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REGULAR ARTICLE

Incomplete incentive contracts in complex task environments: an agent-based simulation with minimal intelligence agents

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Abstract
Incentive contracts often do not govern all task elements for which an employee is responsible. Prior research, particularly in the tradition of principal-agent theory, has studied incomplete incentive contracts as multi-task problems focusing on how to motivate the employee to incur effort for a not-contracted task element. Thus, emphasis is on the "vertical" relation between superior and subordinate, where both are modeled as gifted economic actors. This paper takes another perspective focusing on the "horizontal" interferences of—contracted and not-contracted—task elements across various employees in an organization and, hence, on the complexity of an organization's task environment. In order to disentangle the interactions among tasks from agents' behavior, the paper pursues a minimal intelligence approach. An agent-based simulation model based on the framework of NK fitness landscapes is employed. In the simulation experiments, artificial organizations search for superior performance, and the experiments control for the complexity of the task environment and the level of contractual incompleteness. The results suggest that the complexity of the task environment in terms of interactions among task elements may considerably shape the effects of incomplete incentive contracts. In particular, the results indicate that moderate incompleteness of incentive contracts may be beneficial with respect to organizational performance when intra-organizational complexity is high. This is caused by stabilization of search resulting from incomplete contracts. Moreover, interactions may induce that the not-contracted task elements could serve as means objectives, i.e., contributing to achieving contracted task elements.

Keywords Agent-based modeling · Complexity · Incomplete contracts · NK fitness landscapes · Satisficing

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1 Introduction and background

Incentive contracts are widely used for motivating employees to induce effort. However, measuring the employees' performance often encounters difficulties. For example, accounting literature has extensively examined the goal (in-)congruency of performance metrics (e.g., Banker and Thevaranjan 2000; Lambert 2001; Thiele 2007). Moreover, incentive contracts may be incomplete in the sense that the contract does not cover all parts of an employee's task. It was argued that incomplete incentive contracts are a ubiquitous phenomenon, not least because task elements like innovativeness or courtesy often are hard to measure (e.g., Kreps 1990; Holmström and Milgrom 2009; Sanga 2018).

There is a broad literature studying incomplete incentive contracts in organizations. Research in the tradition of principal-agent theory has usually examined incomplete incentive contracting as multi-task problems. For example, employing closed-form analysis, the conditions were studied for when additional performance metrics or particular job designs and job allocation are helpful (Holmström and Milgrom 1991; Feltham and Xie 1994; Dewatripont et al. 2000). Subjective performance evaluations by superiors are another means to cope with incomplete contracts (MacLeod and Malcomson 1998; Murphy and Oyer 2001) since this could allow for rewarding task elements that are hard to govern by an incentive contract. Another stream of research focuses on the role of trust in incomplete contracts (Fisher et al. 2005). With incomplete contracts, the principal gets some discretion over the agent's rewards. Hence, the agent's trust in the principal is particularly relevant for the agent's willingness to incur effort. For example, there is experimental evidence that a bonus contract provides a more trusting environment and, thus, induces higher efforts of contracted and not-contracted tasks than a penalty contract (Christ et al. 2012).

A dominant trait in prior research on incomplete incentive contracts is the focus on the delegation between the principal and the agent—or more roughly speaking: on the "vertical" relation between superior and subordinate. This paper takes a different perspective. The paper focuses on incomplete incentive contracts in organizations with several subordinate decision-makers where the (contracted and not-contracted) tasks may interact "horizontally" across decision-makers. In particular, building on the thoughts of Herbert A. Simon, the task environment may be complex, incorporating that interactions among subordinate decision-makers' tasks may exist. As shown by Simon (1962), the interactions among the components of a decision problem shape its complexity and, hence, the need for coordination. A (nearly) decomposable decision problem can be decomposed such that intra-sub-problem linkages are stronger than inter-sub-problem interactions. Consequently, sub-problems can be solved independently from each other without taking positive or negative interactions into account. In contrast, if an overall decision problem is non-decomposable, no decomposition into sub-problems can be found that (nearly) diminishes inter-sub-problem interactions (e.g., Rivkin and Siggelkow 2007; Siggelkow 2002). With high complexity, the need for coordination across the sub-problems is high when superior solutions to the overall decision problem are the aim. This appears an exciting issue for interactions among decision-makers' tasks in the presence of incomplete incentive contracts. For example, the (not-contracted) innovativeness of the R&D unit may affect the (contracted) cost efficiency for which the head of operations management is rewarded; cost efficiency, in turn, may affect contracted and not contracted task elements of operations management and other units. How does the incompleteness of contracts in conjunction with cross-unit interactions among tasks affect the overall organizational performance? Hence, the paper focuses on incomplete incentive contracts when contracted and non-contracted tasks interfere across several decision-makers.

Moreover, the paper deviates from major parts of prior research on incomplete incentive contracts regarding decision-makers' cognitive capabilities. In particular, the paper studies incomplete incentive contracts for organizations with decision-makers of relatively limited intelligence. This choice is made for two reasons: First, it has long been noticed that incomplete contracts refer to limited cognitive capabilities. In his seminal paper, Tirole (2009) links incomplete contracts to Simon's bounded rationality (Simon 1955, 1959) and introduces the cost of gathering and processing information as well as heuristics for contract design. A major result is that complete contracts may be wasteful (Tirole 2009).[1] Second, agents' intelligence is limited for methodological reasons. As outlined before, this paper focuses on situations where incompletely governed tasks may interfere with other tasks of the same agent and other agents' tasks. In short, interactions among contracted and not-contracted tasks are at the center of interest. Limiting agents' intelligence contributes to disentangling the agents' behavior from the interactions as was employed in models with zero or minimal intelligence agents (Gode and Sunder 1993; Farmer et al. 2005; Troitzsch 2008).

Hence, the research question of the paper can be summarized as follows: *How do organizations perform in complex task environments when the incentive contracts incompletely cover performance of minimal intelligence agents?*

The paper employs an agent-based simulation based on the framework of NK-fitness landscapes (Kauffman and Levin 1987; Kauffman 1993). In the simulations, artificial organizations search for superior solutions to an overall decision problem. The organizations make use of division of labor, assigning sub-problems of the overall decision problem to subordinate decision-makers who do not behave as optimizers but employ an algorithm inspired by Simon's satisficing (Simon 1955, 1959). Incentive contracts may govern only a part of each subordinate's task.

The remainder of the paper is organized as follows: Section 2 outlines the agent-based model, and Sect. 3 explains the parameter settings for the simulation experiments. Results are provided and discussed in Sect. 4. Section 5 concludes and provides areas for further research.

[1] Studies on incomplete incentive contracts in the tradition of principal-agent theory share the idea of rather gifted economic actors like rational expectations, unlimited memory and unlimited computational capabilities (e.g., Axtell 2007; Leitner and Wall 2021, with overviews on underlying assumptions on actors).

2 Model

2.1 Overview

In the simulations, artificial organizations search for superior solutions for a decision problem modeled according to NK-fitness landscapes' framework (Kauffman and Levin 1987; Kauffman 1993). The organizations have a hierarchical structure and comprise two types of decision-making agents: one headquarters and M managers, each of which is the head of a respective department (or unit) $r = 1, \cdots, M$. Each manager r has decision-making authority on a distinct partition of the organization's overall decision problem. Unit heads seek to maximize compensation when, in each time step t, searching for superior solutions on their partial decision problems.

Following what Katsikopoulos (2014) calls the pragmatic culture of bounded rationality in modeling agents, unit heads do not behave as optimizers. They cannot survey the *entire* search space and, hence, cannot "locate" the optimal solution of their partial decision problem "at once" but have to search stepwise for superior solutions.

For capturing the managers' search behavior, the model employs a *satisficing* algorithm (Wall 2021a) in the spirit of Simon (1955, 1959). Satisficing means a process of sequential search for options until a satisfactory level of utility is achieved. What the decision-maker regards as satisfactory is captured by the aspiration level that may be subject to adaptation.

This requires making a modeling choice on reflecting *search costs* in the model. From a "classical economic perspective," it has been claimed (Stigler 1961) that alternatives and their characteristics may not be known in advance, but that additional information on options has to be searched, reasonably causing search costs. Accordingly, a decision-maker would have to solve a sophisticated problem of economic choice, i.e., whether or not to incur the search cost for better information. This requires forecasting the information's benefits (i.e., better choices) in terms of all its future consequences, including subsequent choices. Therefore, it has been argued that extending the utility-maximizing model to include search costs, though economically stringent, faces principal problems of mathematical tractability or cognitive limitations (e.g., Conlisk 1996; Gigerenzer 2002, 2004). In this vein, Gigerenzer (2002) argues that the rule to stop searching for information when the search cost exceeds benefits (Stigler 1961) may paradoxically necessitate more time, knowledge, and computational abilities of decision-makers ("sophisticated econometricians") than in models with unbounded rationality. In this sense, explicitly including search costs would require modeling decision-making agents with relatively sophisticated cognitive capabilities—instead of minimal intelligence agents as they allow disentangling the agents' behavior from the interactions among contracted and not-contracted task elements as is in the focus of this study (see also Gode and Sunder 1993; Farmer et al. 2005; Troitzsch 2008). However, search costs implicitly play a role as the sequence of search in the satisficing algorithm follows a "closest-first" search policy which reflects that closer options reasonably require lower search costs (see Sect. 2.5).

