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Adaptation of the boundary system in growing firms: an agent-based computational study on the role of complexity and search strategy

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ABSTRACT

The boundary system of a firm is intended to set constraints to the behaviour of organisational participants and, by this, to affect decision-making in the direction of the firm's overall objective. In growing firms, the boundary system is subject to a particular tension: balancing the search for new opportunities and innovation with behavioural constraints to deal with increasing size and intra-organisational complexity. Against this background, the paper studies the adaptation of the boundary system in growing firms. For this, an agent-based simulation based on the framework of NK fitness landscapes is employed which is a rather new approach in the domain of management control systems. The study controls for different levels of task complexity and for different styles in firms' search for new opportunities in terms of exploitative, explorative or ambidextrous search strategies. The results suggest that the level of task complexity subtly interferes with the search strategy employed in respect of the emerging boundaries. In particular, results support the conjecture that growing task complexity leads to more coordination via hierarchy. However, the search strategy employed shapes the predominance of boundaries compared to less constraining modes of coordination granting higher levels of autonomy to subordinates.

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1. Introduction

According to the prominent 'Levers of control' (LOC) framework introduced by Simons (1994a, 1994b), firms employ boundary systems – complementing the diagnostic, interactive and beliefs systems as other sub-systems of management control systems (MCS) – 'to set limits on opportunity-seeking behavior' (Simons, 1994b, p. 7) and to 'delineate the acceptable domain of activity for behaviour of organisational participants' (p. 39). Boundary systems are regarded as a necessary prerequisite for

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the delegation of decision-making incorporated in MCS (Malmi & Brown, 2008; Simons, 1994b; Widener, 2007).

In growing firms, the boundary system is subject to a particular tension: i.e., balancing search for new opportunities and innovation with behavioural constraints to deal with increasing size and intra-organisational complexity (e.g., Bedford, 2015; Bisbe & Otley, 2004; Kruis, Speklé, & Widener, 2016; Widener, 2007). However, while research on MCS for firms of considerable size and age has a long tradition, taking growth together with size (e.g., small growing organisations) into account is a comparably young perspective (Chenhall, 2003). A cornerstone of research on management controls in growing organisations is the seminal paper of Davila (2005) which employs an explorative-empirical approach and caused several further studies (e.g., Davila, Foster, & Jia, 2015; Samagaio, Crespo, & Rodrigues, 2018; for an overview López & Hiebl, 2015). The vast majority of these studies applies an empirical approach with the aim to understand which configurations of MCS are adopted under certain conditions taking the perspective of contingency theory (i.e., assuming that the performance of an organisation is shaped by the fit between its external context and its internal arrangements, e.g., Van de Ven, Ganco, & Hinings, 2013).

However, the findings of the aforementioned stream of research on MCS, and, in particular, boundary systems as emerging in the course of firm growth are ambiguous. Some studies find that increasing size is associated with tighter boundaries for dealing with higher intra-organisational complexity (Andersén & Samuelsson, 2016; Chenhall & Morris, 1986; Davila, 2005; Davila, Foster, & Li, 2009); other studies suggest rather the opposite emphasising that higher complexity requires more flexibility and, thus, more emphasis on informal controls (Chenhall, 2003; Macintosh & Daft, 1987).

These ambiguous findings may indicate on a research gap in the understanding of boundary systems in growing firms. This paper seeks to contribute to closing this gap and to provide some answers for the following research question:

Which boundary systems emerge in the course of firm growth?

At this, the paper also takes a contingency perspective, and focuses on two contingent factors resulting from the aforementioned tension of boundary systems in growing firms: balancing necessity to search for novel solutions with mechanisms to deal with increasing intra-organisational complexity. Hence, the research endeavour considers two sub-questions.

1. How does complexity in terms of interdependencies among the elements of a firm's task and
2. how do different styles of search for new solutions affect the adaptation of the boundary system in the course of growth?

This study employs a simulation model in the spirit of agent-based computational economics and, hence, follows a different methodological approach than the aforementioned empirical studies. In the simulations, organisations are 'grown from scratch' and the adaptation of the boundary system is observed for different levels of complexity and search styles. The simulations are employed for prediction and

explanation (Burton & Obel, 2011; Za, Spagnoletti, Winter, & Mettler, 2018) and, in particular, are intended to pave the way for empirically testable hypotheses. While to the best of the author's knowledge this research method is rather new in the field of MCS (Hesford, Lee, Van der Stede, & Young, 2007; Leitner & Wall, 2015; Wall, 2016), it appears a promising method for this research endeavour for the following reasons.

Simulation was found (with further references, e.g., Davis, Eisenhardt, & Bingham, 2007; Harrison, Zhiang, Carroll, & Carley, 2007) to be particularly useful in managerial science when

1. the research subject addresses a fundamental tension – like the aforementioned tension incorporated in boundary systems in growing firms;
2. various and potentially interacting (contingent) factors may be effective – e.g., intra-organisational complexity and styles of search as captured in this paper's research questions, and
3. processual and, specifically, longitudinal phenomena – like firm growth – are to be investigated posing considerable challenges for empirical research.

Among the various types of simulation (e.g., Za et al., 2018), an agent-based type is chosen for its 'natural' correspondence to the key issue of management control which is to affect the behaviour of organisational members in the direction of the organisation's objective (e.g., Malmi & Brown, 2008). In particular, mechanisms to affect the behaviour of decision-makers ('managers') – given their individual preferences and capabilities – is in the core of MCS. This corresponds to agent-based simulation: being deeply rooted in methodological individualism (Davis and Lay-Yee, 2019), artificial heterogeneous interacting agents are simulated with the properties at the system's level emerging from the individual behaviour and local interactions (e.g., Epstein, 1999; Gilbert & Troitzsch, 2005; Tesfatsion, 2003). This study, in particular, applies the framework of NK fitness landscapes which was originally introduced in evolutionary biology (Kauffman, 1993; Kauffman & Levin, 1987) and broadly employed in managerial science (for overviews Baumann, Schmidt, & Stieglitz, 2019; Wall, 2016). The NK framework allows to depict and conveniently control for complexity which is subject of this paper's research question.

Against this background, the paper promises two-fold contributions: First, it seeks to provide some complementary insights to the existing body of research to predict and understand the adaptation of the boundary system which is likewise relevant for theory and practice. Second, by its computational method, the paper introduces a rather novel approach to MCS which may provide a fruitful methodological extension in the domain.

Four additional sections comprise the remainder of the paper. Based on a brief reference to the theoretical foundations, the next section relates this paper to particularly relevant streams of prior research. [Section 3](#) introduces the simulation model before, in [Section 4](#), the simulation experiments are described. [Section 5](#) presents and discusses the results from the experiments. [Section 6](#) provides concluding remarks.

2. Theoretical background and related work

2.1. Theoretical background

This paper, firstly, builds on prior work in the domain of management accounting and control¹ (MAC) and, secondly, due to its particular methodological approach, is based on agent-based computational economics (ABCE) implying certain theoretical perspectives.

The theoretical foundations in MAC are diverse – reaching from economics over organisational theories to psychology and sociology (Ahrens & Chapman, 2007). With respect to economics, neo-institutional thoughts and, especially, principal-agent theory is of particular relevance (Eisenhardt, 1989). Regarding its roots in organisational thinking, a predominant perspective in MAC is contingency theory (e.g., Van de Ven et al., 2013) which is also adopted here (see Introduction). Hence, prior research on MCS in growing small and medium-sized firms (i.e., size and growth as contingencies) is outlined in Section 2.2.1.

Adopting the perspective of ABCE has some far-reaching theoretical implications which is why two further streams of related research are outlined: In ABCE some assumptions of neoclassical economics and also of neo-institutional economics related to economic agents are relaxed (for an overview Chang & Harrington, 2006). For example, in ABCE it is assumed that economic agents are heterogeneous and, thus, cannot be captured by the ‘representative agent’ of neoclassical economics (Kirman, 1992) and that they show some form of bounded rationality according to Simon (1955). Hence, in ABCE agents cannot identify the global optimum of a solution space ‘instantaneously’; rather they discover the solution space stepwise in search processes for better solutions (e.g., Safarzyńska and van den Bergh, 2010; Leitner & Wall, 2019). It is only based on such ideas, that the search for better and, potentially, ‘innovative’ solutions comes into play. This is why the search strategy is a relevant contingent factor (see above) and, hence, why related research on ‘MCS and innovation’ (Section 2.2.2) is briefly outlined as well as agent-based modelling in domains of organisational design and MAC (Section 2.2.3).

2.2. Related work

2.2.1. MCS in growing small and medium-sized firms

According to Davila (2005), increasing firm size positively affects the overall use of MCS as well as of action controls according to Merchant and Van der Stede (2017) which correspond to the boundary system in Simons’ (1994a, 1994b) framework (Kruis et al., 2016; Langfield-Smith, 2007; Widener, 2007). It was argued that with increasing firm size informal controls become too costly and/or ineffective and, hence, more formal controls for motivation and monitoring are employed as provided by MCS. In a similar vein, Andersén and Samuelsson (2016) find that, for growing small- and medium-sized firms, intense usage of management accounting systems for decision-making is a prerequisite for high entrepreneurial orientation to positively influence firm profitability.

