modular, but near-decomposable structure — certain overlaps and interdependencies between departments always exist (Simon, 1962). Baldwin and Clark (2000) also stated that the overall complexity is inherent to a problem or an environment and can only be reallocated to different departments in various ways, but not be increased or decreased. A big stream of research has used the agent-based simulations approach to analyze the effects of modularity of these systems on their performance (Levinthal, 1997; Rivkin and Siggelkow, 2003; Ethiraj and Levinthal, 2004b). Levinthal and Workiewicz (2018) modeled near-modular systems by differentiating interdependence links between modules and the links within modules. This approach contrasts with near-decomposable systems, where the interdependence links are similar both within and across modules. In our research we particularly focus on the (near-)decomposable systems.

2.3. Conformity

Conformity is a widespread phenomenon that occurs in groups, including the organizational settings (Deutsch and Gerard, 1955). Cialdini and Goldstein (2004) defined conformity as changing one's own behavior to match that of others. They differentiated it from compliance in that the latter refers to a positive response to someone's explicit request, while the former arises solely from individuals internal desire.

Studies have highlighted multiple reasons why individuals conform, such as blending into a group (Brewer and Roccas, 2001), gaining social approval (Cialdini and Trost, 1998), using others' behavior as a shortcut to make decisions without activating their cognitive resources (Chartrand and Bargh, 1999), diffusing responsibility over a risky action (Pryor et al., 2019).

Conformity of agents in organizations has been studied analytically (Bernheim, 1994; Akerlof, 1980) and using agent-based simulations (Khodzhimatov et al., 2021). Khodzhimatov et al. (2022b) studied the effects of conformity on performance and Khodzhimatov et al. (2021) compared the effectiveness of different incentive schemes in guiding the individual behavior of decision makers towards increased (overall) organizational performance in presence of conformity. They found that conformity may crowd out the positive effects of team-based incentives in highly complex environments. In this paper, we study the effects of various forms of task allocation that result in different organizational structures on performance in presence of conformity.

2.4. Search behavior

Finally, we look at the literature on search behavior in organizations. Baumann et al. (2019) highlights that the interdependencies among different subproblems affect the agents' search behavior. Brusoni et al.

(2007) calls this phenomenon when coupled tasks within an organization automatically instigate cooperation between agents the "embedded coordination". This can often lead to coordination problems, which are minimized through a modular problem structure. Related to this discussion, Baldwin and Clark (2000) state that modularity should not be the end goal, as it can be beneficial only if it mirrors the decomposable nature of the underlying problem. Rivkin and Siggelkow (2003)'s model of organizational design advocates for near-decomposition over full decomposition, as it strikes a balance between search and stability.

Moreover, Rivkin (2000) and Ethiraj et al. (2008) showed a dual role of modularity — on one hand, it can improve performance by enabling independent search behavior and adaptation, on the other hand, it exposes the firm to imitation risks by making the solutions easier for competitors to understand and replicate. The firm thus faces a complex decision: it must balance the benefits of improved performance against the potential costs of increased vulnerability to imitation.

In our research, we focus on conformity over imitation, considering them as distinct behavioral patterns. Particularly, conformity comes from an internal desire to gain social approval or to make decisions using shortcuts (see Sec. 2.3), while imitation is a search behavior that seeks to find best solutions by copying decisions of the high performers (Rivkin, 2000; Ethiraj et al., 2008).

In this paper we model the search behavior as efforts by agents to increase their performance and level of conformity together. When the agents face a decline in performance due to conformity, they do not stop conforming, as opposed to imitation as a type of search behavior, when individuals replicate others' behavior to reach their performance level, and stop doing so when the imitation leads to a decline in performance.

3. Model

In this section we introduce the agent-based model of an organization, in which $P = 4$ individuals face a complex task. The task environment is based on the *NK*-framework (Kauffman and Weinberger, 1989; Levinthal, 1997). Agents make decisions to (a) increase their compensation (based on performance) and (b) conform to the behavior of their peers. To get a more detailed understanding of the conformity as a search behavior, we consider agents working on tasks of varying level of similarity, modeled as correlations between the tasks assigned to the agents. Sec. 3.1 introduces the task environment, Secs. 3.2 and 3.3 characterize the agents and describe how conformity is modeled. Sec. 3.4 describes the agents' search process, and Sec. 3.5 provides an overview of the sequence of events in the simulation. We included a more detailed model description using ODD protocol (Grimm and Mengel, 2018) in an online Appendix.

3.1. Task environment

We model an organization that faces a complex decision problem that is expressed as the vector of $M = 16$ binary choices.[1] The decision problem is divided into sub-problems which are allocated to $P = 4$ agents[2], so that each agent faces an $N = 4$ dimensional sub-problem:

$$\mathbf{x} = (\underbrace{x_1, x_2, x_3, x_4}_{\mathbf{x}^1}, \underbrace{x_5, x_6, x_7, x_8}_{\mathbf{x}^2}, \underbrace{x_9, x_{10}, x_{11}, x_{12}}_{\mathbf{x}^3}, \underbrace{x_{13}, x_{14}, x_{15}, x_{16}}_{\mathbf{x}^4}), \tag{1}$$

where bits $x_i \in \{0, 1\}$ represent single tasks. Every decision on a task x_i yields a uniformly distributed performance contribution $\phi(x_i) \sim U(0, 1)$. The decision problem is *complex* in that the performance contribution $\phi(x_i)$, might be affected not only by the decision x_i, but also by decisions x_j, where $j \neq i$.

We differentiate between two types of such interdependencies[3]: (a) *internal*, in which interdependence exists between the tasks assigned to agent p, and (b) *external*, in which interdependence exists between the tasks assigned to agents p and q for $p \neq q$. We control interdependencies by parameters K, C, S, so that

[1] Since we are simulating a very large number of scenarios, we chose $M = 16$ as a baseline. This is comparable to the number of binary choices in other *NK* simulations. For more discussion on the computational complexity of the *NK* simulations see Weinberger et al. (1996).

