Rev Manag Sci (2016) 10:135–193
DOI 10.1007/s11846-014-0139-3

REVIEW PAPER

Agent-based modeling in managerial science: an illustrative survey and study

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Received: 7 March 2014 / Accepted: 12 September 2014 / Published online: 26 September 2014

Abstract This article provides an overview of the current state of agent-based modeling in managerial science. In particular, the aim is to illustrate major lines of development in agent-based modeling in the field and to highlight the opportunities and limitations of this research approach. The article employs a twofold approach: First, a survey on research efforts employing agent-based simulation models related to domains of managerial science is given which have benefited considerably from this research method. Second, an illustrative study is conducted in the area of management accounting research, a domain which, so far, has rarely seen agent-based modeling efforts. In particular, we introduce an agent-based model that allows to investigate the relation between intra-firm interdependencies, performance measures used in incentive schemes, and accounting accuracy. We compare this model to a study which uses both, a principal-agent model and an empirical analysis. We find that the three approaches come to similar major findings but that they suffer from rather different limitations and also provide different perspectives on the subject. In particular, it becomes obvious that agent-based modeling allows us to capture complex organizational structures and provides insights into the processual features of the system under investigation.

Keywords Agent-based modeling · Complexity · Innovation · Management accounting · Organizational structure · Simulation · Strategic management

JEL Classification C63 · L2 · M1

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1 Introduction

In the last two decades a new approach of research in the social sciences has emerged: agent-based modeling (ABM)—often synonymously termed as agent-based computational models, agent-based simulations, multi-agent systems or multi-agent simulations (e.g. Squazzoni 2010). According to Gilbert (2008) ABM "is a computational method that enables a researcher to create, analyze, and experiment with models composed of agents that interact within an environment" (p. 2). ABM is used to derive findings for the system's behavior ("macro level") from the agents' behavior ("micro level") (Bonabeau 2002; Epstein 2006a). This gives reason to believe that ABM could lead to "generative social science" (Epstein 2006a) or to "social science from the bottom-up" (Epstein and Axtell 1996).

ABM involves constructing a computational model of the system under investigation and "observing" the behavior of the agents and the evolving properties of the system in time by extensive experimentation by means of computer simulation. Agent-based simulation in the social sciences can serve several purposes like, for example, predicting consequences, performing certain tasks (which is typically the case in the domain of artificial intelligence), or discovering theory (Axelrod 1997a, b). The latter means that simulation is used to develop structural insights and gain understanding of fundamental processes within a certain area of interest (e.g. Davis et al. 2007; Dooley 2002; Harrison et al. 2007; Gilbert and Troitzsch 2005). Axelrod regards simulation "a third way of doing science" (1997a, p. 3) or a "third research methodology" (1997b, p. 17) which has in common with deduction the explicit set-up of assumptions (though it does not prove theorems by the "classical" mathematical techniques) and which generates data from a set of rules (rather than from measurement of real world data as it is typical for induction). According to Gilbert and Troitzsch (2005), to develop a model the researcher has "to iterate between a deductive and inductive strategy" (p. 26), starting with a set of assumptions, generating data by an experimental method and analyzing the data inductively. Ostrom (1988) regards simulation as a third symbol system, apart from natural language and mathematics, for representing and communicating (theoretical) ideas; in particular, he argues that any theory which can be formulated in either mathematics or natural language can also be expressed by the means of a programming language.

ABM can be called a rather interdisciplinary field of research since researchers from various subject areas such as sociology, economics, managerial science, computer sciences, and evolutionary biology have contributed to the development of methods for ABM and have applied agent-based models to their domains of research as an approach to gaining theoretical insights. As such, in economics the term "Agent-based Computational Economics" has been established for the "computational study of economies modeled as evolving systems of autonomous interacting agents" (Tesfatsion 2001, p. 281). However, it is worth mentioning that ABM is not only characterized by a certain methodological approach but some assumptions of, in particular, neoclassical economics related to agents' behavior are also relaxed. For example, in ABM it is common to assume that agents show some form of bounded rationality in terms of bounded information and bounded computing power (e.g. Epstein 2006a; Axelrod 1997a). As a consequence, in agent-based models agents are usually not able to find the global optimum of a solution space "instantaneously"; rather they discover the solution space stepwise in a process of searching for better solutions (e.g. Safarzyńska and van den Bergh 2010; Chang and Harrington 2006). Hence, the processes by which organizations evolve or technological changes diffuse, for example, based on the behavior of interacting agents, are a major concern in ABM.

This article attempts to provide an overview of the current state of ABM as a research approach for developing theory in the area of managerial science, and, in particular, to illustrate and discuss the potential contributions to and limitations of ABM in managerial science. For this, we take a twofold approach: On the one hand, we focus on research topics in managerial science which have been rather extensively studied using agent-based models to serve as examples. On the other hand, there are also areas of managerial science which, to the very best of the author's knowledge, have rarely employed ABM so far, as in management accounting research. Hence, in order to explore the perspectives of ABM in this area of managerial science, we apply ABM to a well-studied question in management accounting, namely when to apply aggregate measures (in terms of firm-related performance measures) rather than measures related to the business unit. In particular, we compare a "classical" approach in economics based on a principal-agent model and a related empirical study, both conducted by Bushman et al. (1995), with an agent-based simulation model.

The remainder of the paper is organized as follows. In Sect. 2 we give a short overview of the main properties of agent-based computational models. Section 3 provides a brief review of the use of ABM in various fields of managerial science while Sect. 4 comprises a comparison of an analytical, an empirical and an agent-based research approach in the area of management accounting. Section 4 is intended to illustrate potential contributions and shortcomings of ABM as research approach in managerial science by way of example in order to serve as a basis for Sect. 5 where we discuss the opportunities and limitations of ABM for managerial science in a broader perspective.