Findings on MCS in the context of (growing) task complexity are somewhat ambiguous. Low levels of interactions were found to be linked to budgets, operating

procedures and statistical reports while the latter and informal coordination were employed for high task complexity (Macintosh & Daft, 1987). Chenhall and Morris (1986) report that more emphasis on interactions between subordinates and superiors as well as usage of aggregated and integrative information is associated with higher complexity. A reason behind could be that with more interdependencies a lack of control over sub-units becomes more risky leading to more formal controls. However, the tension reflected in boundary systems increases the need for flexibility to deal with interdependencies which suggests more informal controls (Chenhall, 2003). The idea to regard MCS actually as *systems*, not just as ‘collections’ of controls (e.g., Grabner & Moers, 2013), brings about the call for balanced configurations of management controls. In this vein, Kruis et al. (2016) find that high levels of task interdependencies tend to be related to vertical communication for solving co-ordination problems’ which may indicate on a centralisation of decision-making authority.

2.2.2. MCS and innovation

The tension incorporated in boundary systems, i.e., constraining and enabling new solutions at the same time, is particularly relevant in the context of innovation. It was argued, that boundary systems help focussing innovative efforts, i.e., aligning them to the firm’s strategy. According to Bisbe and Otley (2004) the use of boundary systems is positively associated with performance for exploitative innovation – particularly, because they reduce the risk that subordinates pursue activities that are not in line with established processes and control activities at lower organisational levels (for the latter, see also Davila, Foster, & Oyon, 2009). Exploitative innovation with its typically tightly-coupled activities is found to benefit from boundary systems while they, in contrast, are suspected to reduce exploration in the long run (Simons, Dávila, & Kaplan, 2000).

2.2.3. Agent-based modelling in organisational design and MCS

Regarding the research method applied (see Introduction), it should be noted, that there are numerous studies employing simulation in general and agent-based modelling in particular in the domain of organisational design (for overviews, e.g., Chang & Harrington, 2006; Harrison et al., 2007). Many of these studies rely on NK fitness landscapes for their particular capability to depict the complexity of interactions among activities (or decisions) (e.g., Cszasz, 2018; Li et al., 2006). Organisational design comes into play by distributed agents (e.g., managers) searching for superior levels of performance on these landscapes. For example, exploitative (i.e., local search) versus explorative search in terms of ‘long jumps’ was simulated; different decompositions of the overall problem into sub-problems or different objective functions – shaped by incentive schemes – of decision-makers may be modelled (for an overview Baumann et al., 2019). Siggelkow and Rivkin (2005) study the performance gains obtained with different coordination mechanisms when task environments are turbulent and complex which relates to boundary systems. Wall (2016) indicates on the (partially beneficial) effects of imperfect information in the context of different coordination modes.

3. Outline of the simulation model

3.1. Classificatory remarks on the methodology

For being clear and concise on the simulation model from a methodological perspective, it is categorised according to the four-dimensional framework proposed by Za et al. (2018) for simulation-based research in the field of information systems:

1. With respect to the *simulation type*, as argued in the Introduction, an agent-based model is employed. The model captures growing artificial organisations which search for superior solutions to their decision-problem and are resided by self-interested decentralised decision-makers; based on learning, organisations may modify their boundary system.
2. Regarding the *contribution to theory*, as mentioned in the Introduction, the study seeks to predict and, ideally, explain why certain types of coordination emerge. This corresponds to predominant contributions of agent-based simulations as reported by Beese, Haki, Aier, and Winter (2019).
3. In view of the *research domain*, i.e., transferred to our subject, the level of analysis (individual or organisational) is to be specified: the explanandum (i.e., a firm's emerging boundary system) is clearly at the organisational level while being explained from the individual agents' behaviour in their environment (Epstein, 2006).
4. The *view of information* in the model corresponds to what the authors name the representation view and is also relevant for our model since MCS largely rely on information-processing: in the model, information has a certain *meaning* to the agents (i.e., options, expected and actual performance).

Against this background, key components of the model are: (1) the growing decision-problem, (2) its decomposition and delegation to departmental decision-makers with (3) their preferences and search for novel solutions, (4) coordination among decision-makers, and (5) its learning-based adaptation. Subsequently, these components are characterised into detail.

3.2. Growing organisational decision-problem

In line with the NK-framework, at each time step t the organisations face an N -dimensional binary decision-problem, i.e., $\mathbf{d}_t = (d_{1t}, \dots, d_{Nt})$ with $d_{it} \in \{0, 1\}$, $i = 1, \dots, N$, out of 2^N different binary vectors possible.² Each of the two states 0 or 1 contributes to overall performance $V(\mathbf{d}_t)$ by C_{it} which is randomly drawn from a uniform distribution ($0 \leq C_{it} \leq 1$). Parameter K (with $0 \leq K \leq N - 1$) captures the number of those choices $d_{jt}, j \neq i$ which also affect the performance contribution C_{it} of choice d_{it} :

$$C_{it} = f_i(d_{it}; d_{i_1t}, \dots, d_{i_Kt}) \quad (1)$$

with $\{i_1, \dots, i_K\} \subset \{1, \dots, i-1, i+1, \dots, N\}$. Without interactions among choices, K equals 0, and $K = N-1$ for maximum complexity, i.e., every single choice i affecting the performance contribution of each other choice $j \neq i$. Hence, K captures the

a. decomposable

Growth stage $s=1$ ($N_1=6, K_1=2, K_1^{ex}=0$)
Performance Contribution C_j

	1	2	3	4	5	6
Choice d_i Dep 1	X	X	X	-	-	-
Dep 2	X	X	X	-	-	-
Choice d_i Dep 2	X	X	X	-	-	-
Dep 3	X	X	X	-	-	-
Choice d_i Dep 3	-	-	-	X	X	X
Dep 4	-	-	-	X	X	X
Choice d_i Dep 4	-	-	-	X	X	X
Dep 6	-	-	-	X	X	X

Growth stage $s=2$ ($N_2=9, K_2=2, K_2^{ex}=0$)
Performance Contribution C_j

	1	2	3	4	5	6	7	8	9
Choice d_i Dep 1	X	X	X	-	-	-	-	-	-
Dep 2	X	X	X	-	-	-	-	-	-
Choice d_i Dep 2	X	X	X	-	-	-	-	-	-
Dep 3	X	X	X	-	-	-	-	-	-
Choice d_i Dep 3	-	-	-	X	X	X	-	-	-
Dep 4	-	-	-	X	X	X	-	-	-
Choice d_i Dep 4	-	-	-	X	X	X	-	-	-
Dep 5	-	-	-	X	X	X	-	-	-
Choice d_i Dep 5	-	-	-	X	X	X	-	-	-
Dep 6	-	-	-	X	X	X	-	-	-
Choice d_i Dep 6	-	-	-	X	X	X	-	-	-
Dep 7	-	-	-	-	-	-	X	X	X
Choice d_i Dep 7	-	-	-	-	-	-	X	X	X
Dep 8	-	-	-	-	-	-	X	X	X
Choice d_i Dep 8	-	-	-	-	-	-	X	X	X
Dep 9	-	-	-	-	-	-	X	X	X

Growth stage $s=3$ ($N_3=12, K_3=2, K_3^{ex}=0$)
Performance Contribution C_j

	1	2	3	4	5	6	7	8	9	10	11	12
Choice d_i Dep 1	X	X	X	-	-	-	-	-	-	-	-	-
Dep 2	X	X	X	-	-	-	-	-	-	-	-	-
Choice d_i Dep 2	X	X	X	-	-	-	-	-	-	-	-	-
Dep 3	X	X	X	-	-	-	-	-	-	-	-	-
Choice d_i Dep 3	-	-	-	X	X	X	-	-	-	-	-	-
Dep 4	-	-	-	X	X	X	-	-	-	-	-	-
Choice d_i Dep 4	-	-	-	X	X	X	-	-	-	-	-	-
Dep 5	-	-	-	X	X	X	-	-	-	-	-	-
Choice d_i Dep 5	-	-	-	X	X	X	-	-	-	-	-	-
Dep 6	-	-	-	X	X	X	-	-	-	-	-	-
Choice d_i Dep 6	-	-	-	X	X	X	-	-	-	-	-	-
Dep 7	-	-	-	-	-	-	X	X	X	-	-	-
Choice d_i Dep 7	-	-	-	-	-	-	X	X	X	-	-	-
Dep 8	-	-	-	-	-	-	X	X	X	-	-	-
Choice d_i Dep 8	-	-	-	-	-	-	X	X	X	-	-	-
Dep 9	-	-	-	-	-	-	X	X	X	-	-	-
Choice d_i Dep 9	-	-	-	-	-	-	X	X	X	-	-	-
Dep 10	-	-	-	-	-	-	-	-	-	X	X	X
Choice d_i Dep 10	-	-	-	-	-	-	-	-	-	X	X	X
Dep 11	-	-	-	-	-	-	-	-	-	X	X	X
Choice d_i Dep 11	-	-	-	-	-	-	-	-	-	X	X	X
Dep 12	-	-	-	-	-	-	-	-	-	X	X	X

b. non-decomposable

Growth stage $s=1$ ($N_1=6, K_1=3, K_1^{ex}=1$)
Performance Contribution C_j

	1	2	3	4	5	6
Choice d_i Dep 1	X	X	X	-	X	-
Dep 2	X	X	X	-	-	X
Choice d_i Dep 2	X	X	X	-	-	X
Dep 3	X	X	X	-	-	X
Choice d_i Dep 3	-	-	-	X	X	X
Dep 4	-	-	-	X	X	X
Choice d_i Dep 4	-	-	-	X	X	X
Dep 6	-	-	-	X	X	X