[2] Here the agent represents a manager of a department, or the department itself. Thus, $P = 4$ also refers to 4 departments in an organization.

[3] This corresponds to *component* complexity and *interface* complexity by Claussen et al. (2015) mentioned in the previous section.

every task interacts with exactly K other tasks internally and C tasks assigned to S other agents externally (Kauffman and Johnsen, 1991):

$$\phi(x_i) = \phi(x_i, \underbrace{x_{i_1}, ..., x_{i_K}}_{\substack{K \text{ internal} \\ \text{interdependencies}}}, \underbrace{x_{i_{K+1}}, ..., x_{i_{K+C\cdot S}}}_{\substack{C\cdot S \text{ external} \\ \text{interdependencies}}}), \tag{2}$$

where $i_1, \ldots, i_{K+C\cdot S}$ are distinct and not equal to i. The exact choice of the coupled tasks is random with one condition: every task affects and is affected by exactly $K + C \cdot S$ other tasks. In this study we make a two-stage analysis. First stage focuses on the stylized organizational structures: we consider two cases: (i) (potentially) decomposable task environment with $K+C\cdot S = 3$, and (ii) non-decomposable task environment with $K + C \cdot S = 6$. For both cases we consider "tight" allocation of tasks to as few departments as possible, and "loose" allocation of tasks to multiple departments, as depicted in Fig. 1. In the second stage of our analysis we perform simulations for every combination of values K, C, S such that $K + C \cdot S < M = 16$.

Using Eq. 2, we generate *performance landscapes* as follows: for every task x_i we generate performance contribution values corresponding to every combination of interdependent decisions from a uniform distribution. This results in a $N \times 2^{1+K+C\cdot S}$ matrix of uniform random numbers. We generate entire landscapes at the beginning of every simulation run to find the overall global maximum and normalize our results accordingly, to ensure comparability among different simulation runs.

At each time period t, agent p's performance is a mean of performance contributions of tasks assigned to that agent:

$$\phi_{own}(\mathbf{x}_t^p) = \frac{1}{N} \sum_{x_i \in \mathbf{x}_t^p} \phi(x_i), \tag{3}$$

and the organization's overall performance is a mean of agents' performances:

$$\Phi(\mathbf{x}_t) = \frac{1}{P} \sum_{p=1}^{P} \phi_{own}(\mathbf{x}_t^p) \ . \tag{4}$$

The tasks allocated to agents can be similar or distinct. We model this using the pairwise correlations between performance landscapes:

$$\mathbf{corr}\left(\phi(\mathbf{x}_i^p), \phi(\mathbf{x}_i^q)\right) = \rho \in [0, 1], \tag{5}$$

for all $1 \le i \le N$ and $p \ne q$. When $\rho = 0$ and $\rho = 1$, agents operate on perfectly distinct and perfectly identical performance landscapes, respectively.[4]

3.2. Conformity metric

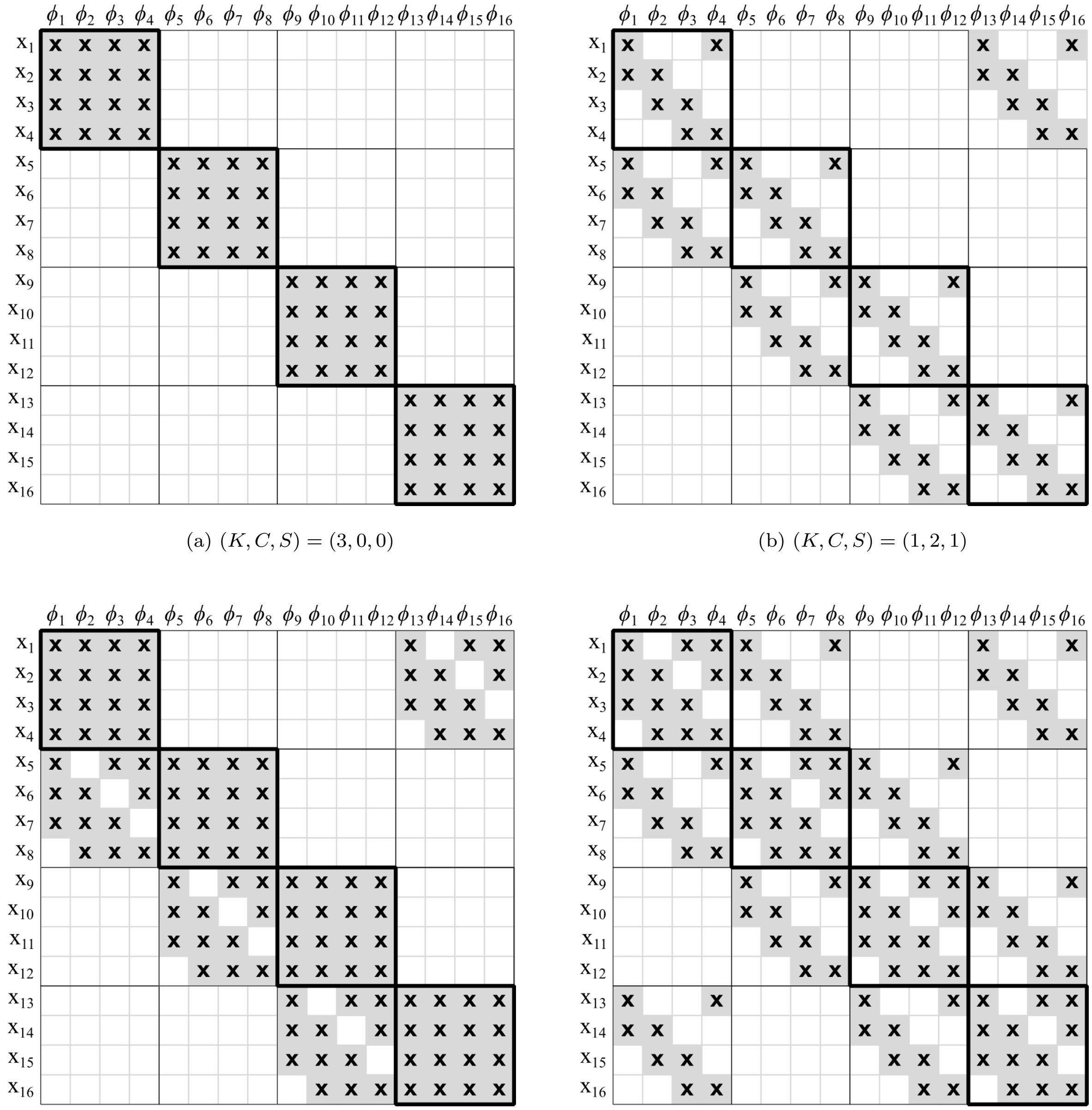
In this section we introduce a measure how much an agent's particular decision conforms to the decisions of other agents. Agents may use this measure in their decisions if they are willing to conform, or ignore it if they are not interested in conforming to the decisions of their peers.