2 Structural features of agent-based models

Agent-based computational models consist of three central building blocks at their very core, (1) the agents, (2) the environment in which the agents reside, and (3) interactions among the agents (e.g. Tesfatsion 2006; Epstein and Axtell 1996). In Sect. 2.1, these are described in more detail, followed by a short overview of typical setups for the simulation experiments applied in ABM in Sect. 2.2.

2.1 Building blocks of agent-based models

Agent-based models are intended to allow for deriving insights into a system's behavior from the micro level, i.e. the agents' behavior. Hence, agents are at the heart of agent-based modeling. Agents are autonomous, decision-making entities pursuing certain objectives (e.g. Bonabeau 2002; Safarzyńska and van den Bergh 2010; Tesfatsion 2006). Autonomy in this sense means that the individual behavior of the agents is not determined directly ("top-down") by a central authority, irrespective of interaction with a possibly existing central unit or feedback from the macro- to the micro-level (Epstein 2006a; Chang and Harrington 2006). The agents receive information from their environments and about other agents, and *react* to the information; however, they also *pro-actively* initiate actions in order to achieve their objectives (Wooldridge and Jennings 1995). Hence, from the perspective of implementing an agent-based model, an agent is a set of data reflecting the agent's knowledge about the environment and other agents and a set of methods describing the agent's behavior (Tesfatsion 2006).

In an agent-based model, agents may represent individuals like, for example, workers, business unit managers or board members of a firm or, in other contexts, for example, consumers or family members. They may also represent a *group* of individuals. For example, it might be appropriate to regard a department or a family as a single agent. Grouping individual agents to "aggregate" agents is particularly interesting in managerial science since, for example, it allows hierarchical structures to be mapped (Chang and Harrington 2006; Anderson 1999). However, agents do not necessarily have to be human or, at least, solely composed of humans; rather they can be biological entities (e.g. animals or flocks, forests) or technical entities (e.g. robots).

With respect to agents' behavior, a common assumption is that agents show some form of bounded rationality (Simon 1955). In particular, agents are assumed to decide on basis of bounded information such that they do not have global information about the entire search space and have limited computational power (Epstein 2006a; Safarzyńska and van den Bergh 2010; Anderson 1999). Hence, although agents are usually modeled as pursuing certain goals, they are not global optimizers. Instead agents merely conduct local search processes, meaning that only solutions which differ but slightly from recent solutions are discovered and considered as alternative options. Thus, agents are assumed to carry out "myopic" actions to achieve their goals (Axtell 2007; Safarzyńska and van den Bergh 2010).

Another important feature of ABM is that the models typically comprise agents which differ in their characteristics, i.e. which are heterogeneous (Safarzyńska and van den Bergh 2010; Epstein 2006a). Agents may show differences with respect to several dimensions such as knowledge, objectives, rules for the formation of expectations, decision rules or information processing capabilities.[1] Thus, in ABM agents are reflected in their diversity (Kirman 1992; Hommes 2006; Epstein 2006a; Axtell 2007) rather than relying on a representative agent, i.e. the "representative" individual that, when maximizing utility, chooses the same options as the aggregate choice of the heterogeneous population of individuals as often employed in economic models (Kirman 1992). According to Stirling (2007), "diversity" or heterogeneity of agents could show up in three dimensions, i.e. variety, balance, and

[1] For example, in agent-based models of financial markets two types of agents could be represented: *fundamentalists*, whose expectations are founded on fundamental market data and economic factors like profit and growth rates, as compared to *chartists*, who base their expectations about the future on historical patterns of prices (Hommes 2006).

disparity. While variety relates to the number of categories into which the agents are subdivided, balance means the ratios which the categories have in the population of agents and disparity qualifies the level of distinctiveness of the categories (Safarzyńska and van den Bergh 2010; Stirling 2007).

In agent-based models, the agents "reside" in an *environment* which captures the second core component of ABM. In a rather abstract formulation, the environment characterizes the tasks or problems the agents face, and, in this sense, the environment also represents the constraints the agents have to respect when fulfilling their tasks (Chang and Harrington 2006). Depending on the subject of the model, the environment might be given by the physical space (i.e. the geographical location and time of agents and artifacts) or the conceptual space (i.e. the "location" in a figurative sense so that "neighbored" agents are more likely to interact) (Axelrod and Cohen 1999). Inspired by evolutionary biology, other authors use the term "fitness landscape" to characterize the environment: "A fitness landscape consists of a multidimensional space in which each attribute (gene) of an organism is represented by a dimension of the space and a final dimension indicates the fitness level of the organism" (Levinthal 1997, p. 935). The landscapes may be highly rugged with numerous peaks and the agents (e.g. organisms or organizations) search for higher levels of fitness. We will return to this aspect in Sects. 2.2 and 4.2.

Hence, the term environment in ABM is used in rather a broad sense and could denote, for example, a landscape of renewable resources (Epstein and Axtell 1996), a dynamic social network, a set of interrelated tasks or just an n-dimensional lattice in which agents are located. However, in ABM two aspects should be clearly stated: First, the environment allows us to determine whether agents are "neighbored", either literally or in a figurative sense, and, thus, whether agents interact "locally" and search "locally" for superior solutions to their concerns. Second, in ABM the environment is usually represented in an explicit space, i.e. the environment is explicitly given (Epstein 2006a), and the agents—due to bounded rationality—usually do not have perfect knowledge of the entire environment.

Capturing the task and the constraints agents have to meet, the environment can be characterized with respect to various aspects: For example, the task might be simple or complex, in terms of being decomposable or not (Chang and Harrington 2006), or the environment could be stable or dynamic over the observation period (Siggelkow and Rivkin 2005). For dynamic environments, various causes of change could be modeled, like the occurrence of new agents (e.g. new firms entering a market) and increasing competition or new technologies being invented (Chang and Harrington 2006).