Growth stage $s=2$ ($N_2=9, K_2=4, K_2^{ex}=2$)
Performance Contribution C_j

	1	2	3	4	5	6	7	8	9
Choice d_i Dep 1	X	X	X	-	X	-	-	X	-
Dep 2	X	X	X	-	-	X	-	X	-
Choice d_i Dep 2	X	X	X	-	-	X	-	X	-
Dep 3	X	X	X	-	-	X	-	X	-
Choice d_i Dep 3	-	-	-	X	X	X	X	-	X
Dep 4	-	-	-	X	X	X	X	-	X
Choice d_i Dep 4	-	-	-	X	X	X	X	-	X
Dep 5	-	-	-	X	X	X	X	-	X
Choice d_i Dep 5	-	-	-	X	X	X	X	-	X
Dep 6	-	-	-	X	X	X	X	-	X
Choice d_i Dep 6	-	-	-	X	X	X	X	-	X
Dep 7	-	-	-	-	-	-	X	X	X
Choice d_i Dep 7	-	-	-	-	-	-	X	X	X
Dep 8	-	-	-	-	-	-	X	X	X
Choice d_i Dep 8	-	-	-	-	-	-	X	X	X
Dep 9	-	-	-	-	-	-	X	X	X

Growth stage $s=3$ ($N_3=12, K_3=5, K_3^{ex}=3$)
Performance Contribution C_j

	1	2	3	4	5	6	7	8	9	10	11	12
Choice d_i Dep 1	X	X	X	-	X	-	-	X	-	-	-	X
Dep 2	X	X	X	-	-	X	-	X	-	-	X	-
Choice d_i Dep 2	X	X	X	-	-	X	-	X	-	-	X	-
Dep 3	X	X	X	-	-	X	-	X	-	-	X	-
Choice d_i Dep 3	-	-	-	X	X	X	X	-	X	-	-	X
Dep 4	-	-	-	X	X	X	X	-	X	-	-	X
Choice d_i Dep 4	-	-	-	X	X	X	X	-	X	-	-	X
Dep 5	-	-	-	X	X	X	X	-	X	-	-	X
Choice d_i Dep 5	-	-	-	X	X	X	X	-	X	-	-	X
Dep 6	-	-	-	X	X	X	X	-	X	-	-	X
Choice d_i Dep 6	-	-	-	X	X	X	X	-	X	-	-	X
Dep 7	-	-	-	-	-	-	X	X	X	-	-	X
Choice d_i Dep 7	-	-	-	-	-	-	X	X	X	-	-	X
Dep 8	-	-	-	-	-	-	X	X	X	-	-	X
Choice d_i Dep 8	-	-	-	-	-	-	X	X	X	-	-	X
Dep 9	-	-	-	-	-	-	X	X	X	-	-	X
Choice d_i Dep 9	-	-	-	-	-	-	X	X	X	-	-	X
Dep 10	-	-	-	-	-	-	-	-	-	X	X	X
Choice d_i Dep 10	-	-	-	-	-	-	-	-	-	X	X	X
Dep 11	-	-	-	-	-	-	-	-	-	X	X	X
Choice d_i Dep 11	-	-	-	-	-	-	-	-	-	X	X	X
Dep 12	-	-	-	-	-	-	-	-	-	X	X	X

- Notes:**
- Scope of primary control of department r
 - X** Choice i affects performance contribution j
 - Choice i does not affect performance contribution j
 - Dep Department

Figure 1. Interaction structures and growth stages in the simulation experiments.

decision-problem’s complexity in terms of interactions among single decisions. The overall performance V_t achieved in period t results as normalised sum of contributions C_{it} from

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

This, so far, captures the ‘standard’ NK framework. However, in this study, the number of decisions to be made by an organisation increases over time due to growth, i.e., $N(t)$. Hence, complexity may rise too, i.e., $K(t)$ (for examples see Figure 1 in Section 4 with explanations). Let $s = (1, \dots, S)$ capture the growth stage and T the observation period. Then, we have

$$N(t) = \begin{cases} N_1 & \text{for } 0 \leq t \leq t_1 \\ \vdots & \\ N_s & \text{for } t_{s-1} < t < t_s \\ \vdots & \\ N_S & \text{for } t_{S-1} < t \leq T \end{cases} \tag{3}$$

and overall performance (see Equation (2)) modifies to

$$V_t = V(\mathbf{d}_t) = \frac{1}{N_s} \sum_{i=1}^{N_s} C_{it} \tag{4}$$

Hence, overall performance is ‘dynamically’ normalised to the growing problem size.

3.3. Decomposition of the decision-problem and delegation

For depicting division of labour and delegation of (some) decision-making tasks, the N_s -dimensional decision-problem is partitioned into M_s disjoint partial problems of, for simplicity’s sake, equal size N_s^r in terms of number of single choices. Each of these sub-problems is delegated to one department r . According to the growing problem space, also the number of departments grows (for examples see [Figure 1](#)). The particular competencies of department r related to its respective sub-problem is subject to the boundary system emerged at that time. However, in each period t the departments, at least, *prepare* the decisions regarding their particular sub-problems.

3.4. Departmental preferences and boundary system

3.4.1. Formation of preferences and boundaries related to departmental search

Each department $r = 1, \dots, M_s$ has a department head which seeks to maximise its compensation. The model captures merit-based compensation which corresponds to empirical findings on high performance work systems in emergent organisations (e.g., Messersmith & Guthrie, 2010). For the sake of simplicity, compensation results from a linear function based on department r ’s contribution $P_t^r(\mathbf{d}_t^r)$ to overall performance V_t (see [Equation \(4\)](#)),

$$P_t^r(\mathbf{d}_t^r) = \frac{1}{N} \sum_{i=1+w}^{N_s^r} C_{it} \tag{5}$$

with $w = \sum_{p=1}^{r-1} N_s^p$ for $r > 1$ and $w = 0$ for $r = 1$.

In each time step t , manager r seeks to identify the best – i.e., compensation maximising – configuration for the ‘own’ choices \mathbf{d}_t^r out of the currently available options. However, with interactions among the sub-problems, captured by $K_s^{ex} > 0$, choices of manager $q \neq r$ affect contributions of manager r ’s choices on r ’s performance and vice versa.

Against this background, departmental decision-makers’ behaviour is shaped by limited cognitive capabilities (Sections 2.1 and 3.1) and by the search strategy enforced through the boundary system. Three aspects are relevant:

First, as mentioned above, decision-makers have to search stepwise for superior solutions. In particular, in each time step t manager r discovers two alternative solutions $\mathbf{d}_t^{r,a1}$ and $\mathbf{d}_t^{r,a2}$ for its sub-problem compared to the status quo $\mathbf{d}_{t-1}^{r,*}$, and, hence, has three alternatives to choose from – including keeping the status quo. However, the boundary system restricts the extent of change allowed (in terms of Hamming distances) which reflects the search strategy. Three search strategies are modelled:

1. ‘*exploitation only*’: both alternatives $\mathbf{d}_t^{r,a1}$ and $\mathbf{d}_t^{r,a2}$ differ from the status quo \mathbf{d}_{t-1}^{r*} by one digit. Hence, the Hamming distance of the first alternative to the status quo given by $h(\mathbf{d}^{r,a1}) = \sum_{i=1}^{N^r} |\mathbf{d}_{t-1}^{r*} - \mathbf{d}_t^{r,a1}|$ equals 1 as well as of the second alternative (i.e., $h(\mathbf{d}^{r,a2}) = 1$).
2. ‘*exploration only*’: in both alternatives two bits are flipped compared to the status quo \mathbf{d}_{t-1}^{r*} , i.e., $h(\mathbf{d}^{r,a1}) = h(\mathbf{d}^{r,a2}) = 2$.
3. ‘*exploitation and exploration*’: managers are allowed to consider different options with $h(\mathbf{d}^{r,a1}) = 1$ and $h(\mathbf{d}^{r,a2}) = 2$.