The model captures two types of minimal intelligence decision-makers at the departmental level:

- Type I decision-makers evaluate the "gross utility" of a newly discovered option against the aspiration level, i.e., not considering the effort required that the implementation of this option would require.
- Type II decision-makers also consider the cost of effort for implementing a newly discovered option and thus compare an option's "net utility" against the aspiration level.

The headquarters' role is to reward the department heads according to the incentive structure contracted. However, the contracts may be incomplete, i.e., governing only a part of the decision problem for which a department head is responsible.

The following sections describe the model in more detail, with Table 1 listing the symbols used.

2.2 Organizational decision problem, agents and delegation

In line with the NK-framework, at each time step t, the organizations face an N-dimensional binary decision problem, i.e., $\mathbf{d_t} = (d_{1t}, \ldots, d_{Nt})$ with $d_{it} \in \{0, 1\}$, $i = 1, \ldots, N$, so there are 2^N different binary vectors. Each of the two states $d_{it} \in \{0, 1\}$ provides a distinct contribution C_{it} to the overall performance $V(\mathbf{d_t})$. The contributions C_{it} are randomly drawn from a uniform distribution with $0 \leq C_{it} \leq 1$. Though randomly drawn, the contributions C_{it} are a function of choices and interactions among choices:

$$C_{it} = f_i(d_{it}; d_{i_1 t}, \ldots d_{i_K t}) \tag{1}$$

with $\{i_1, \ldots, i_K\} \subset \{1, \ldots, i-1, i+1, \ldots, N\}$. Parameter K (with $0 \leq K \leq N-1$) captures the complexity of the decision problem in terms of the number of those choices d_{jt}, $j \neq i$ which also affect the performance contribution C_{it} of choice d_{it}. When choices do not interact, K equals 0, and $K = N - 1$ captures the maximum level of complexity with each single choice i affecting the performance contribution of each other binary choice $j \neq i$.

The overall performance V_t achieved in period t is the normalized sum of contributions C_{it} as given by

$$V_t = V(\mathbf{d_t}) = \frac{1}{N} \sum_{i=1}^{N} C_{it}. \tag{2}$$

The model comprises two types of agents, departmental managers and one headquarters. The headquarters' role is restricted to compensating the departmental managers according to the (incomplete) contract (see Sect. 2.3).

The tasks of the departmental managers result from a decomposition of the N-dimensional overall decision problem into M disjoint partial problems. Each of these sub-problems is delegated to one department $r = 1, \ldots, M$. Shaped by the level K and the structure of interdependencies, indirect interactions among the departments may result (e.g., Fig. 1b). Let K^{ex} denote the level of cross-unit interactions. In case

Table 1 List of symbols

Symbol	Meaning
α_r	Speed of adjustment of aspiration level a^r of manager r
β_r	Speed of adjustment of the maximum number of options $s^{\max,r}(t)$ that manager r may search in period t
ΔB_t^r	Change in value base of compensation of manager r which an alternative promises compared to what the status quo will yield in period t
ΔB_t^{r*}	Change in actual value base of compensation that manager r experiences in period t
σ^r	Standard deviation of errors e^r of manager r's perception of value base B_t^r of compensation
$a^r(t)$	Aspiration level of manager r in time step t
B_t^r	Value base of compensation of manager r in time step t
$\tilde{B}_t^r$	Perceived value base of compensation of manager r in time step t
C_{it}	Contribution of binary choice i in time step t to overall performance V_t
d_{it}	Binary choice i in time step t, i.e., $d_{it} \in \{0, 1\}$)
$\mathbf{d_t}$	N-dimensional vector of binary choices d_{it} in time step t
$\mathbf{d_t^r}$	N^r-dimensional vector of binary choices d_{it} in time step t which manager r is responsible for
$\mathbf{d_t^{s^r}}$	The s-th newly discovered option of manager r in time step t for the N^r-dimensional vector of binary choices d_{it} which manager r is responsible for
d_{t-1}^{r*}	Status quo of manager r's choices, i.e., choices made in period $t-1$
e^r	Error of manager r for ex ante evaluations of options
f_i	Function that gives the performance contribution C_{it} of a single choice i and, eventually, K other choices
$h(\mathbf{d}_t^{s^r})$	Hamming distance of a newly discovered option $\mathbf{d}_t^{s^r}$ to the status quo
i, j	Indices for the single choice of the N-dimensional decision vector $\mathbf{d_t}$
ic^r	Level of incompleteness of manager r's contract: number of decisions assigned to manager r which are not covered in the incentive contract
K	Number of choices $d_{jt}, j \neq i$ which affect the contribution C_{it} of choice d_{it}
K^{ex}	Level of cross-unit interactions
M	Number of managers and units, respectively
N	Number of binary choices to be made by the organization
N^r	Number of binary choices to be made by manager r
P^r	Performance resulting from decisions assigned to manager r
m, q, r	Indices for managers or unit heads
$s^r(t)$	Index for the newly discovered options of manager r in period t
$s^{\max,r}(t)$	Maximum number of options may manager r searches in period t

Table 1 continued

Symbol	Meaning
$\overline{s}^{\max,r}$	Upper bound of options manager r may discover given the N^r-dimensional decision problem of manager r
t	Time step/period within the observation period T
T	Observation period
V_t	Overall performance of an organization achieved in time step t
w	Auxilliary variable, number of choices assigned to departments m other than r, with $s \prec r$
Z^r	Manager r's cost of effort for abandoning the status quo in favor of a newly discovered option
z^r	Coefficient for manager r's cost of effort

of cross-unit interdependencies, i.e., if $K^{ex} > 0$, then the performance contribution of department r's choices to overall performance V is affected by choices made by other units $q \neq r$ and vice versa.

2.3 Decision-makers' objectives and incomplete contracts

Given the decomposition of the overall decision problem, the contribution of each department head r to overall performance (Eq. 2) from those decisions assigned to that manager results from

$$P_t^r(\mathbf{d_t^r}) = \frac{1}{N} \sum_{i=1+w}^{N^r} C_{it} \tag{3}$$

with $w = 0$ for manager $r = 1$ and $w = \sum_{m=1}^{r-1} N^m$ for department heads $r > 1$.

Both types of managers seek to increase compensation which is merit-based and, for the sake of simplicity, depends linearly on the value base of compensation B_t^r achieved in time step t.

At the core of the research effort presented here is that contracts may be incomplete in terms of covering not the entire task assigned to a subordinate. For capturing, this the model assumes that for an N^r-dimensional decision problem of manager r, the performance contributions of a certain number of r's decisions are not considered in the value base of compensation B_t^r. Let parameter $ic^r \in \{0, 1, \ldots, N^r - 1\}$ denote the level of incompleteness for manager r's capturing the number of single choices assigned to manager r whose performance contributions are *not* taken into account in the value base of compensation. In particular, the model assumes that for an N^r-dimensional decision problem of manager r, the performance contributions of the first $N^r - ic^r$ decisions account for r's compensation while the contributions of the "last"

ic^r decisions are not considered in the value base. Hence, we have

$$B_t^r(\mathbf{d_t^r}, ic^r) = \frac{1}{N} \sum_{i=1+w}^{N^r - ic^r} C_{it} \tag{4}$$

with $w = 0$ for manager $r = 1$ and $w = \sum_{m=1}^{r-1} N^m$ for department heads $r > 1$.

With $ic^r \leq N^r - 1$, the performance contribution of, at least, one choice assigned to manager r is rewarded. In case of a complete contract (i.e., $ic^r = 0$), all choices assigned to manager r enter the value base of compensation which equals r's performance contribution (Eq. 3) to overall performance, i.e., then we have $B_t^r(\mathbf{d_t^r}, ic^r = 0) = P_t^r(\mathbf{d_t^r})$.

Type II managers consider the net utility, i.e., they also take the cost of effort into account. In the model, it is assumed that keeping the status quo $\mathbf{d_{t-1}^{r*}}$ does not require any effort (i.e., comes at zero cost), while abandoning the status quo in favor of a newly discovered option $\mathbf{d_t^{s^r}}$ causes cost of effort. In particular, the effort is assumed to be higher the more distant the new option from the status quo. The distance between the status quo and the new option is given by the Hamming distance $h(\mathbf{d}_t^{s^r}) = \sum_{i=1}^{N^r} \left|\mathbf{d}_{t-1}^{r*} - \mathbf{d}_t^{s^r}\right|$. For modeling the cost of effort, as customary in economics (e.g., Baker 1992; Lambert 2001), it is assumed that higher levels of effort are increasingly costly. Hence, for decision-maker r's cost of effort Z^r, we have $Z^r(h)' > 0$ and $Z^r(h)'' > 0$. In particular, the cost of effort $Z^r(\mathbf{d_t^{s^r}})$ of decision-maker r is modeled to be quadratically increasing with the Hamming distance h of a newly found option $\mathbf{d_t^{s^r}}$ to the status quo $\mathbf{d_{t-1}^{r*}}$, i.e.,

$$Z_t^r(\mathbf{d_t^{s^r}}) = z^r \cdot (h(\mathbf{d_{t-1}^{r*}}, \mathbf{d_t^{s^r}}))^2 \tag{5}$$

where z^r is a cost coefficient capturing manager r's cost efficiency.