Interactions among agents constitute the third core building block of agent-based models and can be categorized with respect to different dimensions. With respect to the mode of *communication* among agents, agent-based models could comprise direct and/or indirect interactions (Safarzyńska and van den Bergh 2010; Weiss 1999; Tesfatsion 2001). Direct interaction requires some kind of communication between the agents. For example, agents might inform each other about the actions they intend to take. In the indirect scenario, agents interact with each other through the environment. For example, agents may observe each other, note how the environment is affected by the actions other agents carry out and react to the changes in the environment. Moreover, by observing other agents, they could learn from each other and might imitate each other.

Moreover, interactions could be classified according to the form of *coordination* (Tesfatsion 2001; Weiss 1999): For example, in an agent-based model agents could cooperate (e.g. share their knowledge and other resources) in order to achieve a common goal or compete due to conflicting goals. However, it should be mentioned that ABM also allows the exploration of more complex cooperative interactions like, for example, friendship (Klügl 2000).

In agent-based models, the local interactions among agents induce effects on the macro-level of the system which cannot be directly linked to the individual behavior of the agents. Hence, properties of the system "emerge" from the local interactions of agents which cannot be derived in terms of a "functional relationship" from the individual behaviors of those agents (Epstein 2006a; Epstein and Axtell 1996; Tesfatsion 2006). In order to explain macroscopic regularities, like norms or price equilibria, the question is whether and how they might be the result of simple, decentralized local interactions between heterogeneous autonomous agents. In this sense, Epstein and Axtell (1996, p. 33) define the rather multifaceted term "emergent structure" as "a stable macroscopic or aggregate pattern induced by the local interaction of the agents". From the interactions of both the agent-to-agent and the agent-to-environment type, *self-organization* might evolve (Tesfatsion 2001; Epstein and Axtell 1996).

2.2 Simulation approaches in ABM

A characteristic feature of ABM is the extensive exploitation of computational tools like object-oriented programming and computational power in order to carry out the simulation experiments (Tesfatsion 2001; Chang and Harrington 2006). Hence, even though ABM is sometimes regarded as "a mindset more than a technology" (Bonabeau 2002, p. 7280), some remarks from a more technical perspective of simulation seem appropriate.

In line with Law (2007), simulation models could be categorized according to three dimensions: (1) whether the system under investigation is represented for a certain point in time (static) or whether the system can evolve over time (i.e. static vs. dynamic); (2) whether the model contains random components or not (i.e. stochastic vs. deterministic); and (3) whether in the representation of the system modeled the state variables can change continuously with respect to time or instantaneously at certain points in time (i.e. continuous vs. discrete) where in the latter case different time-advance mechanisms have to be distinguished.

Agent-based simulation models usually include *probabilistic* components and are *dynamic* and *discrete* in nature: agent-based models are often employed to study processes of, for example, adaptation, diffusion, imitation or learning, and to analyze the processes that lead to increased performance in detail, e.g. with respect to the speed of improvement or the diversity of search processes. Accordingly, this is reflected in *dynamic* simulation models. The processes to be studied are represented in *discrete* periods. In particular, in each period of the observation time, agents assess the current situation, search for options, evaluate the options and make their choices as defined in the behavioral rules, all potentially in interaction with each other. Then, these actions and events are aggregated to that period's end state in the system, which is the initial state for the next period. *Stochastic* components in agent-based models might be, for example, the initial state of the system, external shocks (e.g. the occurrence of a new competitor or radical innovations), the options which the agents discover in a certain period (remember that in agent-based models, decision-makers are not able to survey the entire search space at once and, thus, stepwise discover new solutions) or the agents' choice of options depending on propensities (rather than definite preferences) modeled via the probability of taking a certain option and, for example, subject to learning (Duffy 2006).

In agent-based simulations, time mostly is modeled in discrete time steps with a fixed-increment time advance, and, thus, leading to equidistant time steps (Gilbert 2008, p. 28). According to Gilbert (2008), an event-driven simulation is an alternative, in particular, when it is not required that all agents have the chance to act at each time step, i.e. a next-event time advance mechanisms brings the simulation clock forward until the next event occurs, for example, when a decision is made by an agent.

Beyond these rather "formal" classifications, Davis et al. (2007), in studying the potential contributions and pitfalls of simulation methods for theory development, argue that the choice of the simulation approach is crucial "because of its framing of research questions, key assumptions, and theoretical logic" (p. 485). The authors distinguish between structured and non-structured simulation approaches. The former contain some built-in properties, like, for example, key assumptions about the system to be modeled. In contrast, non-structured approaches are customizable, offering more flexibility to the modeler. However, a structured approach has the advantage that it has been used and, thus, vetted by other researchers, and that the approach does not represent "an idiosyncratic world tailor-made by the modeler. This reduces the fear that the model is rigged to produce the desired result" (Rivkin 2001, p. 280). Davis et al. (2007) provide an extensive overview of structured simulation approaches used in the area of managerial science—for simulation studies in general, not only for ABM—and, in particular, mention system dynamics, NK fitness landscapes, genetic algorithms, cellular automata and stochastic processes. From these approaches, cellular automata and NK fitness landscapes are outlined more into detail in the following—cellular automata since, according to Dooley (2002; see also Fioretti 2013), they could be regarded as a rather simple form of ABM and thus are helpful to demonstrate the idea of ABM, and NK fitness landscapes since they were widely used in agent-based models in managerial science (see Sect. 3) and serve as basis in our illustrative study in Sect. 4.