Second, without further communication eventually enforced by the boundary system (Section 3.4.2), department r cannot anticipate the other departments’ $q \neq r$ choices and, thus, assumes that they will stay with their status quo \mathbf{d}_{t-1}^{q*} .

Third, ex ante, i.e., when forming preferences, department heads cannot perfectly evaluate their newly discovered options $\mathbf{d}_t^{r,a1}$ and $\mathbf{d}_t^{r,a2}$ with respect to the value base for compensation $P_t^r(\mathbf{d}_t^r)$ (see Equation (5)). Their ex ante-evaluations are afflicted with some noise: each manager r ’s *perceived* value base for compensation (\tilde{P}) is distorted by an relative error imputed to the true performance (for further types of errors Levitan & Kauffman, 1995). Errors follow a Gaussian distribution $N(0; \sigma)$ with expected value 0 and standard deviations σ^r for every department r and are independent from each other. Thus, the value base for compensation *perceived* by manager r is

$$\tilde{P}_t^r(\mathbf{d}_t^r) = P_t^r(\mathbf{d}_t^r) + e^r(\mathbf{d}_t^r) \tag{6}$$

Hence, each manager r has a distinct partial and imperfect ‘view’ of the true fitness landscape, which reflects heterogeneity of agents (Section 2.1). In contrast to the newly discovered options, from the compensation received in $t-1$, manager r knows the *actual* performance P_t^r of the status quo should it be implemented again.

After ex ante-evaluation of options, each department head r compiles a list $L_t^r = \{\mathbf{d}_t^{r,p1}, \mathbf{d}_t^{r,p2}, \mathbf{d}_t^{r,p3}\}$ of preferences with $\mathbf{d}_t^{r,p1}$ indicating the most preferred option out of status quo \mathbf{d}_{t-1}^{r*} and the two alternatives $\mathbf{d}_t^{r,a1}$ and $\mathbf{d}_t^{r,a2}$; $\mathbf{d}_t^{r,p2}$ denotes the second and $\mathbf{d}_t^{r,p3}$ the third preference. However, preferences may be revised – according to the coordination mechanism emerged in the boundary system at that time.

3.4.2. Boundaries set by the coordination mechanism

The department heads’ preferences related to their sub-problems \mathbf{d}_t^r (captured in the M_s lists L_t^r) have to be transformed into a solution \mathbf{d}_t for the overall decision-problem. For this, the model comprises three different modes of coordination – subject to adaptation (Section 3.5). They differ with respect to communication channels,³ information employed and ‘location’ of authority for final decision-making (Table 1; for these and further modes, Malone, 1987; Siggelkow & Rivkin, 2005).

In the *decentralized mode*, each department is allowed to choose its most preferred option. With this, the overall configuration \mathbf{d}_t results from

$$\mathbf{d}_t = (\mathbf{d}_t^{1,p1}, \dots, \mathbf{d}_t^{r,p1}, \dots, \mathbf{d}_t^{M_s,p1}) \tag{7}$$

Table 1. Overview of the modes of coordination.

	Type of coordination mode		
	Decentralized	Sequential	Proposal
Lateral communication	no	yes	no
Vertical communication	no	no	yes
Headquarter intervening	no	no	yes
Re-evaluation of preferences	no	yes	yes
Departments' final configuration	First preferences $\mathbf{d}_t^{r,p1} \forall r \in \{1, \dots, M_s\}$	First preferences subject to choices of preceding departments, i.e., $\mathbf{d}_t^{r,p1}(\mathbf{d}_t^{r-1,p1})$ for $r > 1$; $\mathbf{d}_t^{r,p1}$ for $r = 1$	First [or second] preferences $\mathbf{d}_t^{r,p1}$ [or $\mathbf{d}_t^{r,p2}$] if $V(\mathbf{d}^C) \geq V(\mathbf{d}_{t-1})$, otherwise \mathbf{d}_{t-1}^*

and for department r 's sub-problem the option according to

$$\mathbf{d}_t^{r*} = \mathbf{d}_t^{r,p1} \quad \forall r \in \{1, \dots, M_s\} \tag{8}$$

is implemented. This type of coordination grants a maximum level of autonomy to the departments and does not require any communication. Headquarters' role is limited to registering the achieved performances \mathbf{d}_t and $P_t^r(\mathbf{d}_t^r)$ in the end of period t and compensating department heads accordingly.

The *sequential mode* reflects 'sequential planning': departments decide sequentially based on lateral communication where, for simplicity's sake, the sequence among departments is given by departments' index $r = (1, \dots, M_s)$. Within each time t , department $r - 1$ informs department r (with $1 < r < M_s$) about the choices made by 'preceding' units $< r$; taking these 'prior' choices into account, department r re-evaluates its 'own' options \mathbf{d}_{t-1}^{r*} , $\mathbf{d}_t^{r,a1}$ and $\mathbf{d}_t^{r,a2}$ which might result in *revised* preferences $L_t^r = \{\mathbf{d}_t^{r,p1}, \mathbf{d}_t^{r,p2}, \mathbf{d}_t^{r,p3}\}$. Department r then chooses $\mathbf{d}_t^{r,p1}$ which now depends on $\mathbf{d}_t^{r-1,p1}$, i.e., is a function of the 'preceding' departments' choices (only department 1 does not have to consider 'previous' choices). Hence, decisions are made according to

$$\mathbf{d}_t^{r*} = \begin{cases} \mathbf{d}_t^{r,p1} & \text{if } r = 1 \\ \mathbf{d}_t^{r,p1}(\mathbf{d}_t^{r-1,p1}) & \text{if } 1 < r \leq M_s \end{cases} \tag{9}$$

The configuration of the overall decision-problem is given by $\mathbf{d}_t = \mathbf{d}_t^{M_s}$. The headquarter does not intervene in decision-making and is confined to observing performances and compensating departments accordingly.

In the *proposal mode*, each unit communicates its preferences L_t^r to the headquarter which compiles the first preferences to a composite configuration $\mathbf{d}^C = (\mathbf{d}_t^{1,p1}, \dots, \mathbf{d}_t^{r,p1}, \dots, \mathbf{d}_t^{M_s,p1})$. Should configuration \mathbf{d}^C not equal the status quo-configuration, the headquarter imperfectly evaluates its performance: i.e., similar to departments, the performance *perceived* by the headquarter $\tilde{V}(\mathbf{d}^C)$ is actual performance (Equation (4)) plus some relative noise with Gaussian distribution, expected value 0 and standard deviation $\sigma^{cent} > 0$. The headquarter decides in favour of the composite vector, i.e., $\mathbf{d}_t = \mathbf{d}^C$, if it promises, at least, the performance of the status quo:

$$\tilde{V}(d^C) \geq V(d_{t-1}^*) \tag{10}$$

Should this condition not be satisfied, a configuration assembled from the departments' second preferences is evaluated. If this also does not satisfy the condition in Equation (10), the status quo is kept (i.e., $d_t = d_{t-1}$).

3.5. Learning-based adaptation of the boundary system

The research question of this paper boils down to which coordination modes emerge in the course of growth taking the contingency factors of search strategy and task complexity into account. For endowing the organisations with capabilities for adapting the boundary system, a simple mode of reinforcement learning (with further references Sutton & Barto, 2012), i.e., a generalised form of Bush and Mosteller's model (1955; Brenner, 2006) is employed.

In particular, in every T^L -th period, the headquarter decides which mode of coordination $a^C(t) \in A^C$ (i.e., 'decentralized', 'sequential' or 'proposal', see Section 3.4.2) is implemented in the next T^L periods. The key idea of reinforcement learning is that the probabilities of options to be chosen for the future are updated according to the – positive or negative – stimuli resulting from these options in the past. For this, the headquarter computes the relative enhancements of overall performance V_t achieved within the last T^L periods:

$$\Delta V_t = \frac{V_t - V_{t-T^L}}{V_{t-T^L}} \tag{11}$$

Whether performance enhancement ΔV_t obtained under the regime of a certain coordination mode $a^C(t)$ is regarded positive or negative, depends on whether, or not, it at least equals an aspiration level v . Hence, the stimulus $\tau(t)$ is

$$\tau(t) = \begin{cases} 1 & \text{if } \Delta V_t \geq v \\ -1 & \text{if } \Delta V_t < v \end{cases} \tag{12}$$

Let $p(a^C, t)$ denote the probability of an alternative $a^C(t)$ at time t (with $0 \leq p(a^C, t) \leq 1$ and $\sum_{a^C \in A^C} (p(a^C, t)) = 1$). The probabilities of options $a^C \in A^C$ to be chosen for the next T^L periods are updated according to the following rule, with λ (where $0 \leq \lambda \leq 1$) giving the learning strength (Brenner, 2006):

$$p(a^C, t + 1) = p(a^C, t) + \lambda \cdot \begin{cases} (1 - p(a^C, t)) & \text{if } a^C = a^C(t) \wedge \tau(t) = 1 \\ -p(a^C, t) & \text{if } a^C = a^C(t) \wedge \tau(t) = -1 \\ -p(a^C, t) & \text{if } a^C \neq a^C(t) \wedge \tau(t) = 1 \\ \frac{p(a^C, t) \cdot p(a^C(t), t)}{1 - p(a^C(t), t)} & \text{if } a^C \neq a^C(t) \wedge \tau(t) = -1 \end{cases} \tag{13}$$

According to the updated probabilities, the mode of coordination employed from $t + 1$ to $t + T^L$ is determined.