First of all, we note that conformity does not necessarily concern all decisions, as individuals might not want to share information on some decisions, or not be willing to adopt some key or specific decisions they perceive to be a matter of their expertise (Fishbein and Ajzen, 2010). Thus, agents want to achieve conformity in a certain number of so-called *social* tasks they observe in their peers. We denote this number by $N_s \le N$. This is a key parameter that represents the extent to which the agents are willing to conform (e.g., $N_s = 0$ represents no desire to conform, and $N_s = N$ represents the desire to conform fully).

Without loss of generality we use the convention that the private tasks come first and social tasks come next. For example, if $N_S = 2$, then the first 2 tasks are social:

$$\mathbf{x}^p = (\underbrace{x_1^p, x_2^p}_{\text{social}}, x_3^p, x_4^p) \tag{6}$$

[4]For implementation details on how to generate matrices with correlated blocks see the methodology of Verel et al. (2013)



(a) $(K, C, S) = (3, 0, 0)$

(b) $(K, C, S) = (1, 2, 1)$

(c) $(K, C, S) = (3, 3, 1)$

(d) $(K, C, S) = (2, 2, 2)$

Figure 1: Stylized interdependence structures with $M = 16$ tasks equally assigned to $P = 4$ agents. The crossed cells indicate inter-dependencies as follows: let (i, j) be coordinates of a crossed cell in row-column order, then performance contribution $\phi(x_i)$ (denoted here by ϕ_i for brevity) depends on decision x_j. Note that the task structure is (potentially) decomposable in examples (a) and (b), and non-decomposable in (c) and (d). For each task structure we consider "tight" and "loose" allocations. Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

We implement our version of the Social Cognitive Optimization algorithm introduced by Xie et al. (2002). At every time step t, agents share their decisions on social tasks with $D < P$ fellow agents, according to the network structure predefined by the modeler. In particular, we use the bidirectional *ring network*, in which each node is connected to exactly $D = 2$ other nodes with reciprocal unidirectional links, where nodes represent agents and the links represent sharing of information (see Fig. 2). Every agent stores the shared information in the memory set L^p for up to $T_L = 50$ periods, after which the information is "forgotten" (removed from L^p).

The measure of conformity of agent p's decisions $\mathbf{x}_t^p$ is computed as the average of the matching social

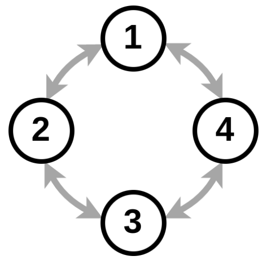


Figure 2: Bidirectional ring network with 4 nodes, where each node is connected to exactly 2 other nodes. Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

bits in the memory:

$$\phi_{soc}(\mathbf{x}_t^p) = \begin{cases} \dfrac{1}{|L_t^p| \cdot N_S} \displaystyle\sum_{\mathbf{x^L} \in L_t^p} \sum_{i=1}^{N_S} [x_i^p = x_i^L], & t > T_L \\ 0, & t \leq T_L \end{cases} \tag{7}$$

where $|L_t^p|$ is the number of entries in agent p's memory at time t, and the statement inside the square brackets is equal to 1 if true, and 0 if false (Iverson, 1962).

Note that, in presence of conformity, the correlation coefficient ρ defined in Eq. 5 starts to play an important role: the conformity can either increase or decrease the organizational performance depending on the correlation among tasks allocated to different agents. We neglect scenarios, when $\rho < 0$ to more accurately capture the collaborative dynamics commonly found in organizations in which all departments are aligned toward mutual objectives. Moreover, even in situations in which the same decision may result in opposite payoffs to different departments (e.g. choosing *Excel* over *SQL* might be beneficial for a Marketing department, but decrease performance for an Operations department), making the same decision is accompanied with sharing of knowledge and relevant expertise, which to some extent makes up for the performance loss (e.g. even though using *SQL* would decrease performance for a Marketing department, if Operations department also uses it, they can provide a technical support to the Marketing department). This relation is best represented by a nonnegative correlation coefficient.

3.3. Individual preferences

We model individual preferences of agents as a function of income ϕ_{inc} and conformity metric ϕ_{soc} (see Eqs. 3 and 7). Previous literature provides different approaches to modeling conformity-based preferences. Fischer and Huddart (2008) frames that conformity reduces cost for the action, Akerlof (1980) claims that individual utility is a function of performance and reputation that depends on the level of conformity. Moreover, Tversky and Kahneman (1991) have introduced *reference-dependent* preferences, in which individuals want to increase their own consumption, however their willingness declines, once they reach a certain reference level. Similarly, Gali (1994) has introduced a preference model called *keeping up with the Joneses* in which individuals want to minimize the distance between their own consumption level and the aggregate level of per capita consumption, i.e. they consider the behavior of others as the reference point for their own behavior.