Cellular automata (Wolfram 1986) consist of a grid where each agent "resides" in a cell and, hence, the lattice reflects a spatial distribution of the agents. The cells can take various states (most simply just the states "0" or "1"). The state $s_{j,t}$ of cell j at time t depends on its own state in the previous period $t-1$ and the previous state of the neighbored cells, for example, cells $s_{j-1,\,t-1}$ and $s_{j+1,\,t-1}$. From this, the two main aspects of cellular automata for ABM can be seen (Walker and Dooley 1999). First, a central idea is that the impact of agents on each other depends on the distance between the agents, i.e. the closer the neighborhood, the greater the influence on each other. Second, the dependence from which the state of a cell (agent) evolves is specified in rules representing the agent's behavior. For example, one rule might be "if the sum of left and right neighbors is two, change to a 1" and another "if the sum of left and right neighbors is lower than 2, change to a 0". Hence, starting from a randomly chosen initial configuration, the states of the cells in the grid change over time according to the specified rules. From the macro perspective of the grid, i.e. the system to be investigated, the researcher is interested in whether and, if so, how certain patterns occur from the spatial interaction processes. The researcher can mainly change two variables within the simulation experiments, i.e. the behavioral rules of the agents and the "radius" of neighborhood (e.g. if only direct neighbors affect each other). Agent-based models implemented via cellular automata mainly seek to study the emergence of macro-level patterns resulting from local interactions like competition, diffusion or segregation in a set of agents (Davis et al. 2007). For example, Lomi and Larsen (1996) apply cellular automata for investigating the characteristics of global dynamics in a branch (e.g. founding or mortality rates) resulting from local competition among organizations.

While cellular automata mainly allow the mapping of evolutionary processes, *NK fitness landscapes* might be regarded as an approach for representing adaptive search and optimization processes (Davis et al. 2007). NK fitness landscapes were originally developed in evolutionary biology (Kauffman 1993; Kauffman and Levin 1987) to study how effectively and how fast biological systems adapt to reach an optimal point. NK fitness landscapes were initially introduced to managerial science by Levinthal (1997). Since our exemplary agent-based model presented in Sect. 4 is based on NK fitness landscapes, including further details of the formal specifications, at this point we confine our remarks to the main ideas of this approach. The term NK fitness relates to the number N of attributes (e.g. genes, nodes, activities, decisions), and the level K of interactions among these attributes. Each attribute i can take two states $d_i \in \{0, 1\}$, $i = 1, \ldots, N$ and, hence, the overall configuration $\mathbf{d}$ is given by an N-dimensional binary vector. The state d_i of attribute i contributes with C_i to the overall fitness $V(\mathbf{d})$ of configuration $\mathbf{d}$. However, depending on the interactions among attributes, C_i is not only affected by d_i, but also by the state of K other attributes $d_{j,j \neq i}$. In the case of $K = 0$, the fitness landscape is single-peaked. If K is raised to the maximum, i.e. $K = N - 1$, altering one single state d_j affects the fitness contributions of all other attributes and, usually, this leads to highly rugged fitness landscapes with numerous local maxima for $V(\mathbf{d})$ (Altenberg 1997; Rivkin and Siggelkow 2007).

The explicit modeling of interactions among attributes might be regarded as the core feature of NK fitness landscapes, explaining its value for research in managerial science: Controlling parameter K, the approach allows to study systems with variable complexity in terms of interdependencies among subsystems (e.g. among subunits or decisions in an organization) with respect to overall fitness. In particular, with the fitness landscape for all possible configurations $\mathbf{d}$ specified according to the structure of interactions, the system under investigation searches for higher levels of fitness (performance) by applying certain search strategies like incremental moves (i.e. only one of the i bits switched) or long jumps. Agent-based models using the idea of NK fitness landscapes mainly allow study of the speed and effectiveness of the adaptation processes of modular systems controlling for the interactions among the modules. In managerial science there have been numerous applications of this simulation approach (for overviews see, e.g. Ganco and Hoetker 2009; Sorenson 2002), as might also become apparent in the next section.

3 Selected applications of ABM in managerial science

3.1 Some remarks on the selection of studies

In this section we seek to illustrate the potential of agent-based modeling for research in managerial science by way of example. Given the rather vast literature related to ABM in managerial science, the decision is required which literature to attend to. For this, we find it helpful to start with the particular strengths that simulation-based research is regarded to unfold in managerial science. As such, it has been argued that simulation in general, not only the agent-based approach, is particularly effective for developing theory "when the research question involves a fundamental tension or trade-off" (Davis et al. 2007, p. 485) like, for example, short- versus long-term or chaos versus order, and when "multiple interdependent processes operating simultaneously" occur (Harrison et al. 2007, p. 1229; in a similar vein Davis et al. 2007, p. 495).

Against this background, we decided to base our selection[2] on whether one or both of two rather prominent tensions in managerial science are captured in the research question: "exploration versus exploitation" (March 1991) and "differentiation versus integration" (Lawrence and Lorsch 1967). We focus on these tensions since they have been widely studied in managerial science, show up in various domains of managerial science and found numerous manifestations in agent-based models.[3]

[2] However, we also applied a formal criterion in that we decided to focus mainly on articles published in academic journals in the area of managerial science and journals dedicated to computational economics and, of course, to follow citations within these articles. It is worth mentioning that we also tried to employ a more structured approach (Petticrew and Roberts 2006) involving the search for relevant terms in literature databases as, for instance, conducted by Hauschild and Knyphausen-Aufseß (2013) or Hutzschenreuter et al. (2012). We found that a considerable number of articles which apparently employ ABM in managerial science and which are published in well-known scientific management journals do not use terms like "agent-based model" or "agent-based simulation" in the title, keywords or abstract—or not even in the entire text (e.g., Denrell and March 2001; Ethiraj and Levinthal 2004; Knudsen and Levinthal 2007). Of course, relying on a less structured approach for the selection of articles included in a survey involves the risk of a selection bias (Petticrew and Roberts 2006). However, given that we aim to provide an illustrative overview on the applications, contributions and pitfalls of ABM in managerial science and that data base search on our topic appears problematic we decided to follow the approach as described above.

[3] It appears worth mentioning, that according to Smith (1995) it does not reflect the perception of managers to categorize "management problems" according to the domains of managerial science (e.g. "marketing problem") and that it was argued that dealing with tensions (trade-offs) is in the core of managerial problems (Nikitin 2013).