2.4 Managers' information and decision-making

Managers perform search and decision-making processes in the spirit of Simon's satisficing (Simon 1955) with the algorithmic representation following Wall (2021a). A core idea of satisficing is that new options are discovered *and* evaluated sequentially: the agent discovers one novel option $\mathbf{d}_t^{s^r}$ and evaluates whether it is satisfactory. If so, search is stopped; otherwise, the next alternative is searched and evaluated and so forth.

For being satisfactory, an option has to promise meeting the aspiration level $a^r(t)$ relevant at that time. Hence, for manager r of Type I seeking to increase the value base of compensation (Eq. 4), an alternative is satisfactory if it promises a favorable change ΔB_t^r in compensation compared to the reward the status quo $\mathbf{d}_{t-1}^{r*}$ will yield. An alternative is satisfactory if the following criterion is met:

$$\Delta B_t^r \geq a^r(t) \tag{6}$$

Type II managers also take the cost of effort Z_t^r for abandoning the status quo in favor of a novel option into account (Eq. 5).[2] Hence, a satisfactory alternative for Type II managers meets the following criterion:

$$\Delta B_t^r - Z_t^r \geq a^r(t) \tag{7}$$

However, when determining ΔB_t^r, subordinate manager r of either type may not be able to perfectly ex ante evaluate the effects of any newly discovered option $\mathbf{d}_t^{s^r}$ on the value base for compensation $B_t^r(\mathbf{d}_t^{s^r})$ (see Eq. 4). Rather, ex ante evaluations are afflicted with noise which is, for the sake of simplicity, a relative error imputed to the actual performance [Wall (2010); for further types of errors see Levitan and Kauffman (1995)]. Errors $e^r(\mathbf{d}_t^{s^r})$ follow a Gaussian distribution $N(0; \sigma)$ with expected value 0 and standard deviations σ^r; errors are assumed to be independent from each other. Hence, manager r ex ante *perceives* the value base of compensation of a *newly discovered option* as

$$\tilde{B}_t^r(\mathbf{d}_t^{s^r}) = B_t^r(\mathbf{d}_t^{s^r}) + e^r(\mathbf{d}_t^{s^r}) \tag{8}$$

For the *status quo* option $\mathbf{d}_{t-1}^{r*}$, it is assumed that manager r remembers the compensation from the last period and, from this infers the *actual* value base B_t^r of the status quo, should the manager choose to stay with it in time step t. Hence, ΔB_t^r in Eq. 6 results from

$$\Delta B_t^r = \tilde{B}_t^r(\mathbf{d}_t^{s^r}) - B(\mathbf{d}_{t-1}^{r*}) \tag{9}$$

However, please recall that for the case of interactions across units' sub-problems (i.e., $K^{ex} > 0$), the value base B_t^r obtained from keeping the status quo $\mathbf{d}_{t-1}^{r*}$ would only remain unchanged if the fellow managers $q \neq r$ stay with their respective status quo option too. As mentioned before, when making their choices, each manager r assumes that the fellow managers $q \neq r$ will stay with the status quo to their partial decision problem. It is only at the end of each period t (or the beginning of $t+1$) that managers observe which choices the fellow managers have made in time step t.

If a newly discovered option appears satisfactory (i.e., promises to meet or exceed the aspiration level in Eq. 6 or Eq. 7, respectively, in conjunction with Eqs. 8 and 9), this option is chosen and implemented, and search is stopped for this time step t. Otherwise, the next option is searched and evaluated against the aspiration level as far as a maximum number of options $s^{\max,r}(t)$ is not reached yet.

2.5 Sequence and adaptations in decision-makers' search

The model of satisficing behavior comprises three further aspects worth mentioning (for more details, see Wall 2021a).

[2] For the sake of simplicity of the model, from the value base of compensation the "weighted" cost of effort are deduced: the cost coefficient z^r in Eq. 5 also calibrates the cost in relation to manager r's share (assumed to be linear and stable over time) of the value base of compensation.

(1) Sequence of search. Manager r faces an N^r-dimensional binary decision problem, and hence, at maximum, $2^{N^r}-1$ alternatives $\mathbf{d}^r$ compared to the status quo exist. Therefore, the upper bound of alternatives, which manager r may discover, is given by $\overline{s}^{\max,r} \leq 2^{N^r}-1$. Let $s^{\max,r}(t)$ denote the maximum number of alternatives considered in time step t with $1 \leq s^{\max,r}(t) \leq \overline{s}^{\max,r}$. Then, for further specifying satisficing behavior, the sequence of the agent's discoveries of new options is to be determined. For the sequence of options' discovery, various possibilities are feasible. For example, one obvious way is to let the agent *randomly* discover one out of the $2^{N^r}-1$ alternatives (if an option has been discovered before in that time step t, the random draw is repeated). The model presented here employs a *"closest-first" search policy*: a manager r starts searching in the immediate "neighborhood" of the status quo. Should this not lead to a satisfactory option, manager r extends the "circle" of search around the status quo. The sequence follows increasing Hamming distances of newly discovered alternatives $\mathbf{d}_t^{s^r}$ to the status quo given by

$$h(\mathbf{d}_t^{s^r}) = \sum_{i=1}^{N^r} \left| \mathbf{d}_{t-1}^{r*} - \mathbf{d}_t^{s^r} \right| \tag{10}$$

Hence, the search starts with options of Hamming distance $h(\mathbf{d}_t^{s^r}) = 1$, then followed by options with a Hamming distance of two and so forth, as long as either the aspiration level is met or the maximum number of options $s^{\max,r}$ to be considered is reached. Among the options with equal Hamming distance, the sequence is given at random.[3] A rationale for a *"closest-first" search policy* is based on considerations of cost of search and change and the idea of stepwise improvement. Small steps could be assumed to show lower cost than more distant options which require more changes. Hence, it appears reasonable that a decision-maker may prefer to search in small steps first.

(2) Adaptation of the aspiration level. A core element in satisficing is the aspiration level which is subject to adaptation based on experience (Simon 1955): The aspiration level may increase (decrease) depending on how easy (difficult) it was to find a satisfactory alternative in the past. In the model, after being compensated for time step t, subordinate managers adjust their aspiration levels according to the experience, i.e., an improvement or deterioration of compensation (Type I manager) or net utility (Type II manager), respectively, achieved over time. In particular, the aspiration level a^r is captured as an exponentially weighted moving average of past changes in the value base of compensation,[4] where α^r denotes the speed of adjustment for manager r of Type I (Levinthal and March 1981; Börgers and Sarin 2000; Levinthal 2016), i.e.,

$$a^r(t+1) = \alpha^r \cdot \Delta B_t^{r*} + (1-\alpha^r) \cdot a^r(t). \tag{11}$$

[3] For example, for a manager's decision problem of size $N^r = 3$, three alternatives to the status quo with a Hamming distance $h(\mathbf{d}_t^{s^r}) = 1$, three alternatives with $h(\mathbf{d}_t^{s^r}) = 2$ and one with $h(\mathbf{d}_t^{s^r}) = 3$ exist. A manager first discovers nearest neighbors; next, options with $h(\mathbf{d}_t^{s^r}) = 2$ are found, where the sequence among equal-distanced options is randomly given.

[4] Please, recall that, for the sake of simplicity, the compensation is a linear and time-invariant function of the value base of compensation.

where ΔB_t^{r*} is the change in the *actual* value bases from time step $t-1$ to t, i.e., $\Delta B_t^{r*} = B(\mathbf{d}_t^r) - B(\mathbf{d}_{t-1}^r)$. For Type II managers, the adaptation of aspiration levels is adjusted based on the net utility accordingly:

$$a^r(t+1) = \alpha^r \cdot (\Delta B_t^{r*} - Z_t^r) + (1-\alpha^r) \cdot a^r(t). \tag{12}$$

Hence, the aspiration level could also become negative—i.e., a *decline* in the value base of compensation becoming acceptable—if declines happened in the past.

(3) Adaptation of the maximum number of options searched. In the satisficing concept, the space of options in which a manager searches may be dynamically adjusted. When it turns out to be difficult to find satisfactory options, the search space for alternatives is broadened; when finding satisfactory options is easy, search space is narrowed (Simon 1955). In the model, this idea is captured as adjustment of the maximum number $s^{\max,r}(t)$ of options that the decision-making agent r may consider in the next time step. For this, as for the adaptation of the aspiration level, an exponentially weighted moving average of past search spaces is employed where β^r denotes the speed of adjustment for manager r, and $s^r(t)$ gives the number of alternatives that decision-maker r has approached in time step t:

$$s^{\max,r}(t+1) = \begin{cases} \beta^r \cdot (s^r(t)+1) + (1-\beta^r) \cdot s^{\max,r}(t) \\ \qquad \text{if } s^r(t) = s^{\max,r}(t) \\ \qquad \text{and } \Delta B^r{}_t < a^r(t) \text{ for Type I managers} \\ \qquad\quad (\Delta B^r{}_t - Z_t^r < a^r(t) \text{ for Type II managers}) \\ \\ \beta^r \cdot (s^r(t)) + (1-\beta^r) \cdot s^{\max,r}(t) \\ \qquad \text{else.} \end{cases} \tag{13}$$

However, since the number of alternatives searched is an integer, the moving average is to be rounded up or down, and the "adjusting" procedure in Eq. 13 does not necessarily result in an adjusted search space $s^{\max,r}(t+1)$ for the next period. Moreover, the upper bound $\overline{s}^{\max,r}$ of options given by the size N^r of the decision problem, as mentioned before, is to be respected.