In this paper we model individual preferences as a linear function, namely a sum of income and conformity metric:

$$u(\mathbf{x}) = \phi_{own}(\mathbf{x}) + \phi_{soc}(\mathbf{x}), \tag{8}$$

where ϕ_{own} and ϕ_{soc} both fall in range between 0 and 1 and have a unit coefficient.[5]

[5]This is a special case of a utility function defined by Khodzhimatov et al. (2021), who showed that modifying their coefficients changes the long-term performance, but does not alter the effect of other parameters on performance.

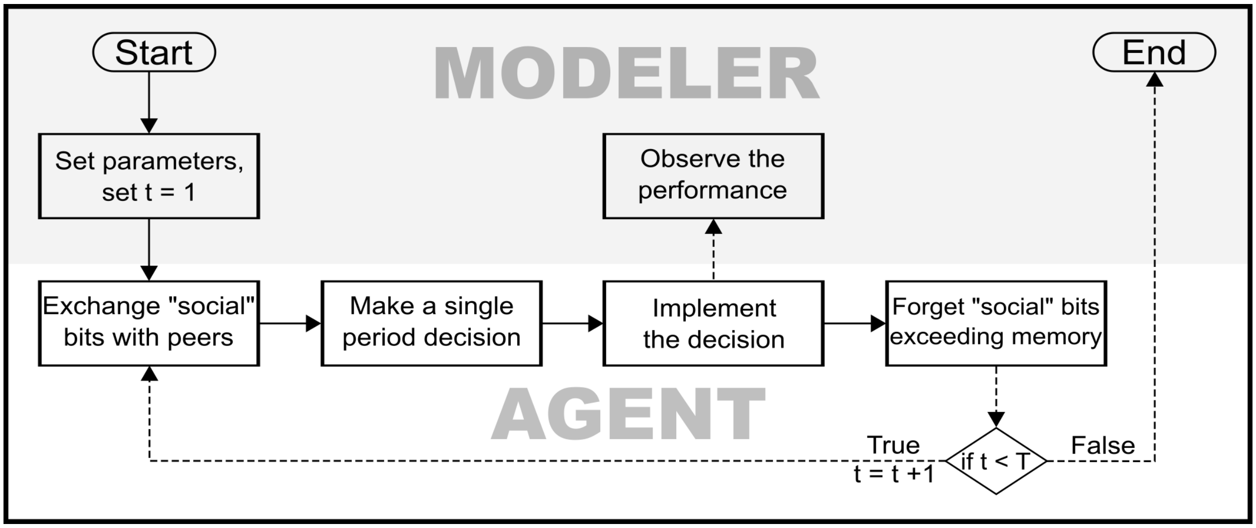


Figure 3: Process overview. Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

3.4. Search process

In line with Simon (1957), our agents are *boundedly rational*. In particular, the agents are not global optimizers and want to increase their utility given limited information: at time t, agents can observe their own performance in the last period, $\phi_{own}(\mathbf{x}_{t-1}^p)$, and the decisions of all agents in the last period *after* they are implemented, $\mathbf{x}_{t-1}$.

In order to come up with new solutions to their decision problems, agents follow the *hill-climbing* algorithm by performing a search in the neighbourhood of $\mathbf{x}_{t-1}$ as follows: agent p randomly switches one decision $x_i \in \mathbf{x}^p$ (from 0 to 1, or vice versa), and assumes that other agents will not switch their decisions (Levinthal (1997) describes situations in which agents switch more than one decision at a time as *long jumps* and states that such scenarios are less likely to occur, as it is hard or risky to change multiple processes simultaneously). We denote this vector with one switched element by $\hat{\mathbf{x}}_t^p$.

Next, the agent has to make a decision whether to stick with the status quo, $\mathbf{x}_t^p$, or to switch to the newly discovered $\hat{\mathbf{x}}_t^p$. The rule for this decision is to maximize the utility function defined in Eq. 8:

$$\mathbf{x}_t^p = \underset{\mathbf{x} \in \{\mathbf{x}_{t-1}^p, \hat{\mathbf{x}}_t^p\}}{\arg\max}\ u(\mathbf{x}), \tag{9}$$

3.5. Process overview, scheduling and main parameters

The simulation model has been implemented in *Python 3.8* and optimized using *Numba* just-in-time compiler. To ensure the validity of the model, detailed debugging and code inspection has been conducted. The model was also tested to replicate the results from established studies. Every simulation round starts with the initialization of the agents' performance landscapes, the assignment of tasks to $P = 4$ agents. For reliable results, we generate the entire landscapes before the simulation, which is feasible for $P = 4$ given modern computing limitations, and the initialization of an $M = 16$ dimensional bitstring as a starting point of the simulation run. After initialization, agents perform the *hill climbing* search procedure outlined above and share information regarding their social decisions in their social networks. We observe the organization for $T = 500$ periods, which we found to be enough for the organizational performance to converge. The memory span of the employees[6] is given by $T_L = 50$, and the number of repetitions in a simulation is fixed at $R = 1,000$ on the basis of the coefficient of variation. Fig. 3 provides an overview of this process and Tab. 1 summarizes the main parameters used in this paper.

[6]We do not focus on this parameter in this paper, but we repeatedly found in our simulations that it does not affect the average performance to which the organization eventually converges (Khodzhimatov et al., 2022a).