In particular, we selected agent-based simulation studies addressing "exploration versus exploitation" and/or "differentiation versus integration" from those fields in managerial science which (a) have seen a remarkable stream of agent-based modeling efforts and (b) are of general interest in managerial science (and, for example, are not related to a certain functional specialization[4]). Given these criteria, we focus on the domains of strategic management, innovation, and organizational structuring and design—where each of which has seen a vast number of studies employing ABM.[5]

Moreover, we decided to address agent-based modeling efforts which are related to the *internal of organizations*, e.g. decision-making or structures within organizations, rather than entire organizations (firms)—or for being more concrete: in the research efforts introduced, with only some very few exceptions,[6] the agents represent entities *within* an organization (e.g. departments, managers) and not entire firms. Beside the valuable effect of further limiting the research efforts to be reported on in this survey, another motivation for this decision is that it allows for keeping a similar level of analysis as provided in our illustrative study in Sect. 4. This gives also reason to a further decision: We limit[7] the exemplary presentation of modeling efforts to those employing NK fitness landscapes (Sect. 2.2) which is also the simulation approach chosen in our illustrative study.

The research efforts which we describe subsequently more into detail are also summarized in Table 5 in the "Appendix", including the publishing journal, the research question, (appearance of) the core tensions addressed and the main explanatory variables and parameters as well as the major outcome variable under investigation.

3.2 Agent-based models addressing the tension of "exploration versus exploitation"

Since the seminal work of March (1991) the terms "exploration" and "exploitation" were increasingly used in domains like, for example, organizational learning, innovation, competitive advantage, organizational design, and technological diffusion. According to March (1991) the "essence of exploitation is the refinement and extension of existing competences, technologies, and paradigms", the "essence of exploration is experimentation with new alternatives" (p. 85). Exploitation is

[4] For example, a considerable body of research employing ABM has been carried out in the fields of logistics and supply chain management (for an overview Hilletofth and Lättilä 2012).

[5] For example, reviews on ABM in the domain of innovation and technological change can be found in Dawid (2006), Dosi et al. (1997), Garcia (2005), Kiesling et al. (2012), Pyka and Fagiolo (2007), Silverberg and Verspagen (2005), Wakolbinger et al. (2013) or Zenobia et al. (2009), surveys on ABM in the area of behavior of organizations and factors affecting organizational performance are given by Chang and Harrington (2006), Carroll and Burton (2000), Fioretti (2013), and Sorenson (2002); surveys on ABM employed for so-called "organizational engineering" are provided by Carley (1995, 2002) and Carley and Gasser (1999).

[6] Some few exceptions are made in so far as they are helpful to stress the lines of development of ABM in managerial science as it is case with the study of Levinthal (1997).

[7] An exception is made for the simulation model of March (1991) for its fundamental relevance in research on the exploration versus exploitation issue.

associated, for instance, with incremental innovation, local search, and stepwise improvement around known solutions whereas exploration includes things like radical innovation, distant search, and identification of new solutions. After reviewing numerous definitions and conceptualizations of the two terms, Gupta et al. (2006) based on March (1991), conclude that both, exploitation and exploration, require some kind of learning, improvement and acquisition of new knowledge, but while exploitation occurs around the same "trajectory", exploration is directed towards entirely different trajectories. As March (1991) points out, there is a fundamental tension between exploration and exploitation since both compete for scarce resources and organizations decide between the two either explicitly or implicitly: explicit choices between the two show up in investment decisions or decisions between alternative competitive strategies; implicit decisions between exploitation and exploration are incorporated, for example, in organizational structures and procedures which affect the balance between the two.

In his seminal work, March (1991) also presents a simulation-based study on "exploration versus exploitation" which is based on the idea of stochastic processes according to the classification of Davis et al. (2007, p. 486) (and not on NK landscapes as in the center here). In the model, agents learn from the organizational code (i.e. wisdom accepted in the organization about how to do things) due to socialization and education; in turn, the code evolves according to the behavior of those agents within the organization whose beliefs correspond better to reality. The diversity of agents' beliefs and learning speed is critical for the dynamics of the organizational code and agents' behavior which in turn affect in how far the organizational code reflects reality.

March's (1991) model allows for the general finding that exploitation is beneficial in the short run but problematic in the long run. However, it was argued that the model lacks some richness, particularly, with respect to properties of the underlying landscape, (i.e. the "reality" as more or less accurately reflected in the organizational code and agents' beliefs) (Chang and Harrington 2006). Subsequently, we illustrate the agent-based stream of research related to the balance of exploration versus exploitation building on the idea of NK fitness landscapes (Kauffman and Levin 1987; Kauffman 1993) and, with that, in particular, the complexity of interactions within the underlying fitness landscapes is inevitably a core issue.

The idea of NK fitness landscapes was initially introduced by Levinthal (1997)[8] in the field of management science. In Levinthal's model the tension "exploration versus exploitation" shows up in the form of "local search versus long jumps" or "local adaptation versus radical organizational change" of organizations searching for superior levels of fitness (or likelihood of survival). Hence, in a rather general perspective, organizations are regarded as agents acting in and reacting to their

[8] From a rather "technical" point of view one might argue that Levinthal's (1997) model comprises a situation with one single agent interacting with the environment, and, hence, does not fully reflect the characteristics of an agent-based model (Chang and Harrington 2006). Moreover, this model regards entire organizations as the agents and not departments or managers as agents and this sense does not meet the criteria as stated in Sect. 3.1. However, due to its fundamental relevance in the field we report on this research effort.