4. Simulation experiments and parameter settings

The simulation experiments are carried out for organic (as opposed to acquisitive) growth in terms of organisations keeping their principle ‘type’ of task complexity in the course of growth (Lockett, Wiklund, Davidsson, & Girma, 2011; Majumdar, 2008). Corresponding to a factorial design of experiments (Lorscheid, Heine, & Meyer, 2012) two rather pronounced types of *task complexity* are studied (see Figure 1).

The ‘*decomposable*’ type (Figure 1(a)) captures organisations consisting of self-contained ‘units’ (e.g., Galbraith, 1974; Thompson, 1967) with intense intra-unit, but no cross-unit interactions (e.g., Rivkin & Siggelkow, 2007). For example, units may reflect ‘product divisions’ related to largely different products where, in the course of growth, further products, and divisions accordingly, are added without interactions among the ‘old’ and ‘new’. Another example is a sales company which expands its sales regions, and sales units correspondingly, without regions interfering.

In contrast, the ‘*non-decomposable*’ type (Figure 1(b)) may reflect reciprocal interdependencies according to Thompson’s (1967) prominent classification. For example, organisations with functional specialisation (i.e., R&D, procurement, production, sales) typically show high levels of interrelations between departments. Growth may come along via vertical integration, e.g., establishing an in-house production of certain intermediate products and/or by integrating subsequent trade levels. In either case, the principle type of high task complexity is kept across growth stages.

The *search strategy* is the second contingent factor captured in this study. The boundary system, established by the headquarter, defines the search strategy of the departments which could be of an exploitative, explorative and ambidextrous type, characterised by the number of alternative options and the allowed (Hamming) distance to the status quo (for details Section 3.4.1).

Hence, with two types of interaction structures and three search strategies (see upper part in Table 2), six different scenarios are simulated. For this, further parameters have to be defined which are fixed across scenarios (lower part in Table 2).

As such, the organisations are observed for $T=750$ periods and in every $T^G=250$ -th period they grow resulting in $s=3$ growth stages. In the first stage, organisations face an $N_{s=1} = 6$ -dimensional decision-problem decomposed into $M_{s=1} = 2$ sub-problems of equal size assigned to two departments accordingly.⁴ With every further growth stage, three additional binary choices are to be made for which one department is added, i.e., $M_{s=2} = 3$ and $M_{s=3} = 4$. Finally, the organisations face an $N_{s=3} = 12$ -dimensional decision-problem.

In case of perfect information, no noise would occur (i.e., σ^r and $\sigma^{\text{cent}} = 0$). However, some empirical evidence suggests that in management control noise of about 10% of actual value is at a reasonable range (Redman, 1998). For capturing specialisation (e.g., Galbraith, 1974; Lawrence & Lorsch, 1967), departments employ rather precise information though related only to their respective sub-problems, while the headquarter disposes of comparably imprecise, but broad information, i.e., related to the entire decision-problem. Hence, we have $\sigma^r < \sigma^{\text{cent}}$.

In every $T^L = 10$ -th period, the headquarter learns about the coordination mode employed recently. With an aspiration level $\nu=0$, even keeping a once achieved

Table 2. Parameter settings.

Parameter	Values/Types
Subject to variation across experiments	
Interaction structures	'Decomposable' and 'non-decomposable' (see also Figure 1)
Search strategies	'Exploitation only': $h(\mathbf{d}^{r,a1}) = 1$ and $h(\mathbf{d}^{r,a2}) = 1$ 'Exploitation and exploration': $h(\mathbf{d}^{r,a1}) = 1$ and $h(\mathbf{d}^{r,a2}) = 2$ 'Exploration only': $h(\mathbf{d}^{r,a1}) = 2$ and $h(\mathbf{d}^{r,a2}) = 2$
Fixed for all experiments	
Observation period	$T = 750$
Growth stages	$s \in \{1,2,3\}$
Interval of growth stages	$T^G = 250$
Number of choices	$N_{s=1} = 6, N_{s=2} = 9, N_{s=3} = 12$
Number of departments	in growth stage $s = 1$: $M_1 = 2$ with $\mathbf{d}_1 = (d_1, d_2, d_3)$, $\mathbf{d}_2 = (d_4, d_5, d_6)$; in growth stage $s = 2$: $M_2 = 3$ departments as in $s = 1$ and additionally $\mathbf{d}_3 = (d_7, d_8, d_9)$; in growth stage $s = 3$: $M_3 = 4$ departments as in $s = 2$ and additionally $\mathbf{d}_4 = (d_{10}, d_{11}, d_{12})$
Precision of ex-ante evaluation	$\sigma^r = 0.05 \forall r$ and $\sigma^{cent} = 0.1$
Modes of coordination	$a^c \in \{\text{decentralized, sequential, proposal}\}$
Interval of learning	$T^L = 10$
Aspiration level	$v = 0$
Learning strength	$l = 0.5$
Simulation runs	per scenario 5000: 20 runs on 250 performance landscapes

performance level leads to a positive feedback (Equation (12)) which captures moderate learning dynamics. The same holds for the learning strength – reasonable varying between 0 (no learning) and 1 (learning only from the most recent experiences) – which is set to 0.5.

For each scenario, 5000 simulations are conducted (i.e., 250 landscapes with 20 runs on each). In every run, the organisations start with the 'decentralized' mode of coordination and keep this until $t=10$. Then, they 'discover' the two alternative modes (see Section 3.4.2) and choose randomly one option out of the three modes where each has the same initial probability. With this 'set-up' procedure the learning processes start from a 'defined' initial configuration and do not interfere with the strong performance increases typically occurring in the very first periods of adaptive walks. A 'story' behind is that the organisations start, in fact, without any coordination, for example, because they were newly founded without having a more 'elaborated' boundary system.

5. Results and discussion

5.1. Overview

For analysing the experiments, for each of the six scenarios the simulation runs were grouped according to that mode of coordination which has emerged in the last period of observation. These sub-groups were analysed individually as displayed in Table 3: column (a) reports the relative frequencies of the coordination modes employed in the final period. Two metrics inform about the effectiveness of search: (1) final performances $V_{t=750}$, i.e., performance⁵ achieved in the last period (with confidence intervals at a 99.9% level of confidence) in col. b and (2) the relative frequency of how often organisations finally have found the global maximum of the respective performance landscape (col. c). The ratio of periods in which the status quo is altered

Table 3. Condensed results of the simulation experiments. Each row represents averaged/aggregated results of 5000 runs.

Scenario	(a) Frequency of coordination mode c' in $t = 750$			(b) Final performance $V_{t=750}$ (confidence interval ^(*))			(c) Frequency of global maximum found in $t = 750$			(d) Frequency of false positive alterations of d_t		
	Decent.	Sequ.	Prop.	Decent.	Sequ.	Prop.	Decent.	Sequ.	Prop.	Decent.	Sequ.	Prop.
Decomposable structure												
Exploitation only	32.8%	33.1%	34.1%	0.957±0.0035	0.9576±0.0035	0.957±0.0035	19.5%	21.2%	17.2%	2.5%	2.5%	2.8%
Exploitation and exploration	35.8%	39.7%	24.5%	0.9929±0.0012	0.9936±0.0011	0.9899±0.0019	57.7%	60.2%	48.0%	3.1%	2.8%	3.1%
Exploration only	31.4%	34.7%	33.9%	0.9167±0.005	0.919±0.0047	0.9171±0.0047	4.3%	6.1%	4.5%	3.2%	3.3%	2.9%
Non-decomposable structure												
Exploitation only	27.2%	34.5%	38.3%	0.899±0.006	0.899±0.0051	0.9091±0.0043	8.2%	6.8%	7.2%	2.1%	2.2%	2.4%
Exploitation and exploration	17.8%	30.2%	52.0%	0.8764±0.0127	0.8973±0.081	0.9306±0.0041	11.0%	13.9%	18.0%	7.2%	7.3%	8.0%
Exploration only	13.7%	22.6%	63.8%	0.833±0.0124	0.844±0.0085	0.8695±0.0036	1.2%	1.7%	2.0%	6.2%	6.3%	5.7%