Parameter	Description	Value
M	Total number of tasks	16
P	Number of agents	4
N	Number of tasks assigned to a single agent	4
K	Number of internally coupled tasks	0, 1, 2, 3
C	Number of externally coupled tasks	0, 1, 2, 3, 4
S	Number of peers with coupled tasks	0, 1, 2, 3
ρ	Pairwise correlation between landscapes	0, 0.3, 0.6, 0.9, 1.0
T_L	Memory span of agents	50
N_S	Number of social tasks (conformity level)	0, 1, 2, 3, 4
D	Number of connected peers (node degree)	2
T	Observation period	500
R	Number of simulation runs per scenario	1,000

Table 1: Main parameters. Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

4. Results

In this section, we present an in-depth analysis of our simulation results, specifically focusing on the functional, divisional, and geographic organizational structures. We examine the impact of conformity on performance, and further analyze the relationship between task allocation, conformity, and performance through linear regression. Our analysis also provides insights into the short- and long-term effects of conformity.

4.1. Stylized organizational structures

We focus on stylized organizational structures defined by various task environments, characterized by combinations of parameters — interdependence of tasks between departments (K, C, S) and the degree of correlation across departments (ρ). Below we summarize these organizational structures as defined by Daft (2015) and Tab. 2 presents a brief overview of these structures.

Functional structure. In a Functional structure tasks are grouped together by common function in the organization (e.g. Marketing department, HR department etc.) Since every department works on an aspect of a product, we expect high interdependencies and low similarity in tasks between departments.

Divisional structure. Divisional structure organizes departments that are self-contained and focus on one product (e.g. cosmetics and beverage divisions in Unilever). When divisions work on different and unrelated products, low correlation is expected even for the same function, e.g. the same Marketing strategy might help one division and hurt another.

Geographic structure. Geographic structure is a type of a "multi-unit" structure that groups tasks by location so that each department includes all functions required to produce and market a product (e.g. Asian and European subsidiaries of a company). We expect there to be a high similarity between tasks serving the same function, e.g. Finance or Production tasks are similar at all locations. Furthermore, we assume low interdependence between departments due to the geographic divide.

We do not focus on the situations when organization's divisions have a highly similar payoff structure while also having high degree of interdependence. This scenario may occur if divisions work on very similar, yet competing products (e.g. if Thinkpad and Ideapad laptops would be produced in two unrelated divisions of Lenovo with their own manufacturing lines). We capture this structure among others in our exhaustive analysis in Sec. 4.4, but we will not be focusing on it separately.

In the structures mentioned above the interdependence between departments corresponds to the *interface* complexity by Claussen et al. (2015). We study these three structures in two environments — (potentially) decomposable (illustrated in Fig. 1 (a-b)) and non-decomposable (illustrated in Fig. 1 (c-d)).

	Low correlation	High correlation
Low interdependence	Divisional structure (e.g. Personal Computers division and Servers division)	Geographic structure (e.g. Lenovo Beijing and Lenovo Morrisville)
High interdependence	Functional structure (e.g. Marketing, Finance, HR)	—

Table 2: Stylized organizational structures explained. Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

4.2. Performance metric

We perform $R = 1,000$ simulations for every combination of parameters presented in Tab. 1. In every simulation run $r \in \{1, ..., R\}$ we are interested in the average performance of an organization throughout its lifespan of $T = 500$ periods. To ensure comparability among different performance landscapes, we normalize the performance values by the maximum performance Φ^r_{max} attainable in the corresponding simulation run r:

$$\Phi = \frac{1}{R \cdot T} \sum_{r=1}^{R} \sum_{t=1}^{T} \frac{\Phi^r_t}{\Phi^r_{\max}} \tag{10}$$

4.3. Effects of conformity on performance

Our study first turns its attention to examining the effects of conformity across different organizational structures. As illustrated in Fig. 4 (a), we analyze decomposable task structures and observe a consistent pattern: conformity, in most cases, results in a decline in performance. This pattern is particularly pronounced in divisional and functional organizational structures. Interestingly, the geographic structure deviates from this trend, exhibiting the potential to see an increase in performance as conformity rises. Furthermore, we note that regardless of the level of conformity (represented by the number of social tasks N_S), the functional structure consistently underperforms compared to the other structures, even when compared to scenarios in which their performance drops due to conformity.

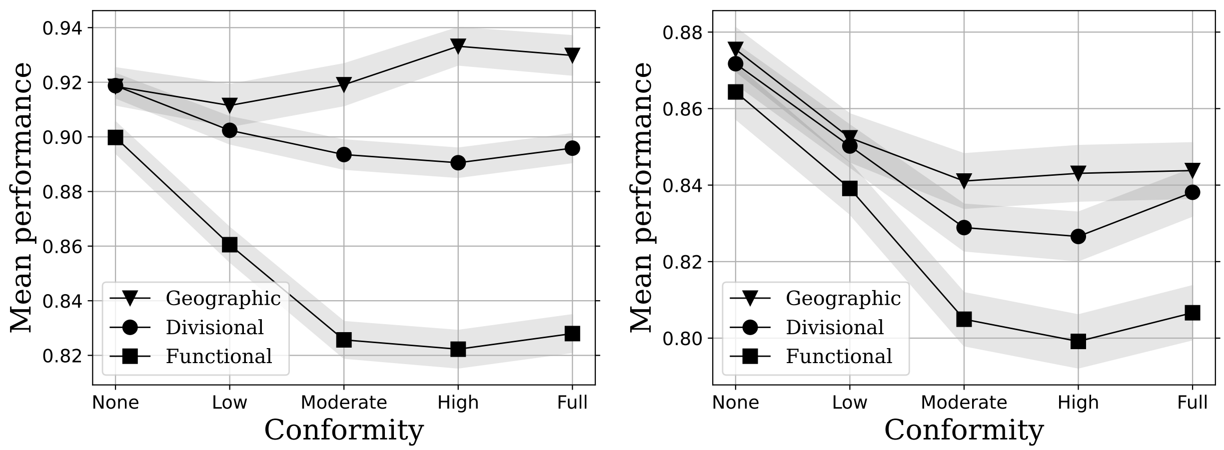
Next, we analyze the results in non-decomposable (i.e. highly complex) environments. Fig. 4 (b) shows that conformity results in a performance decrease for all organizational structures without exception. This result confirms that conformity could be a challenge to organizational performance, particularly in situations where tasks environments are non-decomposable.