competitive environment and seeking to generate competitive advantages which could be described in terms of selection and fitness (Hodgson and Knudsen 2010). Levinthal's analysis aims to figure out whether the initial configuration of an organization persists and, by that, affects firm heterogeneity. According to the idea of NK fitness landscapes, in Levinthal's model the fitness of an organization is regarded to depend on its N characteristics ("genes") which could, for example, represent features of its organizational form or strategic policy; moreover, in line with the NK framework, the K interactions between the firm's characteristics are taken into account where highly interactive characteristics lead to highly rugged fitness landscapes with multiple peaks of nearly similar fitness. The organizations conduct a form of local search meaning that in each period they have the choice of keeping up with the status quo of its N characteristics or to choose one of N other configurations where just one of the N features is changed. Additionally, in each period the organizations discover one radically different configuration of the N characteristics in the sense that each of the N dimensions are specified new at random. Whether the status quo configuration is abandoned in favor of one these $N + 1$ alternatives depends on whether a higher level of fitness can be achieved. When organizations are in the beginning of their adaptation radical changes occur rather frequently, but when organizations have achieved a rather high level of fitness in highly rugged landscapes (i.e. complex interrelations among the N dimensions) radical changes become rare since it is relatively unlikely that a promising radically changed alternative is discovered. The results suggest that the initial characteristics of an organization have a persistent effect on its future form if the fitness landscape is highly rugged. Hence, firm heterogeneity, rather than being induced by the different environments the firms are operating in, emerges by processes of local search and adaptation from the starting configuration when the firm was founded. Levinthal (1997) concludes with the finding that tightly coupled organizations (i.e. organizations with highly interrelated characteristics or high levels of K) "can not engage in exploration without foregoing the benefits of exploitation" while "more loosely coupled organizations can exploit the fruits of past wisdom while exploiting alternative bases of future viability" (p. 949).

Based on Levinthal's seminal work (1997), Rivkin (2000) aims at identifying the optimal level of complexity within a firm's strategy in order to prevent imitation. Inimitability is regarded a major cause of competitive advantage in prominent schools of thought in strategic management. For instance, according to the "resource-based view of the firm" inimitability could result from causal ambiguity or tacit knowledge (e.g. Powell et al. 2006); according to the "market-based view of the firm" as based on industrial economics, high barriers could prevent competitors from market entrance even if imitation is feasible in principle (e.g. (Caves and Porter 1977). In contrast to these hypotheses, Rivkin (2000), employing an agent-based model, argues that imitation could be effectively hampered by the sheer complexity of a strategy. In this study, the tension of exploration versus exploitation occurs in the form of different imitation strategies of the imitator: incremental improvement in terms of stepwise adoption of the strategy to be imitated versus informed copying in the sense that the imitator reconfiges radically the own strategy in the direction of the leading firm's strategy. In particular, based on the framework of NK landscapes Rivkin (2000) provides evidence on the imitation-preventing effect of complexity in three steps: First, he shows that the complexity of interactions among elements leads to intractability with respect to finding the global optimum, since even for a moderate time required for the evaluation for newly discovered configurations, an exhaustive search is too time-consuming (NP completeness). In the second step, a simulation is applied to show that an imitator who engages in incremental improvements in order to copy a successful firm is doomed to failure in the face of complexity. Third, Rivkin shows by simulation that even a more advanced form of imitation, i.e. copying on the basis of careful observation of the high-performing leader, is prone to failure if complexity is high. The reason is that in the case of highly coupled decisions, some of the leader's decisions tend to catapult the imitator into a performance basin rather than to the desired performance peak.

Another strand of research is directed towards the *design and structure* of new products and processes relying on NK fitness landscapes. In particular, the level of *modularity (complexity)* of design and the implications for firm performance as well as the persistence of competitive advantages have been analyzed. Ethiraj and Levinthal (2004)—regarding modularization as a way to deal with complexity—study the implications of over- or under-modularity compared to some "true" level of modularity as given by the structure of interdependencies within the design problem. The tension between exploration and exploitation appears in form of two distinct key processes of how product design could evolve: by local search or/and by recombination, i.e. substituting one module by another (either from within the organization or from copying a module of another firm). Obviously, recombination provides the opportunity of new ("distant") solutions in terms of exploration. The authors find that too extensive modularization may induce designers' ignorance toward relevant interdependencies between modules and may potentially lead to inferior designs. Moreover, potential speed gains from a modular (i.e. parallelized) design might be balanced out by an inefficient integration and testing phase, cyclic behavior and low performance improvements.

In a similar vein, Ethiraj et al. (2008) analyze how the modularity of new products affects the trade-off between innovation and imitation by competitors. In this modelling effort the tension of "exploration versus exploitation" occurs in a trade-off between the incremental innovation of an innovation leader and the imitation of a low-performing firm. In particular, innovation is represented as a process of incremental local search where managers seek to enhance the performance of product modules by incremental intra-module changes; imitation by competitors has the form of distant search: the imitator, substitutes a subset of the own choices and/or interdependencies among choices with an equivalent set of choices and/or interdependencies copied from the innovation leader. The authors find that modularity of design induces a trade-off between innovation performance and deterrence to be imitated. The experimental results indicate that nearly modular structures yield persistent performance differences between innovation leaders and imitators.

The research efforts introduced exemplarily so far focus mainly on "exploration versus exploitation" in the context *of complexity* versus *modularity of strategy,* *products or processes* without going more into detail of how managers make their choices. The studies that we present briefly in the following address *managerial decision-making* more in detail.

In this sense, the research effort of Gavetti and Levinthal (2000) addresses the tension between exploration and exploitation in form of different modes of strategic decision-making. In particular, the authors distinguish forward-looking search processes from backward-looking ones. In the forward-looking search, the decision maker relies on "beliefs about the linkage between the choice of actions and the impact of those actions on outcomes" (Gavetti and Levinthal 2000, p. 113). The decision maker disposes of a (simplified) cognitive representation of the (true) fitness landscape allowing for identifying those areas in the fitness landscape that promise high fitness levels and thus "moving" to these areas at once in a "long jump" (i.e. altering many characteristics of the *N*-dimensional configuration of an organization's strategy at once). In contrast, experiential search is represented as a process of local search, meaning that only one or some attributes of the current state, i.e. the *actual experience*, are changed, and, should this change appear to be productive, it is used as a basis for a new local search. Gavetti and Levinthal (2000) focus on situations where the cognitive representation of the fitness landscape is a simplified version of the true landscape. In particular, the cognitive representation includes fewer dimensions of actions than the true landscape incorporates. Hence, by applying a forward-looking search in the *perceived* landscape, the decision maker seeks to identify a superior region in the true landscape, and then tries to exploit this region with the experiential search, i.e. local search as described above. Gavetti and Levinthal find that even simplified representations of the actual landscape provide powerful guidance for subsequent experiential searches in the actual landscape.