3 Simulation experiments and parameter settings

This section is to describe the simulation experiments and explain the parameter settings as summarized in Table 2. In the simulation experiments, artificial organizations search for superior solutions to an $N = 12$-dimensional decision problem according to the structure of interdependencies among single choices d_i. Hence, generating a performance landscape according to the interaction structure marks the beginning of a simulation run. Moreover, for each of the $M = 4$ departmental managers, a distinct "view" of the landscape is calculated respecting the decomposition of the overall decision problem into four equal-sized sub-problems, the contract including its level of completeness and the distortions resulting from imprecise ex ante evaluations. In particular, for each configuration $\mathbf{d}$ of the overall decision problem and for each manager

Table 2 Parameter settings

Parameter	Values / types
Applying to all scenarios	
Observation period	$T = 250$
1Simulation runs	Per scenario 2500 runs with 25 runs on 100 distinct fitness landscapes
Number of choices	$N = 12$
Number of managers	$M = 4$
Managers' decision problem	Problem size $N^r = 3$ for all managers $r = (1, \ldots, 4)$, i.e., $\mathbf{d}^1 = (d_1, d_2, d_3)$, $\mathbf{d}^2 = (d_4, d_5, d_6)$, $\mathbf{d}^3 = (d_7, d_8, d_9)$, $\mathbf{d}^4 = d_{10}, d_{11}, d_{12})$
Managers' precision of ex-ante evaluation	$\sigma^r = 0.05$ for all managers $r = (1, \ldots, 4)$
Aspiration level	
In the beginning	$a^r(t = 0) = 0$ for all managers $r = (1, \ldots, 4)$
Speed of adjustment	$\alpha^r = 0.5$ for all managers $r = (1, \ldots, 4)$
Max. number of alternatives	
In the beginning	$s^{\max,r}(t = 0) = 2$ for all managers $r = (1, \ldots, 4)$
Speed of adjustment	$\beta^r = 0.5$ for all managers $r = (1, \ldots, 4)$
Subject to variation across scenarios	
5Interaction structures	Decomposable: $(K = 2; K^{ex} = 0)$ (see Fig. 1a)
	Non-decomposable:
	Low: $(K = 3; K^{ex} = 1)$;
	Moderate: $(K = 5; K^{ex} = 3)$;
	Medium: $(K = 7; K^{ex} = 5)$; (see Fig. 1b);
	High: $(K = 9; K^{ex} = 7)$
Contract incompleteness	$ic^r \in \{0, 1, 2\}$ for all managers $r = (1, \ldots, 4)$
Cost of effort	Type I managers: cost of effort not considered (i.e., $z^r = 0$ for all managers $r = (1, \ldots, 4)$)
	Type II managers: $z^r = (0.001, \ldots, 0.01)$ in steps of 0.001 for all managers $r = (1, \ldots, 4)$

r, the actual and perceived value base of compensation is computed. Then, organizations are randomly "thrown" in the performance landscape and the organizations' adaptive walks are observed over 250 periods.[5]

While each manager has a distinct "view" on the performance landscape due to decomposition of the overall task, managers' decision-making is characterized by the same parameter settings. When ex ante assessing the value base of compensation of newly discovered options, the managers suffer from some level of noise (see Eq. 8) following a Gaussian distribution with mean 0 and a standard deviation of 0.05. This parameterization intends to reflect some empirical evidence indicating that

[5] This observation period was based on pretests indicating that the results do not principally change when the organizations are observed for a longer time.

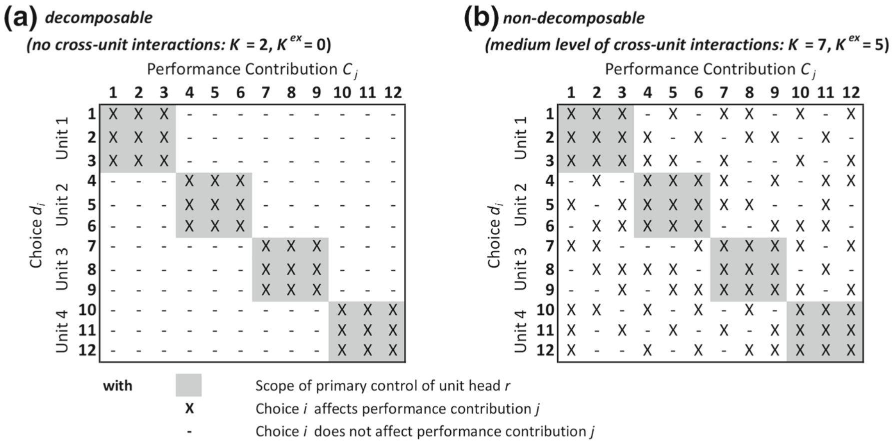

Fig. 1 Examples of **a** decomposable and **b** non-decomposable interaction structures

error levels around 10 percent could be a realistic estimation (Tee et al. 2007; Redman 1998). The aspiration levels of performance enhancements start at a level of zero to capture the desire to avoid, at least, situations of not-sustaining an already achieved performance level. The maximum search space starts at a moderate level of just two alternatives. Regarding the speed of adjustment for both the aspiration level of performance enhancements and the maximum number of alternatives, the present observation and the past are weighted equally with $\alpha^r = 0.5$ and $\beta^r = 0.5$.

This paper is particularly interested in the effects of incomplete incentive contracts in complex task environments emerging at the organizational level with the two types of limited intelligence agents. Therefore, in the simulations, three components are varied, (1) the interaction structure which captures the task environment the organizations are operating in, (2) the level of incompleteness of the incentive contracts between headquarters and department heads, and (3) the type of managers, i.e., whether or not managers take the cost of effort for implementing a novel option into account.

(1) The experiments are conducted for different task environments which differ in the levels of complexity of the organizations' decision problems. The organizations may have a perfectly decomposable interaction structure of decisions. Figure 1a displays an example of a situation without interactions across managers' sub-problems (i.e., $K = 2$, $K^{ex} = 0$). This may capture an organization whose overall task is perfectly decomposable along geographical regions or products without any interdependencies across regions or products, respectively (Galbraith 1974; Rivkin and Siggelkow 2007; Simon 1962). Alternatively, the interaction structures captured in the experiments may exhibit a low, moderate, medium, or high level of interactions across sub-problems assigned to units. For example, Fig. 1b shows a case of a medium level of cross-unit interactions (i.e., $K = 7$, $K^{ex} = 5$). This structure may represent interdependencies due to constraints of resources (budgets or capacities), market interactions (prices of one product may affect the price of another) or functional interrelations (e.g., the product design sets requirements for procurement processes) (Thompson 1967; Galbraith 1973; Rivkin and Siggelkow 2007).

(2) In the simulations, the incompleteness of incentive contracts can take the three levels $ic^r \in \{0, 1, 2\}$ where the upper bound is determined by size of the units' decision problem: It is assumed that at least, one of the single choices d^i assigned to manager r is contracted so that for the problem size of $N^r = 3$, $ic^r = 2$ is the maximum level of incompleteness. The case of a complete contract, i.e., $ic^r = 0$, marks the other extreme.

(3) The simulations are run for the two types of minimal intelligence agents, i.e., ignoring (Type I) or considering (Type II) the cost of effort. For the Type II managers, ten levels of nonzero cost coefficients are simulated in order to study the sensitivity of results to the cost of efforts. In particular, assuming that managers are homogeneous with respect to cost efficiency, the cost coefficient z^r is varied between 0.001 and 0.01 in steps of 0.001.

With three levels of contracts' incompleteness, five interaction structures and eleven levels of cost of effort (including its ignorance), the experimental setup comprises 165 different scenarios. For each scenario, 2500 simulations—with 25 runs on 100 performance landscapes—are run.

4 Results and discussion

The results of the experiments are presented and discussed in three steps. Following the idea of factorial design of simulation experiments (Lorscheid et al. 2012), the analysis starts with two baseline scenarios with Type I managers to showcase effects of incomplete performance contracting for a simple task environment (Sect. 4.2) and a relatively complex task environment (Sect. 4.3) captured in a decomposable and a non-decomposable interaction structure, respectively. In Sect. 4.4, the effects of incomplete contracting with Type I managers are studied for a broader range of task environments for highlighting the sensitivity to the complexity of the organizational decision problem. In the third step of the analysis (Sect. 4.5), incomplete contracting with Type II managers is studied with a particular focus on the sensitivity of results to managers' cost of effort. However, in the beginning, some remarks on the metrics employed in the analysis appear helpful.