Additionally, we find that there exist cases where a functional organization outperforms divisional or geographic structure — in particular, when we compare functional organizations that do not feature conformity with divisional or geographic structures, in which conformity takes place. This result serves as a justification for the existence of functional organizations, even though they are *loosely* coupled, by introducing a new dimension (i.e., conformity) to the discussion.

4.4. In-depth analysis

In the following sections, we conduct a more detailed analysis. We create a new set of data by running our simulations for all parameter combinations. We then perform a linear regression analysis to identify the exact patterns and relationships between conformity, organizational structure, and performance. These regression results support the detailed findings we will discuss in the next sections.

The organization's task environment interdependence structure is characterized by parameters K, C, and S, where, K refers to within-department interdependence, C is the count of tasks interdependent with other departments, and S refers to the number of departments involved in interdependent tasks. Here K corresponds to the *component* complexity, while C and S together correspond to the *interface* complexity. Each of these factors impacts organizational performance differently. Above, we considered three stylized structures to encapsulate diverse organizational structures, but we did not show whether these findings hold up for different parameter combinations. For example, does the performance vary if there is high interdependence within a small number of departments ($C = 3, S = 1$) versus lower interdependence spread across more departments ($C = 1, S = 3$)? To answer such questions, we perform simulations for all values of K, C, and S given in Tab. 1. Moreover, we repeat this analysis for different levels of conformity (N_S) and



(a) Decomposable

(b) Non-decomposable

Figure 4: Mean performance for different levels of conformity for different organizational structures (99% confidence interval). Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

correlation between tasks allocated to different departments (ρ), totalling $2,000$ simulation scenarios with $R = 1,000$ repetitions in each scenario.

After running the simulations, we ran the results through log-linear regressions. To capture the interaction between the parameters, we introduced the interaction variables $(K \cdot C)$, $(K \cdot S)$, and $(C \cdot S)$. Similarly, we introduced the interaction $(N_S \cdot \rho)$ to study the difference in the effects of conformity depending on the correlation between tasks. The regression equation is given in Eq. 11:

$$\log \Phi = \theta_0 + \theta_1 K + \theta_2 C + \theta_3 S + \theta_4 N_S + \theta_5 K \cdot C + \theta_6 K \cdot S + \theta_7 C \cdot S + \theta_8 N_S \cdot \rho \tag{11}$$

To study the average, short-term, and long-term effects of the variables, we performed four regressions for the following dependent variables: the logarithms of the mean organizational performance throughout its lifespan of 500 periods (Φ_{500}) during its first 50 periods (Φ_{50}), and during its first 100 periods (Φ_{100}), and the logarithm of the maximum achieved performance ($\Phi_{\max}$) the logartihms of the which allows us to study the effect over different time spans. The log-linear formulation is convenient, as it allows us to study how a unit change in parameter effects the percentage change in the performance by simply looking at the parameter's coefficient (Wooldridge, 2015). Tab. 3 presents the results of these four regressions. More on the choice of the variables is explained in Appendix B.

4.4.1. Allocating complexity

Our analysis reaffirms the conventional understanding that the complexity of task environment, represented by the number of internal interdependencies (K) and interdepartmental interdependencies (C, S), typically decreases the average performance, as shown by the negative coefficients of these variables.

Particularly, we find that the number of interdependent departments (S) has a greater (negative) impact on performance than the number of interdependent tasks (C). As suggested by the larger coefficient of S relative to C, it seems the scale of departmental interdependencies has a more pronounced negative effect on organizational performance.

Apart from that, our results introduce an interesting finding. We note that when the interdependencies across departments surpass a threshold level ($C, S > 2$), increasing the internal interdependencies (K) could unexpectedly improve performance, even if this increases the overall complexity ($K + C \cdot S$). This intriguing finding is evident in the positive coefficients of the interaction terms $K \cdot C$ and $K \cdot S$ that crowd out the negative effect of K under these high-interdependence scenarios. This highlights the possibility that, under certain conditions, increasing internal complexity could be strategically advantageous for performance.

Both of these findings also hold in presence of conformity, which is captured by the absence of interaction terms between parameters K, C, S and N_S in the regression (see Appendix B for more details).

4.4.2. Further findings

In alignment with our prior findings, the analysis reaffirms that conformity plays a negative role in the organizational performance, as shown by the negative coefficient of N_S. However, this effect is partially offset by the similarity between tasks assigned to different departments, as can be understood from the positive coefficient of the interaction term $N_S \cdot \rho$. This also explains the increase in performance due to conformity in the case of the geographic organizational structure — it is simply a special case with low C and S, and high ρ.

Finally, our regression model, despite being based on an underlying simulation model, which is inherently nonlinear, surprisingly exhibits an almost linear relationship with respect to the parameters under consideration. (See Appendix A for details). These findings further illustrate the complex interplay of the parameters defining the interdependence structure and conformity behaviour, adding nuanced detail to our understanding of organizational dynamics.

	Dependent variable:			
	$\log(\Phi_{500})$	$\log(\Phi_{100})$	$\log(\Phi_{50})$	$\log(\Phi_{\max})$
	(1)	(2)	(3)	(4)
K	-0.040^{***}	-0.037^{***}	-0.036^{***}	-0.042^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
C	-0.021^{***}	-0.020^{***}	-0.021^{***}	-0.022^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
S	-0.037^{***}	-0.035^{***}	-0.035^{***}	-0.038^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
$K \cdot C$	0.010^{***}	0.009^{***}	0.009^{***}	0.011^{***}
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$K \cdot S$	0.016^{***}	0.014^{***}	0.013^{***}	0.017^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
$C \cdot S$	-0.022^{***}	-0.026^{***}	-0.026^{***}	-0.019^{***}
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
N_S	-0.017^{***}	-0.012^{***}	-0.010^{***}	-0.017^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
$N_S \cdot \rho$	0.012^{***}	0.011^{***}	0.010^{***}	0.010^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	0.018^{***}	0.001	-0.014^{***}	0.028^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	2,000	2,000	2,000	2,000
R^2	0.897	0.924	0.922	0.870
Adjusted R^2	0.897	0.924	0.921	0.870
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3: Regression results. Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

5. Discussion

In this study, we studied how different organizational structures effect the organizational performance, and the role of conformity in this relationship. Using the *NKCS* model, we studied how various factors interact within the organization, often in surprising and novel ways. These findings present valuable insights into organizational behavior and organizational design. In this section, we will discuss our key findings and their implications in detail.