In a similar vein, the "exploration versus exploitation" tension shows up in the study of Gavetti et al. (2005). The study addresses the question of how effective so-called analogical reasoning is in situations of novelty and complexity compared to "deductive reasoning and rational choice" on the one side and the idea that "firms discover effective positions through local, boundedly rational search and luck" (p. 692) on the other side. While the former enables decision makers to directly identify and move to the global optimum—however "distant" from the status quo it is—does the latter allow for stepwise improvements related to the status quo only. Analogous reasoning is regarded as something in between meaning that, when facing a new situation, decision makers apply insights developed in one context to a new setting (p. 693). The authors study the effects of certain managerial characteristics on the contribution of analogical reasoning to firm performance. They find that analogical reasoning especially contributes to firm performance when managers are able to effectively distinguish similar industries from different ones. Moreover, analogical reasoning appears to become less effective with depth of managerial experience but more effective with increasing breadth of experience.

Sommer and Loch (2004), focusing on complexity in innovation projects and unforeseeable uncertainty, investigate the contributions of trial and error learning in contrast to so-called "selectionism". Complexity refers to the number of parts (variables) and the interactions among them while unforeseeable uncertainty is defined “as the inability to recognize and articulate relevant variables and their functional relationships” (p. 1334). Two approaches to dealing with complexity and unforeseeable uncertainty are studied with respect to the effects on project payoff. *Trial and error learning* means “flexibly adjusting project activities and targets to new information, as it becomes available” (p. 1335) via local search. If an organization implements *selectionism*, several solutions are developed in parallel and the most appropriate one is selected ex post. However, ex post identifying the most appropriate solution requires employing a test for the solutions developed. Hence, apart from the complexity of the system to be designed, the quality of the test is the second factor to be considered. The results indicate that trial and error learning is the more robust approach since it yields higher pay-offs in the case of imperfect tests, in particular, when the project incorporates a manifold of interactions; moreover, trial and error learning turns out to be more advantageous even in the case of a perfect ex ante test when the system size is large.

Ghemawat and Levinthal (2008) argue that a strategy is specified by two complementary approaches, i.e. ex ante design and ex post adjustment. The first represents a top-down pre-specification of some major principles and some particular policy choices; the latter describes the emergence of strategic positions and tactical alignment. Hence, in terms of fitness landscapes, top-down pre-specification means strategic guidance for positioning an organization in one or another region of the landscape whereas the latter is related to stepwise improvement. Hence, top-down pre-specification is associated with long jumps (exploration) whereas tactical alignment relates to local search (exploitation). The balance between these two elements of strategic specification also shapes the requirements for strategic planning: if, for example, only a few higher-level choices make subsequent lower-level decisions more or less self-evident, than strategic planning is subject to relatively modest requirements compared to a situation where the strategic action plan has to be completely specified in advance. In modifying the symmetric structure as given in the standard NK model, Ghemawat and Levinthal (2008) take into account that some choices might be more influential (“strategic”) than others. The simulation results reveal, first, that it is beneficial with respect to long-term performance to ex ante focus on the more influential choices rather than on a random selection of choices; second, the results indicate that tactical adjustments could compensate for mis-specified strategic choices if these are highly interactive with other strategic decisions but not if they have low levels of interactions with other policy choices. Hence, in this model, in a way the tension of “exploration versus exploitation” is studied with respect to the *sequence in time* of how the two are considered in decision-making.

Another strand of research addresses the relevance of *attitudes in favor of innovation* taking place. Denrell and March (2001) in an simulation-based study (employing stochastic processes) show that adaptive processes tend to reproduce success and, thus, lead to a bias against risky and novel alternative options unless, for example, adaptation is based on some erroneous information. Baumann and Martignoni (2011) extend this idea in analyzing whether a systematic pro-innovation bias could increase firm performance. The “exploration versus exploitation” tension is addressed in a way that decision-makers *intend* to conduct exploitation in terms of incremental improvement but where exploration happens "*accidentally*" due to a systematic pro-innovation bias. The authors motivate their analysis with observations that several "mechanisms" at the individual as well as organizational level tend to prevent rather than foster innovations and change like, for example, the status quo bias in individual decision making (Kahneman et al. 1982) or inadequate applications of standard financial tools like the discounted cash flow method (Christensen et al. 2008). Building on the idea of NK fitness landscapes, Baumann and Martignoni (2011) find that a moderate systematic bias in favor of innovation could increase performance in the long run in the case of complex and stable environments, since a pro-innovation bias enhances exploration; however, in most cases an unbiased evaluation of options turns out to be most effective.

3.3 Agent-based models addressing the tension of "differentiation versus integration"

"Differentiation versus integration" is the second prominent tension we consider in our illustrative survey. These notions are widely used in managerial science and they date back to the seminal work of Lawrence and Lorsch (1967), notwithstanding the fact that the notions capture issues which were connected ever since and inevitably to organizational structuring. In particular, differentiation denotes "the state of segmentation of the organizational system into subsystems, each of which tends to develop particular attributes in relation to the requirements posed by its relevant external environment" (Lawrence and Lorsch 1967, pp. 3–4); integration "is defined as the process of achieving unity of effort among the various subsystems in the accomplishment of the organization's task" where a task is regarded as "a complete input-transformation-output cycle involving at least the design, production, and distribution of some goods or services" (p. 4). Differentiation is associated with issues like division of labor, specialization and delegation; integration is related to, for example, coordination by hierarchies, incentives or sharing of norms. Lawrence and Lorsch (1967) point out, that "differentiation and integration are essentially antagonistic, and that one can be obtained only at the expense of the other" (p. 47) and, hence, the need for specialization is to be balanced with the need for coordination. Several studies apply an agent-based approach to figure out core issues of the "differentiation versus integration" tension. Subsequently, we report on some research efforts building on the framework of NK fitness landscapes.