4.1 Preliminary remarks on the analysis

Figure 2 plots the performance levels obtained in the course of adaptive walks over time for each of the six baseline scenarios—i.e., combinations of three levels of contractual incompleteness and two interaction structures with Type I managers. Table 3 reports condensed results obtained from the simulation experiments for the baseline scenarios. For each scenario, the table displays four metrics—two informing about the effects on the overall organizational performance and two for characterizing the adaptive walks in more detail:

1. The final performance $V_{t=250}$ informs about the effectiveness of the search processes in terms of organizational performance obtained in the last period of the

Table 3 Condensed results of baseline scenarios with Type I managers

Level ic of incomplete- ness of contract	Final performance $V_{t=250}$ ±confidence interval (1)	Frequ. of global maximum found in $t = 250$ (2)	Ratio of periods with altered config. **d** (false positive alterations) (3)	Av. number of altered choices d_i per period (4)
Decomposable (no cross-unit interactions: $K = 2$, $K^{ex} = 0$)				
0	0.9919 ± 0.0012	60.96%	24.19% (11.48%)	0.4032
1	0.8972 ± 0.0040	1.88%	0.82% (0.04%)	0.0138
2	0.7412 ± 0.0062	0.12%	0.17% (0.00%)	0.0024
Non-decomposable (medium level of cross-unit interactions: $K = 7$, $K^{ex} = 5$)				
0	0.7547 ± 0.0097	4.76%	82.26% (41.85%)	2.1515
1	0.8304 ± 0.0048	1.24%	3.72% (1.62%)	0.0695
2	0.7019 ± 0.0061	0.04%	0.26% (0.05%)	0.0035

Confidence intervals are given at a level of 0.999. Each row represents results aggregated/averaged from 2500 simulation runs. For parameter settings, see Table 1

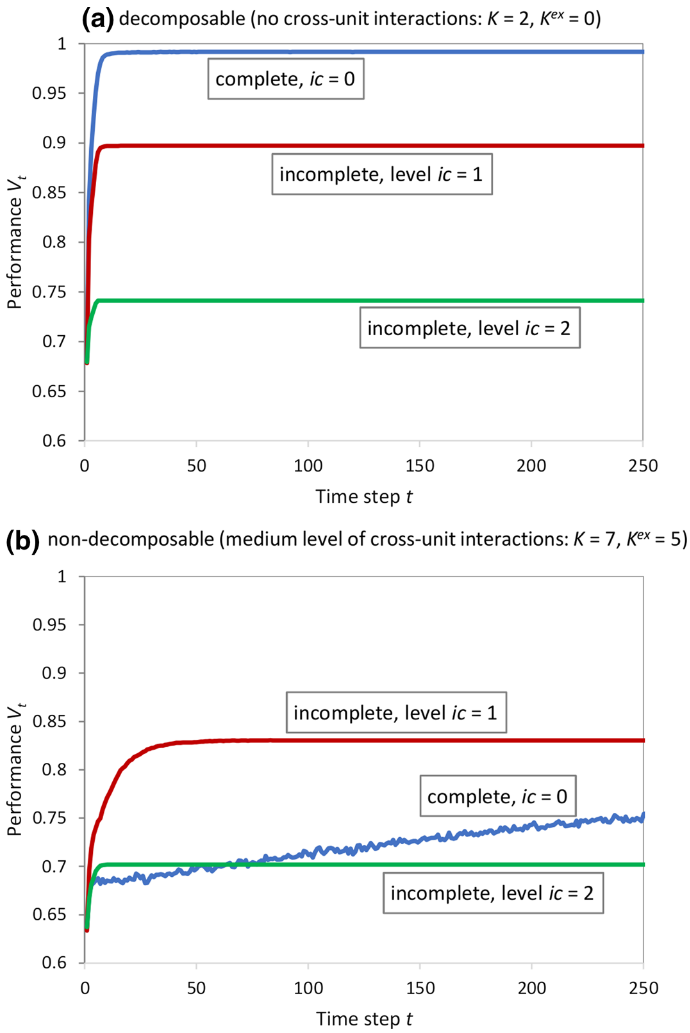

Fig. 2 Adaptive walks with contracts of different levels of incompleteness in a **a** decomposable and **b** non-decomposable interaction structure with Type I managers. Each line represents the average of 2500 simulation runs. For parameter settings, see Table 2

observation time. The numbers displayed give the average obtained in the 2500 simulation runs per scenario [6] with the confidence intervals at a level at a 0.999.

2. The relative frequency of how often the global maxima in the respective performance landscapes have been found in the 2500 simulation runs per scenario also informs about the effectiveness of the search processes. However, it is obviously a

[6] In the analysis of simulation experiments, the metrics related to performance V_t are given relative to the global maxima of the respective performance landscapes: otherwise, the results were not comparable across different performance landscapes.

stricter criterion for the effectiveness of the search processes than the final performance.
3. The ratio of periods in which the overall configuration $\mathbf{d}^t$ is altered informs about the *frequency* of changes induced by search activities. In brackets is the ratio of periods in which a change in favor of a false positive configuration occurs, i.e., an alternative configuration reducing the performance level achieved.
4. The rightmost column displays a metric for the *extent* of change. In particular, the entries give the number of single choices in the $N = 12$-dimensional decision problem, which have been altered on average per time step in the observation time $T = 250$ (and averaged over the 2500 runs per scenario).

4.2 Baseline scenario of a simple task environment

For a closer analysis, we start with the *decomposable interaction structure*. According to Fig. 2a, employing a complete contract clearly outperforms incomplete performance-contracting in terms of the performance levels of the organization obtained. The superiority of complete contracting is even more obvious with respect to the frequency of global maximum found in $t = 250$ which is the case in about 61 percent of runs compared to not even two percent or nearly zero percent with incomplete contracts. Inspecting the search processes in more detail reveals that incomplete contracts reduce change: With incomplete contracts, frequency of alterations is reduced considerably from about 24 percent of periods to not even one percent ($ic^r = 1$) or near inertia ($ic^r = 2$). The extent of alterations per period shows a similar effect.

These results are in line with intuition and what, for example, principal-agent theory suggests: when a task is rewarded only partially and no further institutions or mechanisms apply, actions (alterations) related to the not-covered parts of the task do not pay off for the subordinate, and the subordinate will reasonably pay less attention to the not-covered parts of the task posing an incentive problem for the superior (e.g., Feltham and Xie 1994). Moreover, if parts of the task are ignored by subordinate decision-makers, it is unlikely that the global maximum—comprising the entire task—at the organizational level is found which also shows up in the simulation results.

However, it is worth mentioning that in this interaction structure ($K = 2$, $K^{ex} = 0$), there are intense intra-unit interactions: Even when the contract does not cover parts of a manager's task, alterations in these parts may affect the contributions of the contracted partial task to the value base of compensation. Hence, a decision-maker r will also consider the not contracted parts of the decision problem but not for their "own" performance contribution—or: for their "own sake"—but as a means for increasing the performance contributions of the contracted parts. This conjecture is also supported by the ratio of false positive alterations. For complete contracts, this ratio is about half of the ratio of alterations. This appears reasonable given that the error in ex ante evaluations has a Gaussian distribution with expected value of zero. However, with incomplete contracts, the ratio of false positive alterations decreases remarkably below this "half-level." We argue that this is since a manager employs the not-contracted part only to increase the contracted elements of the respective decision-problem. The following section comes back to the "exploitation effect" and its consequences in a broader perspective.

4.3 Baseline scenario of a complex task environment

In the *non-decomposable interaction structure* ($K = 7$, $K^{ex} = 5$), things apparently change. Best results regarding the overall performance level V_t are not achieved under the regime of the complete contract, but with slight incompleteness as can be seen in Fig. 2b. Finally, the performance excess with slight incompleteness is about 7.5 points of percentage. Moreover, from the figure, it is noteworthy that the performance achievement in the first periods of the adaptive walks with highly incomplete contracts ($ic^r = 2$) goes beyond the level achieved with complete contracts.

With higher levels of complexity, it is more challenging to identify the global maximum; due to interactions among sub-problems, the global maximum cannot be found by identifying the optima for the sub-problems as in the decomposable structure. This shows up in the relatively low frequency of not even 5 percent for global maximum found with complete contracts; with incomplete contracts, the frequencies are very low similar to the decomposable structure. The results show again that incomplete contracting considerably reduces alterations in frequency and extent of the search processes. For example, with complete contracting, on average more than two of the 12 single choices are revised in every period in contrast to 1 single choice altered in about every 17th time step (or 0.069 per period) with slight incompleteness.

The performance excess obtained with contractual incompleteness compared to complete contracts calls for an explanation. For a start, it worth considering the effects of the incentive scheme employed, which—regardless of its level of incompleteness—rewards the departmental performance. In a non-decomposable structure, the incentive scheme induces some ignorance on the side of the unit heads. When altering $\mathbf{d}^r$, manager r does not consider the effects of this on the rest of the organization and only seeks to increase the own $P^{r,own}$ or the contracted part of thereof (see Eqs. 3 and 4 , respectively). Due to relatively dense interactions, an alteration in $\mathbf{d}^r$ by manager r likely affects the value base of compensation of each fellow manager $q \neq r$. With the limited cognitive capabilities captured in the model, this comes as a surprise for manager $q \neq r$ and is not foreseen when manager q makes a choice in time step t. Hence, in the next period $t + 1$, manager q's likely will adjust to manager r's choice; this adjustment will "backfire" to manager r's value base of compensation, who will adjust in the subsequent period $t + 2$ and so forth. Hence, with cross-unit interactions, each myopic movement may induce fellow managers' reactions and, thus, frequent mutual adjustments occur.