5.1. Conformity

The first significant result of our research relates to the role of conformity in organizational performance. Our findings suggest that conformity decreases the performance in most situations. This can be attributed to two factors. First of all, when agents are willing to follow others' decisions due to their inner reasons and not as a part of the search for the optimal solution, they may ignore that the tasks the other agents are facing, might not necessarily be similar to their own tasks. Secondly, even when all agents face highly similar tasks, their interdependence may require for a coordination in which agents' decisions must complement each other but not necessarily duplicate each other.

Moreover, our analysis adds nuance to this general notion by identifying specific contexts in which conformity does not decrease performance or might even slightly enhance it, such as when the agents operate on highly correlated but not interdependent tasks, which we referred to as the *georgraphic* organizational structure. We notice that this particular structure is identical to the models in which all agents operate on exactly one landscape (which is, obviously, perfectly correlated with itself and there are no other landscapes to be interdependent with), and that such models might be operating under an implicit assumption of the geographic structure, which is only a special case in our model.

This discovery aligns with prior studies emphasizing the complex nature of conformity and its effects on an organization's output (Cialdini et al., 1990). However, by providing a deeper exploration into how this principle manifests in distinct scenarios, our findings contribute to a more granular understanding of the impact of conformity on organizational performance.

5.2. Functional structures

The second main insight drawn from our study pertains to the performance of different organizational structures. Our simulations strongly indicate that functional structures, which distribute complexity across multiple departments, consistently result in decreased organizational performance when compared to other models. While this outcome can be anticipated given the foundational principles of the *NK* model (Levinthal, 1997; Rivkin and Siggelkow, 2003; Ethiraj and Levinthal, 2004b), it nonetheless raises an important question: does our formulation of the *NK* model provide a rational reason to utilize functional structures, given that they are ubiquitous in real-world organizations?

Our research suggests that an explanation might lie within the concept of conformity. It appears that functional structures free of conformity yield better results than divisional structures that incorporate conformity. This discovery not only addresses the seeming paradox of functional structure utilization but also uncovers a specific circumstance under which functional structures may be beneficial. Therefore, our findings shed new light on the role and value of conformity within functional organizational structures and provide a potential justification for their continued use in certain contexts. This finding aligns well with a general advice that functional structures can be effective if there is no need for horizontal coordination between departments (Anand and Daft, 2007; Daft, 2015).

5.3. Exploring the NKCS model

Our research provides a deep analysis of the functioning of *NKCS* model by investigating a wide range of parameter combinations. A significant revelation of our simulations is that the concentration of tasks within fewer departments leads to a notable boost in performance when compared to spreading the same number of tasks across a larger number of departments. This observation introduces an innovative contribution to our understanding of the *NKCS* model's dynamics and enriches the literature on organizational structure and performance.

Until now, no known study had provided a comprehensive analysis of this aspect of the *NKCS* model, primarily due to the model's inherent non-linearity and the vast number of potential parameter combinations.

By conducting exhaustive simulations, our research fills this gap, making future explorations of this model more manageable and well-informed. This finding contributes significantly to methodological advancement within the field and offers practical insights for organizational design. Moreover, we find that the effect of conformity on performance in the *NKCS* landscapes is not sensitive to the changes in parameters K, C, S. Further studies could use this finding when modeling the NK landscapes for their own research.

6. Conclusion

In conclusion, this research has shed new light on how task allocation and organizational structures impact overall performance in presence of conformity. The findings suggest that conformity can negatively impact performance, a notion supported by earlier studies but clarified with new nuances in our research. Specifically, we point out the (often unintentional) implicit assumption made by other studies regarding the landscapes in which agents engage in search behavior and exhibit conformity, and we present a more general setting.

Moreover, our research shows that conformity might add another dimension to analyzing organizations. Particularly, we use conformity to provide a new explanation to why organizations use functional structures, even though they feature high interdependencies between departments.

Apart from that, we run *NKCS* simulations for all parameter combinations and perform a statistical analysis of the simulation results. We find that the parameter S has a higher effect on performance than the parameter C, i.e. concentrating a greater number of tasks in fewer departments can yield better performance than spreading them thinly across many departments. More surprisingly, when overall complexity is high, augmenting the internal complexity can actually improve performance. We also find that the effects of conformity on performance do not interact with the parameters K, C, S, and are the same for all task environments.

This study serves as an initial exploration into how organizations can best navigate and manage complexity to achieve their objectives. However, there are some limitations that need to be mentioned. First, the agents in our model do not evaluate the impact of conformity on their performance. This is challenging to model, since in complex environments the same decisions can yield different outcomes depending on the actions of other agents. This is an avenue for future research. Second, our agents are not actively aware if their tasks are correlated with those of other agents, which could impact the effectiveness of their decision-making. Third, we model preferences for performance and conformity as a weighted sum, which is only one of many conformity formulations in the literature. Moreover, we have only looked at the situations in which the departments are equal in size, while this might not always be the case in the real organizations. A further study that considers unbalanaced departments will be of a great interest. Lastly, the model currently assumes that agents work independently on their tasks. Exploring the situations, in which different agents collaborate on the same task, could provide interesting insights into organizations' ability to manage complexity effectively.