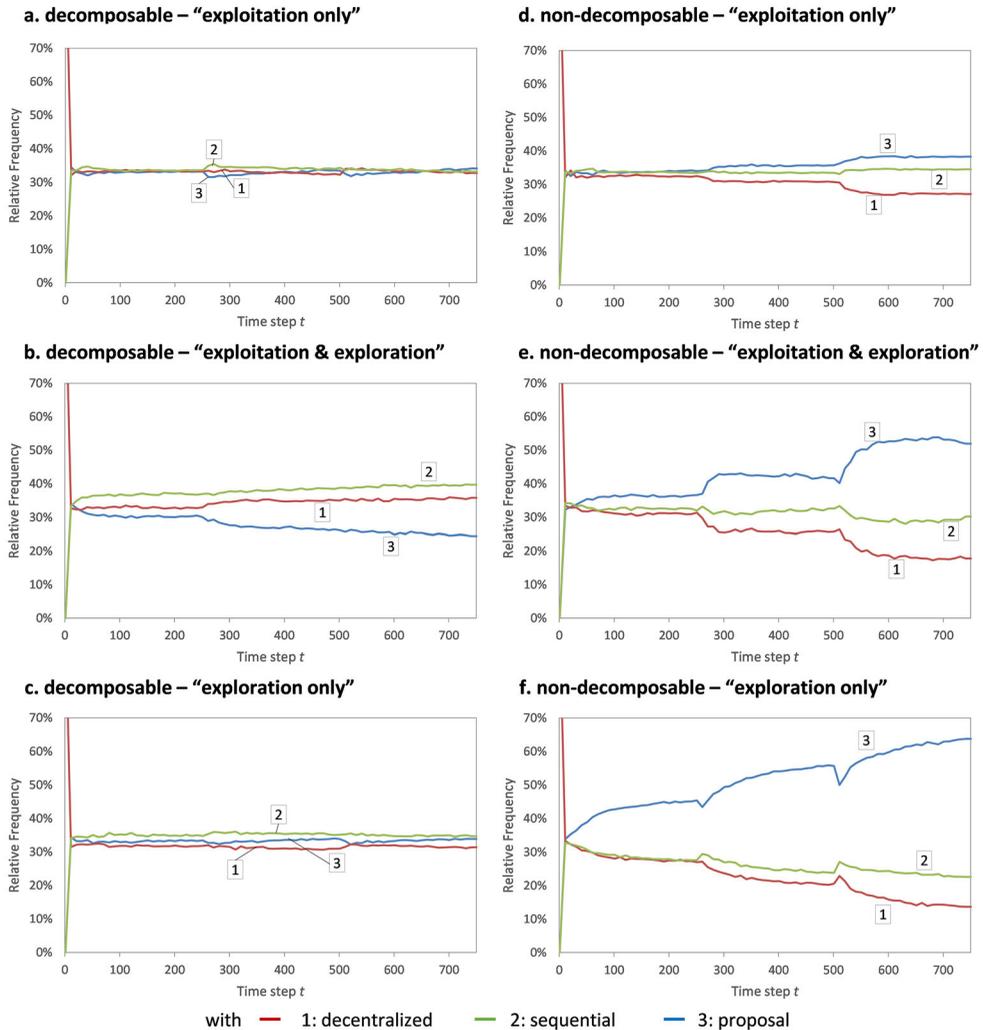


Figure 2. Relative frequencies of types of coordination modes in the course of growth. For parameter settings see Table 2.

informs about the diversity of search; the ratio of periods with false positive alterations (i.e., reducing V_t) indicates on the efficiency of search (col. d). Additionally, the plots in Figure 2 display – for each of the six scenarios – the relative frequencies of the three modes of coordination in the observation period.

With respect to the research questions posed in the Introduction, results suggest that the boundary systems emerging in the course of growth differ remarkably across the levels of task complexity and search strategies. Moreover, the results indicate on interactions among task complexity and search strategy. This leads to the following hypotheses:

1. For low cross-departmental interactions throughout growth and with exploitative or explorative search, no particular coordination mode emerges predominantly

while with ambidextrous search coordination modes prevail which leave decision-making authority at the subordinates' side.

2. *For intense cross-departmental interactions throughout growth, hierarchical coordination predominates and this the more the higher the extent of alterations enforced by the search strategy.*
3. *For intense cross-departmental interactions throughout growth, search strategy and coordination counterbalance each other in the tension between novelty allowed and constraints established via coordination.*

The subsequent sections provide a closer analysis and explanations for these results.

5.2. Decomposable interaction structure

For a closer understanding of results captured in Hypotheses 1 (Section 5.1), the coordination need related to the interaction structure is a helpful starting point: In the decomposable structure there is, in fact, no need for coordination across the sub-problems and, accordingly, among departments since for none of the growth stages interactions among sub-problems exist (Figure 1(a)). Hence, as far as no costs of coordination are considered (like in this study), for a given search strategy, the three modes of coordination should not show remarkable differences in performance achieved and learning-based frequencies of occurrence correspondingly. This conjecture is broadly supported by the results of 'exploitation only' and 'exploration only' search: relative frequencies and final performances are at similar levels for the three coordination modes (cols. a and b in Table 3). However, for ambidextrous search, the proposal mode (i.e., employing hierarchy) is increasingly predominated by the other modes (see Figure 2(b)); accordingly, final performances achieved with decentralized and sequential coordination go beyond the level obtained with the proposal mode.⁶ Moreover, 'ambidextrous' search provides remarkably higher final performances than obtained with the other strategies.

To explain these observations the sources of coordination need are helpful which are, broadly speaking,

1. interactions across sub-problems and departments resulting from differentiation (e.g., Lawrence & Lorsch, 1967);
2. conflicts of interests, particularly subordinates not pursuing the organisation's, but their parochial objectives – as contract theory emphasises (e.g., Eisenhardt, 1989; Lambert, 2001);
3. imperfect and heterogeneous information as elaborated in information economics (e.g., Sah & Stiglitz, 1986), contract theory (e.g., Lambert, 2001) as well as in the tradition of bounded rationality (Simon, 1955).

In the decomposable structure, aspects (1) and (2) should not be relevant: without interactions across sub-problems and departments (1) even the merely parochial objectives (2) of departmental decision-makers do not affect the overall performance

which – across all growth stages – results just as a sum of the units’ performances without complementarities or substitutes. However, aspect (3) is of relevance: in the proposal mode, the headquarter with its rather imprecise information enters decision-making without that its organisation-wide perspective makes a contribution since there is no coordination need resulting from aspects (1) or (2).

This appears particularly relevant in ambidextrous search: It grants departments the highest flexibility in shaping the novelty of solutions to their partial problems, and, combined with the departments’ rather precise information, allows them to adjust rather fast to the (local) maxima of the sub-problems. This is supported by the frequency of the global maximum found (col. c) being, by far, the highest across search strategies. However, the headquarter – with its rather imprecise information whose broadness does not contribute in decomposable structures – reduces the effectiveness of search and, hence, the proposal mode loses ‘shares’.

5.3. Non-decomposable interaction structure

With a high level of cross-unit interactions results change remarkably, i.e., hierarchical coordination predominates and namely the more the higher the extent of alterations enforced by the search strategy (see Hypothesis 2 in Section 5.1): This reaches from slight predominance (38.3%) for exploitative and more than half of runs (52%) for ambidextrous search to clear prevalence (63.8%) for the ‘exploration only’ strategy (see Figure 2(d)–(f)). Correspondingly, the performances achieved differ across the combinations of coordination and search strategy: For ‘exploitation only’, with all coordination modes, around 90% of the maximal performance is achieved (however, according to Welch’s test, the proposal mode significantly performs best at a 99.9% confidence level). In contrast, with ‘pure’ exploration, final performance, at maximum, is around 87% (with the decentralized mode performing worst with 3.5% points less). For the ambidextrous strategy, the proposal mode provides significantly higher performance (93%) than the other modes and the highest obtained for this structure at all. The frequency of the global maximum directs in the similar direction.

For an explanation, it is worth mentioning, that now superior configurations for the overall problem cannot be found by locating superior (or optimal) solutions for the sub-problems. Moreover, stepwise search is likely to end up in local maxima causing inertia (e.g., Li et al., 2006; Wall, 2016). Each of the aforementioned three sources of coordination need is relevant now: (1) cross-departmental interactions increasing in the course of growth, (2) departmental managers focussing on parochial performance and (3) decision-makers employing imperfect information. In consequence, in growing task environments with high complexity throughout the growth, coordination provided by the headquarter – with its orientation towards overall performance, relying on upward communication and employing aggregate, organisation-wide information – apparently yields highest performance and, hence, emerges most often.

This corresponds to empirical findings on intra-firm interdependencies as a contingent factor in MCS (see Section 2.2.1) indicating that higher levels of interdependencies are associated with more vertical information flows and use of aggregated information (Chenhall & Morris, 1986; Kruis et al., 2016; Macintosh & Daft, 1987).

Similarly, Davila (2005) argues that the use of formal controls increasing in firm size may be driven by increasing complexity.