The results let us hypothesize that *incomplete performance contracts mitigate frequent mutual adjustments and, hence, stabilize search*. This comes from two interrelated effects which Fig. 3 intends to illustrate:

(1) *"Immunization effect"*: Other managers' decisions affecting a performance contribution which is not covered by the contract of manager r, do not induce mutual adjustments by manager r. In more detail, with a task d_i^r whose performance contribution is not contracted, the decision-maker is insensitive to any effects on contribution

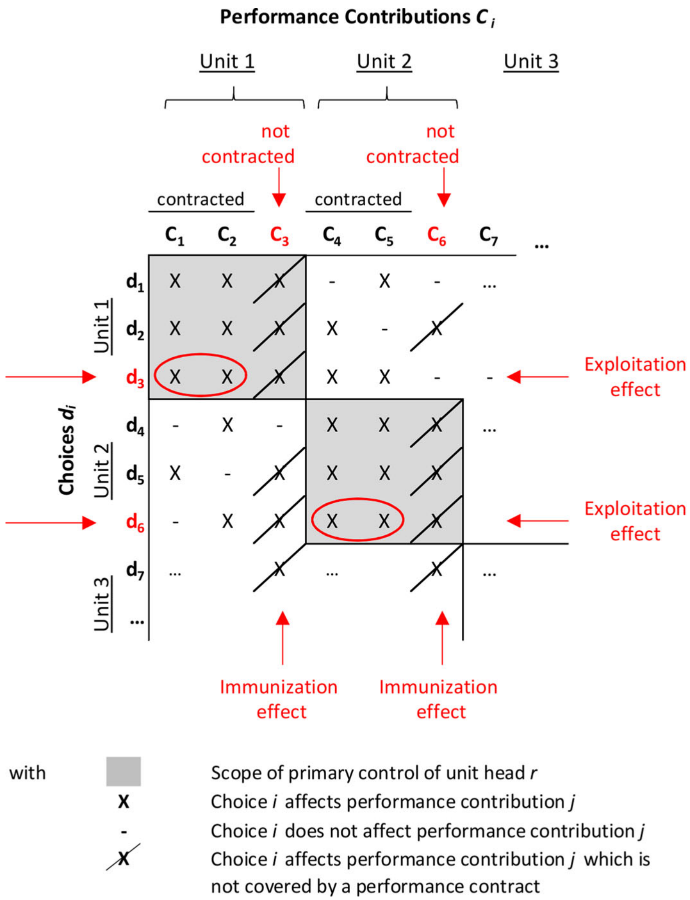

Fig. 3 Detail of the non-decomposable interaction structure in Fig. 1b on irrelevant interactions of not-contracted performance contributions and "remaining" interactions of related choices for a level $ic^r = 1$ of contractual incompleteness

C_i—may they result from choices of the fellow managers $q \neq r$ or from own decisions. In Fig. 3, this becomes apparent from the "crossed out" entries of columns for performance contributions C_3 and C_6, i.e., performance contributions which the performance contracts of unit 1 or unit 2, respectively, do not cover.

(2) *"Exploitation effect"*: If a manager r's value base of compensation is affected by fellow managers' choices, then manager r might react with alterations affecting r's contracted performance. This may also include exploiting decisions whose performance contributions are not covered by the contract. For example, in Fig. 3, let choice d_3 be assigned to manager 1, while contribution C_3 is not covered by the performance contract. Hence, choice d_3 is not relevant due to its "own" contribution C_3 to manager 1's compensation. However, this does not imply that choice d_3 is irrelevant. Rather, an alteration in d_3 may promise positively affecting the performance contributions of the contracted tasks via intra-unit interactions. In this sense, the not-contracted parts

are relevant for manager r as far as they serve as *means* for improving the contracted part of a manager's decision problem. In Fig. 3, this can be seen from the rows of the choices d_3 and d_6. These choices might be employed to increase the contracted performance. Due to cross-unit interactions, this may also affect the respective other units' value base of compensation and, consequently, induce adjustments. However, this effect depends on the particular interaction structure.[7]

These considerations also serve to explain the rather different dynamics showing up for the different levels of contractual completeness in Fig. 2b when task complexity is high. As already mentioned, in this interaction structure, the dense mutual interactions lead to frequent surprises from the fellow managers' choices which induce adjustments causing further surprises and adjustments, and so forth. In Fig. 2b, this effect is apparent for the case of *complete contract* leading to slow and noisy ("oscillating") performance inclines; when one manager alters her/his partial configuration, other managers presumably react, i.e., modify their partial solution, and this based on imperfect ex ante evaluations due to cognitive limitations. In this sense, the frequent mutual adjustments persistently distract the organizations' search from quick performance inclines. These "distractions" are caused by mutual "surprises," and they are effective from the beginning, i.e., with a randomly chosen initial configuration, even in a stage of the organizational search when performance inclines are relatively "easy" to achieve. In contrast, as argued above, with the incompleteness of the contract, the "immunization" effect reduces the mutual adjustments, so that fast performance inclines in the beginning are feasible. Figure 2b shows this for both levels of contractual incompleteness. With moderately incomplete contracts (i.e., $ic^r = 1$), performance increases until about time step $t = 50$ without notable "oscillations", especially compared to the complete contract plot. As mentioned above, the "exploitation effect" could induce that even the not-contracted task elements may be considered in decision-making. Hence, the immunization effect and exploitation effect here "outperform" contractual completeness. However, with a highly incomplete contract (i.e., $ic^r = 2$ and $N^r = 3$), a manager is likely to focus only one-third of the decisions assigned to that manager. While the exploitation effect may have a moderating effect here, this reasonably narrows the search too much, which is why at about time step $t = 70$, the search with complete contracts performs better.

The considerations on how not-contracted elements affect organizational search processes could also be seen from a broader perspective and, in particular, may *contribute to explaining the relative importance of certain types of objectives in organizational decision-making*:

- First, the analysis suggests that not-contracted task elements may indirectly affect decision-making if they are relevant for the performance obtained from the contracted task elements. Hence, the particular interaction structure among the task elements is relevant for this exploitation effect.
- Second, the not-contracted task elements become only "means" to increase performance contributions of other choices, i.e., their "character" changes toward merely instrumental in the target system. Moreover, the immunization effect reduces the

[7] For example, in Fig. 3, decision d_6 of unit 2 also affects the not contracted performance contribution C_3 of unit 1—which due to the immunization effect—would not induce a further adjustment by unit 1.

sensitivity of decision-makers to the performance of not-contracted task elements. This may be particularly interesting for which task elements are not governed by a contract: As mentioned in the introduction, these often are task elements that are hard to measure (e.g., creativity, customer orientation, courtesy) (Holmström and Milgrom 2009). With this, the results also refer to prior research on the relative weight of financial vs. non-financial performance measures in performance contracts (with an overview, Ittner et al. 2003).

4.4 Effects of intra-organizational complexity

The next step of the analysis studies the effects of incomplete contracts for a broader range of task environments. Particular focus is on how sensitive the effects of contractual incompleteness are to intra-organizational complexity. For this, simulations for two additional intermediate levels and a high level of complexity with Type I managers are run (see Table 2). Figure 4 displays for each of the five task environments, and the three levels of contractual incompleteness under inspection two of the metrics introduced in Sect. 4.1—namely the final performance (left axis) and the average number of choices switched per period (right axis). The plots allow the following observations:

1. With the increasing complexity of the task environment, moderately incomplete contracts ($ic^r = 1$) become less adverse than complete contracts or even outperform complete contracts.
2. A highly incomplete contract ($ic^r = 2$) leads to lower organizational performance than a moderately incomplete contract for all levels of complexity.
3. Incomplete performance contracts reduce alterations considerably compared to complete contracts. This effect is the higher the more complex the task environment.
4. With highly incomplete contracts ($ic^r = 2$), adaptive walks nearly approach inertia in terms of negligible alterations.

For a closer analysis, two particular observations may serve as starting point: With moderate complexity (Fig. 4c), the final performance achieved under the regime of a complete contract equals the level obtained with low incompleteness ($ic^r = 1$); in the highly complex task environment, a complete and a highly incomplete contract show similar performance levels (Fig. 4e).

Together with the metric on the alterations, these observations suggest that two traits of search processes are balancing out, and thus, resulting in similar performance levels—namely width and stability. The width refers to whether the search covers all components of the decision problem and the entire performance landscape is searched. Stability means that superior solutions, once found, are not abandoned and, if possible, even further improved. In the moderate complexity case with complete contracts (Fig. 4c), the width of search comes at the cost of lower stability which results in the same performance level as moderate incompleteness inducing higher stability. When complexity is high (Fig. 4e), the width of search is associated with low stability ("hyper-activity") due to intense intra-organizational interactions. This leads to a similar low level of performance as a narrowed search due to contractual incompleteness, which precludes interactions from affecting search, increasing stability to near inertia.