Overall, our research provides a clearer understanding of the dynamics of modularity, conformity, and complexity within organizational structures, and provides the groundwork for further explorations into the intricate dynamics of organizational structures and performance. It is our hope that this study inspires more researchers to dive into these complexities, to help organizations operate more effectively in today's increasingly complex and fast-paced world.

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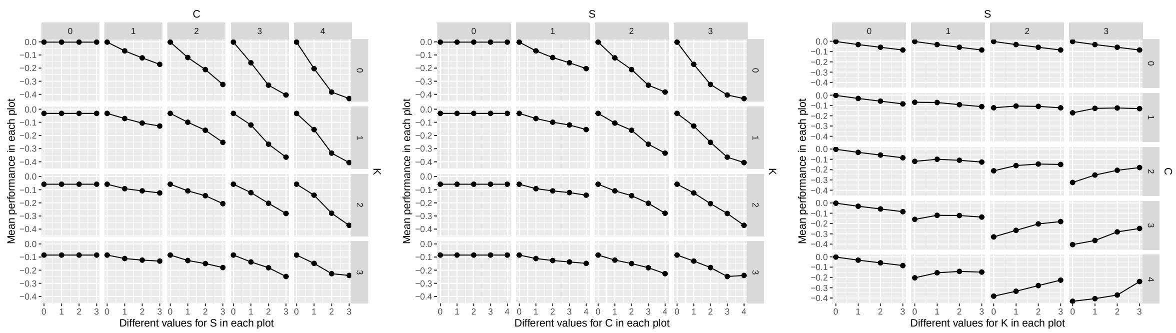
Appendix A. Scatter plots corresponding to the regression results

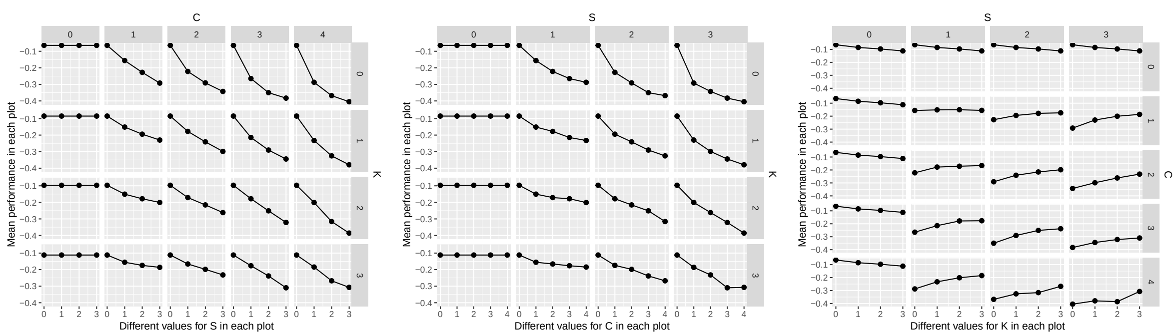
Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

In this Appendix we present the faceted (conditional scatter) plots corresponding to the regression results in Tab. 3. We can see in Fig. A.5 that for high C and S, the plots are increasing in K. Also, we can see that slopes for S are steeper than for C. Fig. A.6 shows that this finding also holds in presence of conformity



$\Phi_{500} \sim S$ for fixed K, C $\quad$ $\Phi_{500} \sim C$ for fixed K, S $\quad$ $\Phi_{500} \sim K$ for fixed C, S

Figure A.5: Matrices of scatter plots of mean organizational performance Φ_{500} against values of one of (K, C, S) holding the other two values fixed in the absence of conformity.



$\Phi_{500} \sim S$ for fixed K, C $\quad$ $\Phi_{500} \sim C$ for fixed K, S $\quad$ $\Phi_{500} \sim K$ for fixed C, S

Figure A.6: Matrices of scatter plots of mean organizational performance Φ_{500} against values of one of (K, C, S) holding the other two values fixed in the presence of conformity.

Appendix B. Stepwise regression results

Credit: Ravshanbek Khodzhimatov, Stephan, Leitner, Friederike Wall.

The following table presents the stepwise regression results that show that the explanatory (independent) variables we omitted in the regression were not statistically significant or had small coefficient.

	$\log(\Phi_{500})$				
	(1)	(2)	(3)	(4)	(5)
K	-0.040^{***}	-0.040^{***}	-0.042^{***}	-0.042^{***}	-0.042^{***}
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
C	-0.021^{***}	-0.021^{***}	-0.021^{***}	-0.022^{***}	-0.022^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
S	-0.037^{***}	-0.037^{***}	-0.037^{***}	-0.037^{***}	-0.035^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$K \cdot C$	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$K \cdot S$	0.016^{***}	0.016^{***}	0.016^{***}	0.016^{***}	0.016^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$C \cdot S$	-0.022^{***}	-0.022^{***}	-0.022^{***}	-0.022^{***}	-0.022^{***}
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
N_S	-0.017^{***}	-0.016^{***}	-0.018^{***}	-0.019^{***}	-0.017^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$N_S \cdot \rho$	0.012^{***}	0.011^{***}	0.011^{***}	0.011^{***}	0.011^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ρ		0.004	0.004	0.004	0.004
		(0.003)	(0.003)	(0.003)	(0.003)
$N_S \cdot K$			0.001^{**}	0.001^{**}	0.001^{**}
			(0.0005)	(0.0005)	(0.0005)
$N_S \cdot C$				0.0004	0.0004
				(0.0004)	(0.0004)
$N_S \cdot S$					-0.001^{**}
					(0.0005)
Intercept	0.018^{***}	0.016^{***}	0.020^{***}	0.021^{***}	0.018^{***}
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Observations	2,000	2,000	2,000	2,000	2,000
Adjusted R^2	0.897	0.897	0.897	0.897	0.897
Note:					*p<0.1; **p<0.05; ***p<0.01