However, the results suggest that the two mechanisms of the boundary systems studied, i.e., search strategy and coordination mode, considerably interfere when task complexity is high. In particular, the two mechanisms apparently counterbalance each other: the more novelty is enforced by the search strategy the more likely coordination becomes more rigid (Hypothesis 3 in Section 5.1). This indicates on the tension incorporated in the boundary system: it was argued (Simons, 1994a; Simons et al., 2000) that the boundary system could facilitate renewal enforcing managers to search for largely new ways (as with 'exploration only' search); at the same time, rigid coordination (as in the 'proposal mode') is intended to align parochial choices with the firm's overall objectives. Rigid limits for search as in the 'exploitation only' strategy reduce diversity of search and, hence, more rigid coordination (proposal mode) is less relevant than for explorative search. As already mentioned, the ambidextrous strategy grants the highest flexibility to the departments in terms of allowing for varying levels of novelty of solutions; apparently, the combination of departmental flexibility and centralised final choices provides the highest organisational performance when complexity is increasingly high. This relates to empirical findings of Bedford (2015) who argues that in firms following the ambidextrous strategy the boundary system may be a substitute to other components of the MCS.

6. Conclusion

With an agent-based computational approach, this paper studies, for growing firms, the adaptation of boundary systems which comprise a particular tension: balancing the search for new solutions with behavioural constraints to cope with increasing intra-organisational complexity. The results suggest that search strategy and coordination mode subtly interfere subject to the task complexity of the growing firm. A closer analysis provides explanations on the emerging patterns of coordination. The results pave the way for forming hypotheses which ideally can be tested in empirical research. Moreover, the study employs a research method which is rather new to the domain of MCS and allows to 'replicate' some findings obtained in empirical research.

With respect to practice, the study suggests that the coordination mode employed should be reconsidered in the course of growth: In the simulations, the adaptation of coordination admittedly emerges from rather simple (for not to say simplistic) behavioural rules; however, periodical learning based on evaluations of the coordination mechanisms induced noteworthy changes. In this sense, results sensitise to the necessity of learning and organisational change in growing firms.

For the further development of theory on MCS, the results provide strong support for calls to respect internal consistency among the controls employed in MCS. Moreover, the results also direct towards the relevance of contingent factors. Both issues, i.e., internal consistency and external fit, pose considerable challenges for empirical research and, in this sense, the particular potential of computational studies for further theory-building on MCS might be stressed by this paper.

Regarding coordination as a key issue in MCS, the study reflects a range from, in fact, granting full decision-making autonomy to subordinates over lateral coordination to hierarchical coordination. However, the study does, by far, not capture all feasible coordination modes, nor does it take the cost of different coordination modes into account. Further research efforts appear worthwhile to gain a broader understanding of coordination in these respects.

Obvious extensions of the research effort presented here are to study the emergence of coordination in growing firms for further types of management controls like, for example, incentive schemes. Moreover, the emergence of boundary systems in other growth strategies, like growth by acquisition, may be interesting to study with an agent-based computational approach.

Notes

1. ‘Management accounting’ and ‘Management control’ usually are regarded as jointly forming a discipline though the former particularly focuses on (cost) accounting, while the latter directs more to organisational thinking (for further references, e.g., Hesford et al., 2007; Shields, 1997).
2. More technically, NK landscapes are stochastically generated pseudo-boolean functions with N bits, i.e., $F : \{0, 1\}^N \rightarrow \mathbb{R}^+$ (Li et al., 2006).
3. The model assumes communication to work perfectly. For coordination with unintended communications errors see Wall (2019).
4. In the simulation experiments, the number of departments mirrors the growth of the decision-problem for avoiding interference with effects of varying department size (e.g., Querbes and Frenken, 2018; Wall, 2018).
5. Performances are normalized to the global maxima of the respective performance landscapes; otherwise they could not be compared over time and across different landscapes.
6. Employing Welch’s (1938) method, the mean of performance differences against the proposal mode are significant at a confidence level of 99.9%.

Disclosure statement

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References

- Ahrens, T., & Chapman, C. S. (2007). Theorizing practice in management accounting research. In C. S. Chapman, A. G. Hopwood, & M. D. Shields (Eds.), *Handbook of management accounting research* (Vol. 1, pp. 99–112). Amsterdam etc.: Elsevier.
- Andersén, J., & Samuelsson, J. (2016). Resource organization and firm performance: How entrepreneurial orientation and management accounting influence the profitability of growing and non-growing SMEs. *International Journal of Entrepreneurial Behavior & Research*, 22(4), 466–484. doi:10.1108/IJEBR-11-2015-0250

- Baumann, O., Schmidt, J., & Stieglitz, N. (2019). Effective search in rugged performance landscapes: A review and outlook. *Journal of Management*, 45(1), 285–318. doi:10.1177/0149206318808594
- Bedford, D. S. (2015). Management control systems across different modes of innovation: Implications for firm performance. *Management Accounting Research*, 28, 12–30. doi:10.1016/j.mar.2015.04.003
- Beese, J., Haki, M. K., Aier, S., & Winter, R. (2019). Simulation-based research in information systems. *Business & Information Systems Engineering*, 61(4), 503–521. doi:10.1007/s12599-018-0529-1
- Bisbe, J., & Otle, D. (2004). The effects of the interactive use of management control systems on product innovation. *Accounting, Organizations and Society*, 29(8), 709–737. doi:10.1016/j.aos.2003.10.010
- Brenner, T. (2006). Agent learning representation: Advice on modelling economic learning. In L. Tesfatsion, & K. L. Judd (Eds.), *Handbook of computational economics* (Vol. 2, pp. 895–947). Amsterdam etc.: Elsevier.
- Burton, R. M., & Obel, B. (2011). Computational modeling for what-is, what-might-be, and what-should-be studies—and triangulation. *Organization Science*, 22(5), 1195–1202. doi:10.1287/orsc.1100.0635
- Bush, R. R., & Mosteller, F. (1955). *Stochastic models for learning*. Oxford: John Wiley & Sons.
- Chang, M.-H., & Harrington, J. E. (2006). Agent-based models of organizations. In L. Tesfatsion, & K. L. Judd (Eds.), *Handbook of computational economics* (Vol. 2, pp. 1273–1337). Amsterdam etc.: Elsevier.
- Chenhall, R. H. (2003). Management control systems design within its organizational context: Findings from contingency-based research and directions for the future. *Accounting, Organizations and Society*, 28(2-3), 127–168. doi:10.1016/S0361-3682(01)00027-7
- Chenhall, R. H., & Morris, D. (1986). The impact of structure, environment, and interdependence on the perceived usefulness of management accounting systems. *Accounting Review*, 61(1), 16–35. doi:10.1016/0361-3682(94)90010-8
- Csaszar, F. A. (2018). A note on how NK landscapes work. *Journal of Organization Design*, 7(1), 1–6. doi:10.1186/s41469-018-0039-0
- Davila, A. (2005). An exploratory study on the emergence of management control systems: Formalizing human resources in small growing firms. *Accounting, Organizations and Society*, 30(3), 223–248. doi:10.1016/j.aos.2004.05.006
- Davila, A., Foster, G., & Jia, N. (2015). The valuation of management control systems in start-up companies: International field-based evidence. *European Accounting Review*, 24(2), 207–239. doi:10.1080/09638180.2014.965720
- Davila, A., Foster, G., & Li, M. (2009). Reasons for management control systems adoption: Insights from product development systems choice by early-stage entrepreneurial companies. *Accounting, Organizations and Society*, 34(3-4), 322–347. doi:10.1016/j.aos.2008.08.002
- Davila, A., Foster, G., & Oyon, D. (2009). Accounting and control, entrepreneurship and innovation: Venturing into new research opportunities. *European Accounting Review*, 18(2), 281–311. doi:10.1080/09638180902731455
- Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing theory through simulation methods. *Academy of Management Review*, 32(2), 480–499. doi:10.5465/amr.2007.24351453
- Davis, P., & Lay-Yee, R. (2019). *Simulating societal change: Counterfactual modelling for social and policy inquiry*. Cham: Springer International Publishing.
- Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of Management Review*, 14(1), 57–74. doi:10.5465/amr.1989.4279003
- Epstein, J. M. (1999). Agent-based computational models and generative social science. *Complexity*, 4(5), 41–60. doi:10.1002/(SICI)1099-0526(199905/06)4:5<41::AID-CPLX9>3.0.CO;2-F
- Epstein, J. M. (2006). Agent-based computational models and generative social science. In J. M. Epstein (Ed.), *Generative social science: Studies in agent-based computational modeling* (pp. 4–46). Princeton: Princeton University Press.

- Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 4(3), 28–36. doi:10.1287/inte.4.3.28
- Gilbert, N., & Troitzsch, K. G. (2005). *Simulation for the social scientist* (2nd ed.) Buckingham: Open University Press.
- Grabner, I., & Moers, F. (2013). Management control as a system or a package? Conceptual and empirical issues. *Accounting, Organizations and Society*, 38(6-7), 407–419. doi:10.1016/j.aos.2013.09.002
- Harrison, J. R., Zhiang, L. I. N., Carroll, G. R., & Carley, K. M. (2007). Simulation modeling in organizational and management research. *Academy of Management Review*, 32(4), 1229–1245. doi:10.5465/amr.2007.26586485
- Hesford, J. W., Lee, S.-H. S., Van der Stede, W. A., & Young, S. M. (2007). Management accounting: A bibliographic study. In C. S. Chapman, A. G. Hopwood, & M. D. Shields (Eds.), *Handbooks of management accounting research* (Vol. 1, pp. 3–26). Amsterdam etc.: Elsevier.
- Kauffman, S. A. (1993). *The origins of order: Self-organization and selection in evolution* Oxford: Oxford University Press.
- Kauffman, S. A., & Levin, S. (1987). Towards a general theory of adaptive walks on rugged landscapes. *Journal of Theoretical Biology*, 128(1), 11–45. doi:10.1016/S0022-5193(87)80029-2
- Kirman, A. P. (1992). Whom or what does the representative individual represent? *Journal of Economic Perspectives*, 6(2), 117–136. doi:10.1257/jep.6.2.117
- Kruis, A.-M., Speklé, R. F., & Widener, S. K. (2016). The levers of control framework: An exploratory analysis of balance. *Management Accounting Research*, 32, 27–44. doi:10.1016/j.mar.2015.12.002
- Lambert, R. A. (2001). Contracting theory and accounting. *Journal of Accounting and Economics*, 32(1-3), 3–87. doi:10.1016/S0165-4101(01)00037-4
- Langfield-Smith, K. (2007). A review of quantitative research in management control systems and strategy. In C. S. Chapman, A. G. Hopwood, & M. D. Shields (Eds.), *Handbook of management accounting research* (Vol. 2, pp. 753–783). Amsterdam etc.: Elsevier.
- Lawrence, P. R., & Lorsch, J. W. (1967). Differentiation and integration in complex organizations. *Administrative Science Quarterly*, 12(1), 1–47. doi:10.2307/2391211
- Leitner, S., & Wall, F. (2015). Simulation-based research in management accounting and control: An illustrative overview. *Journal of Management Control*, 26(2-3), 105–129. doi:10.1007/s00187-015-0209-y
- Leitner, S., & Wall, F. (2019). Decision-facilitating information in hidden-action setups: An agent-based approach. arXiv Preprint arXiv:1908.07998.
- Levitán, B., & Kauffman, S. A. (1995). Adaptive walks with noisy fitness measurements. *Molecular Diversity*, 1(1), 53–68. doi:10.1007/BF01715809
- Li, R., Emmerich, M. M., Eggermont, J., Bovenkamp, E. P., Bäck, T., Dijkstra, J., & Reiber, J. C. (2006). Mixed-integer NK landscapes. In T. Runarsson, H.-G. Beyer, E. Burke, J. Merelo-Guervós, L. D. Whitley, & X. Yao (Eds.), *Parallel problem solving from nature-PPSN IX* (Vol. 4193, pp. 42–51). Berlin: Springer.
- Lockett, A., Wiklund, J., Davidsson, P., & Girma, S. (2011). Organic and acquisitive growth: Re-examining, testing and extending Penrose's growth theory. *Journal of Management Studies*, 48(1), 48–74. doi:10.1111/j.1467-6486.2009.00879.x
- López, O. L., & Hiebl, M. R. W. (2015). Management accounting in small and medium-sized enterprises: Current knowledge and avenues for further research. *Journal of Management Accounting Research*, 27(1), 81–119. doi:10.2308/jmar-50915
- Lorscheid, I., Heine, B.-O., & Meyer, M. (2012). Opening the 'black box' of simulations: Increased transparency and effective communication through the systematic design of experiments. *Computational and Mathematical Organization Theory*, 18(1), 22–62. doi:10.1007/s10588-011-9097-3
- Macintosh, N. B., & Daft, R. L. (1987). Management control systems and departmental interdependencies: An empirical study. *Accounting, Organizations and Society*, 12(1), 49–61. doi:10.1016/0361-3682(87)90015-8

- Majumdar, S. (2008). Modelling growth strategy in small entrepreneurial business organisations. *The Journal of Entrepreneurship*, 17(2), 157–168. doi:10.1177/097135570801700204
- Malmi, T., & Brown, D. A. (2008). Management control systems as a package—Opportunities, challenges and research directions. *Management Accounting Research*, 19(4), 287–300. doi:10.1016/j.mar.2008.09.003
- Malone, T. W. (1987). Modeling coordination in organizations and markets. *Management Science*, 33(10), 1317–1332. doi:10.1287/mnsc.33.10.1317
- Merchant, K. A., & Van der Stede, W. A. (2017). *Management control systems: Performance measurement, evaluation and incentives* (4th ed.). New York: Pearson Education.
- Messersmith, J. G., & Guthrie, J. P. (2010). High performance work systems in emergent organizations: Implications for firm performance. *Human Resource Management*, 49(2), 241–264. doi:10.1002/hrm.20342
- Qerbes, A., & Frenken, K. (2018). Grounding the ‘mirroring hypothesis’: Towards a general theory of organization design in new product development. *Journal of Engineering and Technology Management*, 47, 81–95.
- Redman, T. C. (1998). The impact of poor data quality on the typical enterprise. *Communications of the ACM*, 41(2), 79–82. doi:10.1145/269012.269025
- Rivkin, J. W., & Siggelkow, N. (2007). Patterned interactions in complex systems: Implications for exploration. *Management Science*, 53(7), 1068–1085. doi:10.1287/mnsc.1060.0626
- Safarzyńska, K., & van den Bergh, J. (2010). Evolutionary models in economics: A survey of methods and building blocks. *Journal of Evolutionary Economics*, 20(3), 329–373. doi:10.1007/s00191-009-0153-9
- Sah, R. K., & Stiglitz, J. E. (1986). The architecture of economic systems: Hierarchies and polyarchies. *American Economic Review*, 76(4), 716–727.
- Samagaio, A., Crespo, N. F., & Rodrigues, R. (2018). Management control systems in high-tech start-ups: An empirical investigation. *Journal of Business Research*, 89, 351–360. doi:10.1016/j.jbusres.2017.12.028
- Shields, M. D. (1997). Research in management accounting by North Americans in the 1990s. *Management Accounting Research*, 9, 3–62. doi:10.1006/mare.1998.0081
- Siggelkow, N., & Rivkin, J. W. (2005). Speed and search: Designing organizations for turbulence and complexity. *Organization Science*, 16(2), 101–122. doi:10.1287/orsc.1050.0116
- Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99–118. doi:10.2307/1884852
- Simons, R. (1994a). How new top managers use control systems as levers of strategic renewal. *Strategic Management Journal*, 15(3), 169–189. doi:10.1002/smj.4250150301
- Simons, R. (1994b). *Levers of control: How managers use innovative control systems to drive strategic renewal*. Boston, MA: Harvard Business Press.
- Simons, R., Dávila, A., & Kaplan, R. S. (2000). *Performance measurement & control systems for implementing strategy*. Upper Saddle River, NJ: Prentice Hall.
- Sutton, R. S., & Barto, A. G. (2012). *Reinforcement learning: An introduction* (2nd ed.). Cambridge, MA: MIT Press.
- Tesfatsion, L. (2003). Agent-based computational economics: Modeling economies as complex adaptive systems. *Information Sciences*, 149(4), 262–268. doi:10.1016/S0020-0255(02)00280-3
- Thompson, J. D. (1967). *Organizations in action. Social science bases of administrative theory*. New York, NY: McGraw-Hill.
- Van de Ven, A. H., Ganco, M., & Hinings, C. R. (2013). Returning to the frontier of contingency theory of organizational and institutional designs. *Academy of Management Annals*, 7(1), 393–440. doi:10.5465/19416520.2013.774981
- Wall, F. (2016). Agent-based modeling in managerial science: An illustrative survey and study. *Review of Managerial Science*, 10(1), 135–193. doi:10.1007/s11846-014-0139-3
- Wall, F. (2018). Emergence of task formation in organizations: Balancing units’ competence and capacity. *Journal of Artificial Societies and Social Simulation*, 21(2), 1–25. doi:10.18564/jasss.3679

- Wall, F. (2019). Coordination with erroneous communication: Results of an agent-based simulation. *Knowledge and Information Systems*, 61(1), 161–195. doi:10.1007/s10115-018-1292-9
- Welch, B. L. (1938). The significance of the differences between two means when the population variances are unequal. *Biometrika*, 25, 350–362. doi:10.1093/biomet/29.3-4.350
- Widener, S. K. (2007). An empirical analysis of the levers of control framework. *Accounting, Organizations and Society*, 32(7-8), 757–788. doi:10.1016/j.aos.2007.01.001
- Za, S., Spagnoletti, P., Winter, R., & Mettler, T. (2018). Exploring foundations for using simulations in IS research. *Communications of the Association for Information Systems*, 42, 268–300. doi:10.17705/1CAIS.04210