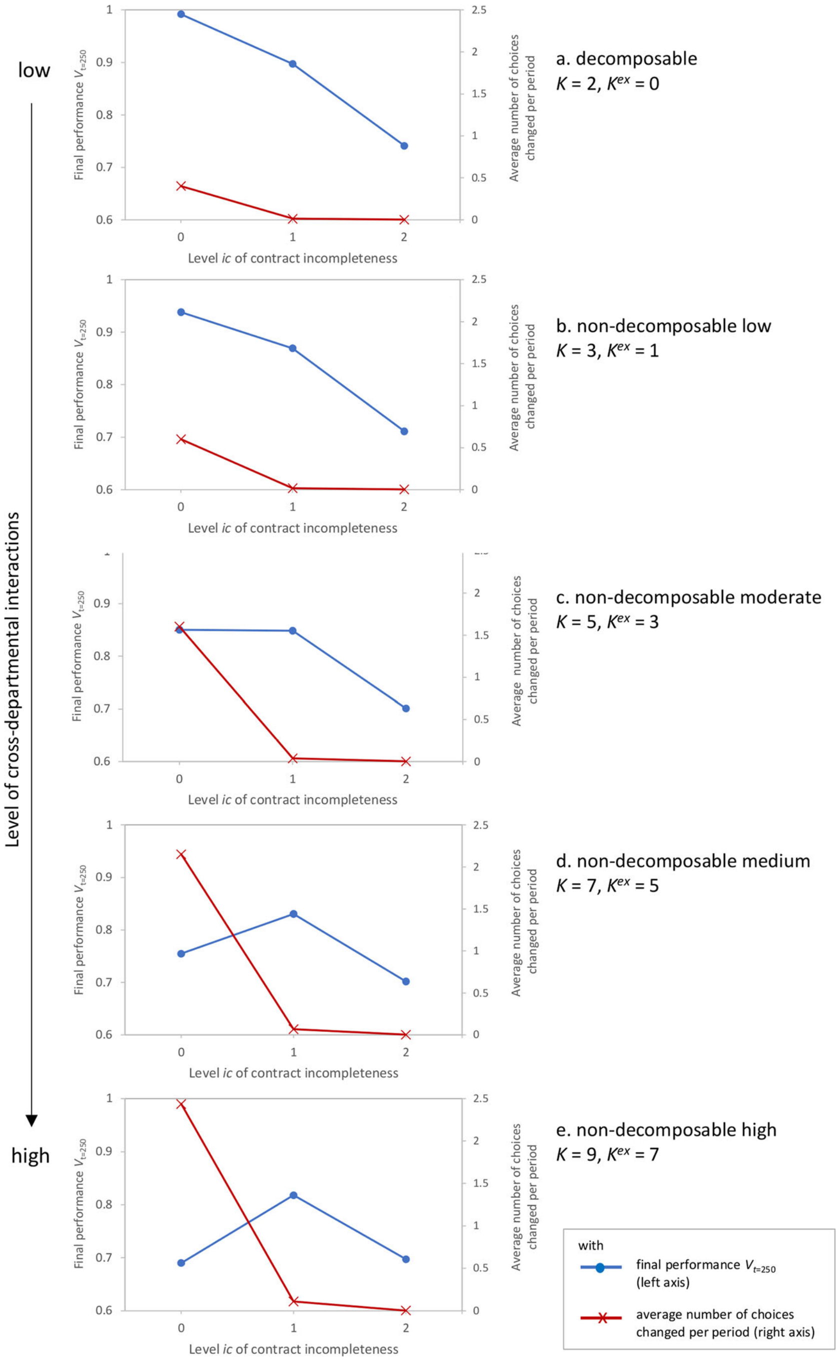

Fig. 4 Final performance and level of change per period with contracts of different levels of incompleteness and complexity of cross-unit interactions and for Type I managers. The level of change is measured as the number of single choices d_i of the $N = 12$-dimensional decision problem that are changed per time step averaged over the observation time $T = 250$. Each mark represents the average of 2500 simulation runs. For parameter settings, see Table 2

In more general, the considerations could be summarized in the following hypothesis: *Incomplete contracts reduce the width of search and increase the stability of search. The level of contractual incompleteness in conjunction with the complexity of an organization's task environment shapes how far these two effects are beneficial or detrimental.*

This allows to motivate the results of the other scenarios shown in Fig. 4:

- Without or with only a few interactions across units (plots a and b), the stabilizing effect of incomplete contracts is irrelevant. Hence, the detrimental effect of narrowing search predominates, and complete contracts are preferable.
- With the relatively high complexity of the task environment, moderate incompleteness of contracts appears to be beneficial for its stabilizing effect. However, there seems to be a tipping point; when incompleteness is too high, detrimental effects of narrowing search prevail.

This interpretation of the experimental results may also be seen in the light of so-called "nervousness" in planning as it was broadly studied in supply chain management and, in particular, in material requirements planning (MRP) (e.g., Blackburn et al. 1986). With interdependencies within the process, instability at one stage tends to propagate across the process since plans at subsequent stages are adjusted too. Various strategies to cope with this building-up of adjustment decisions have been studied—among them, the freezing of plans once made, or improved forecasting (for surveys, e.g., Atadeniz and Sridharan 2020; Damand et al. 2019). In this sense, one may regard incomplete contracting also as a strategy for reducing "nervousness" in a system; the "immunization" effect mentioned above reduces the propagation of adjustments among units since certain consequences of a "surprise" from fellow managers' choices get ignored—however, at the cost of narrowed search and potential performance losses. Charging extra costs for unscheduled adjustments has been suggested as another strategy to reduce nervousness in planning (Carlson et al. 1979; Blackburn et al. 1986) which also directs to the next step of our simulation study.

4.5 Sensitivity to cost of effort

The third step of this analysis turns to the effects of incomplete performance contracts when decision-makers also take the cost of effort into account (Type II managers). Figure 5 displays the final performances and the average level of change per period obtained for different task environments, types of contracts, and cost levels given by the cost coefficient z. The results allow for the following observations:

- With incomplete performance contracts, the final performance obtained declines with increasing cost of effort—*regardless of the level of task complexity*.[8]
- In contrast, for complete contracts, the effect of cost of effort on final performance is affected by the task environment; the final performance slightly *decreases* in decomposable structures ($K^{ex} = 0$) and *increases* with higher levels of complexity ($K^{ex} \geq 3$) in the cost coefficients studied.

[8] The performance loss under maximal cost coefficient studied ($z = 0.01$) compared to Type I managers (in the plots at $z = 0$) is about 4 to 6 points of percentage for moderate incompleteness ($ic = 1$) and around 3 points of percentage for highly incomplete contracts ($ic = 2$).

- The average level of alterations decreases in the costs of effort for all levels of complexity and contractual incompleteness. However, while the decline is remarkable for complete contracts, it is low or even negligible for search under incomplete contracts.

For explaining these observations, it appears helpful to start with the effects of managers considering the (nonzero) cost of effort on search processes. The criterion (Eq. 7) for leaving the status quo in favor of an alternative is more strict than with Type I managers. Type II managers only switch to an alternative option whose perceived performance gains exceed the cost of effort for switching. Broadly speaking, the evaluation of alternatives is more "selective." This also means that frequent mutual adjustments due to interactions and surprises from fellow managers' behavior are reduced, which is reflected in the results. These considerations, in principle, apply to situations with complete and incomplete contracts.

When contracts are complete, the effects of higher "selectivity" on performance are shaped by the level of complexity: Without interactions, no mutual adjustments occur, and, hence, only the "downside" of a more strict criterion is effective, i.e., reducing the diversity of search. In contrast, with increasing complexity, the stabilizing effect of cost of effort becomes more relevant, meaning that only "worthwhile" alterations happen and, thus, the "nervousness" in the search processes is reduced. For complete contracts, this effect prevails for higher levels of complexity, as shown in Fig. 5.

The question remains why, with incomplete contracts, the final performance decreases with increasing cost of effort for all levels of task complexity—other than with complete contracts. This is the more remarkable as, with incomplete contracts, two potentially stabilizing effects are at work—first, the immunization effect as highlighted in the previous sections, and, second, the higher selectivity of the decision criterion. One may argue that combining these two effects simply means too much reduction in the diversity of search (i.e., further lowering an even low level of alterations).

However, the incompleteness of contracts has a further particular effect on search processes with Type II managers. In particular, incomplete contracts here induce some "imbalance" in the evaluation of options. While the perceived performance effects of only the contracted task elements enter a novel option's evaluation on the "positive" side, the cost of effort for changing both the contracted and not-contracted task elements enter the "negative" side of the evaluation criterion (see Eq. 7). In more general words: *With incomplete contracts, perceived performance gains of the contracted task elements have to "earn" the cost of effort not only of the contracted but also of the not-contracted task elements.*

This brings us back to the considerations in Sect. 4.3, and, in particular, to the "exploitation" effect (Fig. 3). In the case of intra-task interactions of a manager's task, a not-contracted task element may be relevant as a *means* to increase the performance contributions received from the contracted task elements. However, when the costs of effort are taken into account, the performance effects of the not-contracted on the contracted task elements via interactions have to cover the costs of effort of the not-contracted parts. This refers to the "horizontal" interactions among a manager's task elements, i.e., the *intra-unit* interactions and not to the cross-unit interactions—which

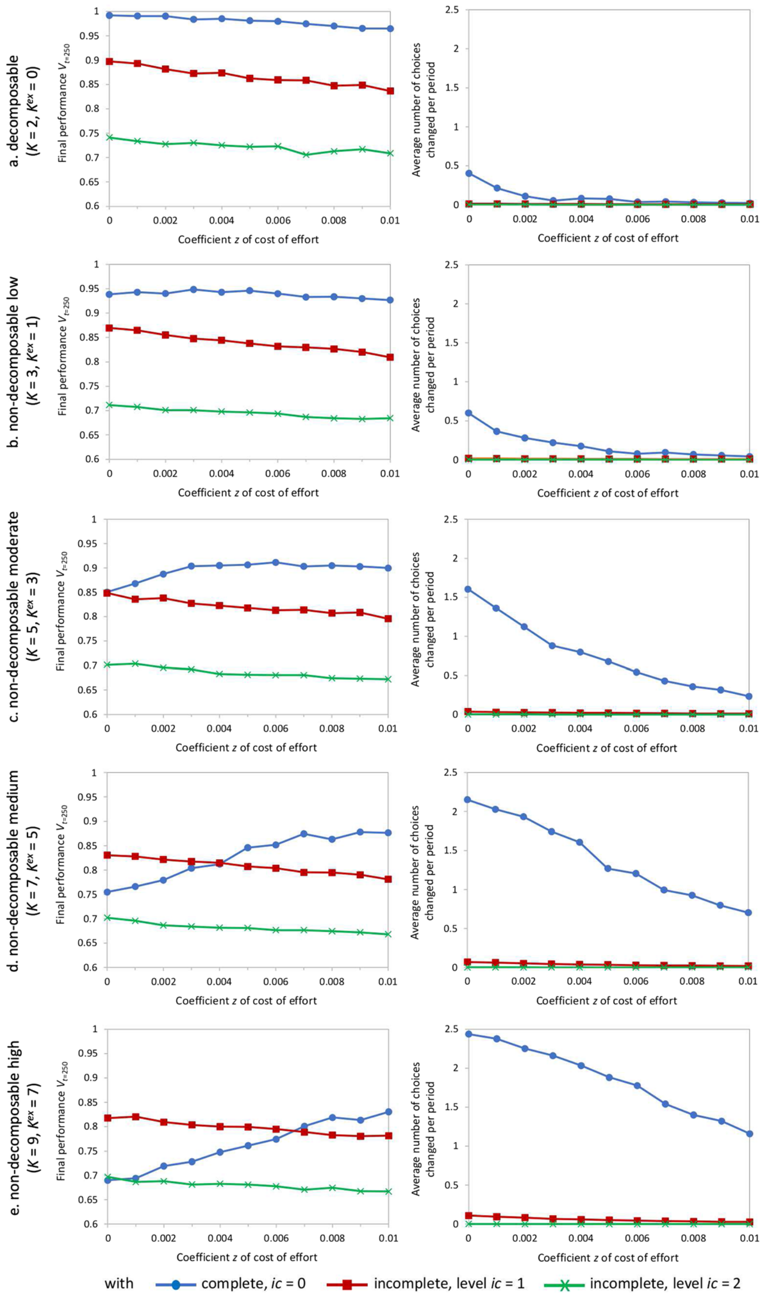

Fig. 5 Final performance (left side) and level of change per period (right side) with contracts of different levels of incompleteness, task complexity and cost of effort given by the cost coefficient z (Type II managers). Results of Type I managers (ignoring cost of effort) are depicted as if their cost level were $z = 0$. The level of change is measured as the number of single choices d_i of the $N = 12$-dimensional decision problem that are changed per time step averaged over the observation time $T = 250$. Each mark represents the average of 2500 simulation runs. For parameter settings, see Table 2

explains the performance decline in increasing cost coefficients for all levels of cross-unit complexity when contracts are incomplete.

These considerations suggest that it becomes even more unlikely that the not-contracted parts of a task are considered when the decision-maker takes costs of effort into account. As highlighted above, particularly those task elements that are hard to measure (e.g., courtesy, creativity) are not captured in performance contracts. The analysis for Type II managers reveals that these task elements may remain undervalued because, first, they are not contracted and, second, because their eventually positive spillover effects on the contracted task elements have to meet particularly high hurdles.

5 Conclusion

The results of the agent-based simulation study suggest that the complexity of the task environment in terms of the structure of interactions among task elements may considerably affect the effects of incomplete incentive contracts on organizational performance. In particular, the results indicate the beneficial effects of moderate incompleteness of performance contracts when intra-organizational complexity is high—the stabilization of search resulting from incomplete contracting causes this. Hence, incompleteness may not only reduce the "wastefulness" of complete contracts according to Tirole (2009), but it may also reduce some kind of "hyperactivity" in mutual adaptations, which also refers to the "nervousness" due to interdependencies in operational planning (e.g., Blackburn et al. 1986; Atadeniz and Sridharan 2020). The "ingredients" of the stabilization of search are two interrelated effects of incomplete contracting. First, incomplete incentive contracts let a decision-maker be less sensitive to other decision-makers' choices should they affect the not-contracted task elements due to interactions (immunization effect). Second, the decision-maker may only put some effort in the not-contracted task elements if this positively contributes to the contracted task elements, as shaped by the interaction structure (exploitation effect). For effort-sensitive decision-makers, positive spillover effects of the not-contracted on the contracted task elements have to "earn" the costs of effort for the not-contracted task elements.

The results suggest that the not-contracted task elements may receive relatively low weight in organizational decision-making—even if they remarkably may affect overall performance, directly or indirectly via interactions with contracted task elements. In this sense, this study may also contribute to the field of organizational goal systems and related formation processes (e.g., Kotlar et al. 2018). The results indicate that the character of the not-contracted tasks may be "reduced" to that of means objectives, i.e., being pursued as far as they contribute to achieving other objectives which, for effort-sensitive decision-makers, has to exceed the related cost of effort. In broader terms, from this, a line of events could be hypothesized. The performance achieved for certain task elements is hard to measure (e.g., creativity), which, consequently, are not covered by an incentive contract. This makes decision-makers insensitive to losses in performance regarding these task elements per se, which, hence, are "reduced" to means for other task elements. The model presented here does not explicitly study the weight that decision-makers assign to task elements. However, an exciting model extension could study whether the "chain reaction" hypothesized before emerges.

Several further avenues for future research appear worth pursuing. First, the experiments introduced here build on the homogeneity of decision-making agents and the symmetry of interaction structures. An essential extension would be to study situations with heterogeneous agents and asymmetries of interactions. In particular, in this study, decision-makers (unit heads) are—apart from different single choices assigned to them—homogeneous in all traits, i.e., the number of assigned choices, search behavior, cognitive capabilities, costs of effort, and incentives provided including the level of contractual incompleteness. Moreover, interaction structures are symmetrical in the experiments, meaning that each decision-maker has to cope with the same intra-unit and cross-unit complexity. Hence, a necessary extension is to study the effects of heterogeneity among decision-makers. In this vein, some decision-makers may have incomplete performance contracts while the contracts of others cover all task elements. This may induce interesting effects, particularly if combined with asymmetrical interaction structures—i.e., where the not-contracted task elements are influential for many or all other decisions in the organization (e.g., creativity in the R&D unit affecting the performances obtained in the units). In a similar vein, it could be of interest to study incomplete performance contracts when the management team is a "mix" of Type I and Type II decision-makers, i.e., some being sensitive to cost of effort, while others ignore these. This also refers to previous agent-based simulations of workforce diversity (Wall 2021b), which suggest that nonlinear effects may emerge from multi-attributive heterogeneity in management teams.

Second, the simulation study presented here captures organizations with rather rudimentary institutional arrangements. In particular, apart from the division of labor and linear (incomplete) incentive contracting related to individual performance, the artificial organizations in the model do not employ any further arrangements. Hence, a further developed simulation model could capture, for example, other incentive schemes (e.g., team-based rewards) or more sophisticated vertical or lateral coordination modes (e.g., via hierarchy or sequential planning) (Bushman et al. 1995; Siggelkow and Rivkin 2005; Wall 2017).

Third, regarding the methodological side, to the best of the author's knowledge, it is the first time that incomplete incentive contracting is studied employing minimal intelligence agents. Hence, one might also regard the paper as a methodological contribution to the field of incomplete incentive contracting. However, it might be interesting to increase the "intelligence" of agents (Chen 2012) by endowing agents with memory, with a—more or less—appropriate cognitive model of the task environment and learning capabilities. This would allow studying in how far results are robust toward decision-makers' intelligence. Correspondingly, it is worth mentioning that in the model introduced, also the headquarters (i.e., the principal in terms of agency theory), operates at a minimal intelligence level. Future variants of the model could endow headquarters with the capability to learn about subordinate decision-makers' behavior regarding the not-contracted task elements and, eventually, trust them.

This leads, fourth, to avenues of future research concerning the social dynamics among agents captured in the model. The model presented here employs what has been called "conditional choice" (Rolfe 2009) meaning that agents base their choices on what others do. However, it is well-noticed that incomplete contracts and, in a broader sense, relational contracts may unfold and be subject to complex social dynamics: the building of (dis-)trust, recognition of reputation and trustworthiness, formation of trust networks or self-reinforcement (e.g., Coletti et al. 2005; Cook and Gerbasi 2009; Wall and Leitner 2021). Agent-based modeling allows capturing social dynamics as they are relevant when incomplete incentive contracts are employed. Hence, further modeling efforts to integrate more complex social dynamics appear a promising endeavor.

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