In their agent-based approach Dosi et al. (2003) construe differentiation as a "division of cognitive labour" (p. 413), meaning that it affects how new solutions are generated (e.g. which scope the search process has for new solutions and who searches); integration is regarded as the determination of how and which solutions are selected. At the heart of Dosi et al.'s paper is the relation between decomposition (i.e. how search in the organization is configured) on the one hand and incentives (related to individual, team or firm performance) and the power to veto the decisions of other agents as selection mechanism on the other hand. In this modeling effort, the N "genes" of the N-dimensional "genom" of the NK framework represent the decisions which an organization has to make in order to fulfil its task; hence, the organizations face an *N*-dimensional binary decision problem which, in the course of differentiation, is partitioned with the partitions assigned to organizational sub-units. Interactions within the decomposed overall decision problem of the organization are mapped according to the framework of NK fitness landscapes. However, it is of interest whether interactions across partitions assigned to sub-units occur. In particular, in the case that the organizational decomposition and assignment to sub-units does not perfectly reflect the true interactions between decisions (meaning that cross-unit decisional interactions occur), according to Dosi et al. (2003) incentives could induce sub-units to mutually perturb each other's search processes, in which case hierarchical or lateral veto power turns out to be useful in preventing endless perturbations.

How well different organizational forms can cope with changes in the environment while searching for higher levels of performance is a major issue in Siggelkow and Rivkin (2005). They introduce an agent-based model which has some features in common with the model of Dosi et al. (2003) as sketched above. However, two distinctive features in Siggelkow and Rivkin's model deserve closer attention. First, to represent environmental turbulence, the authors let the fitness landscapes undergo correlated shocks at periodic intervals. Second, with respect to coordination—or integration in terms of Lawrence and Lorsch (1967), Siggelkow and Rivkin do not only take the incentive system (firmwide versus departmental incentives) and veto power into account but also distinguish a variety of intermediate coordination mechanisms between centralized and completely decentralized decision-making. Thus, keeping the decomposition of decisions fixed (two sub-units of equal decisional scope), the turbulence and the complexity of the environment (in terms of interactions between the decisions) for the different coordination modes is varied. Complexity stresses the importance of a broad search for superior solutions, while turbulence raises the relevance of speedy adjustments. Furthermore, the results indicate that in the most demanding case of highly turbulent plus complex environments, two organizational forms turn out to have the best balance for a speedy and broad search: first, an organization relying on lateral communication and firm-wide incentives and, second, a centralized organization where both forms are required to have considerable information processing capabilities to evaluate alternatives.

This brings us to the third focal aspect of this section, a reflection on *information processing in organizations* in agent-based models. In the two models sketched so far, the decision makers have limited information about the entire landscape of solutions they are operating in and, thus, have to explore the solution space stepwise in order to find superior configurations. Moreover, the information processing capacities of organizational members are integrated in the model in terms of how many alternatives can be evaluated at once (e.g. Siggelkow and Rivkin 2005). However, another aspect is that the decision makers might have difficulties evaluating the consequences of alternative solutions, once discovered.

Some agent-based models have been introduced which seek to fill this gap. In this sense, the tension of "differentiation versus integration" is analyzed from the angle of information processing capabilities in organizations. As such, the research of Knudsen and Levinthal (2007) should be mentioned. Knudsen and Levinthal build on the seminal works of Sah and Stiglitz (1988, 1986, 1985), which provide fundamental insights into the robustness of different organizational structures against Type I errors (accepting inferior options) and Type II errors (rejecting superior options) in a project-selection framework. In particular, Knudsen and Levinthal (2007) introduce path dependence and interactions into the project-selection framework: While in the original framework, the projects to decide on are randomly drawn from a fixed distribution of options, in Knudsen and Levinthal's model, the availability of alternative project proposals depends on the current state of the organization. Relying on the idea of local search and NK fitness landscapes, the authors draw alternative projects from the "neighborhood" of the current practice, i.e. alternative options only differ in a few attributes from the current state. The so-called "task environment" describes whether changing one attribute from the current state in favor of an alternative option also has an effect on the performance contributions of other attributes or not. Knudsen and Levinthal (2007) investigate how the imperfect screening capabilities of evaluators, i.e. imperfect capabilities to assess the consequences of alternatives, affect the performance achieved in search processes and under the regime of different organizational forms between hierarchies and polyarchies. With respect to the tension of "differentiation versus integration" the study of Knudsen and Levinthal (2007) reveals that with delegation of decision-making the mode of integration (in terms of polyarchies versus hierarchies) should be seen in the light of the accuracy of the screening capabilities. For example, hierarchies tend to be efficient in case of rather inaccurate evaluations and are particularly prone to stick to local maxima in case of perfect evaluators.

These findings motivated further agent-based simulation studies on the imperfections of ex ante evaluations and under various organizational arrangements, whether the imperfections are of an unsystematic nature (Wall 2010, 2011) or due to systematic errors (biases) (Tversky and Kahneman 1974) when evaluating alternatives (e.g. as already reported on Baumann and Martignoni 2011; Behrens et al. 2014).

3.4 Agent-based models addressing both tensions

In this section we seek to introduce studies which employ ABM to address the "exploration versus exploitation" and the "differentiation versus integration" tension in conjunction with each other. This is of interest, for example, to investigate which organizational forms foster innovation.

In their widely recognized paper, Rivkin and Siggelkow (2003) raise a similar question, i.e. how to balance the search for good solutions and stability around good solutions once discovered in an organization where the former addresses "exploration" and the latter "exploitation" according to March (1991, see also Sect. 3.2). The authors identify five organizational components affecting organizational performance, (1) the allocation (decomposition) of decisional tasks to sub-units, (2) the authority of a central office, (3) the alternative possible solutions the sub-units discover and inform a central authority about, (4) the incentive system which might reward sub-units for firm performance or for their departmental performance,

(5) the information-processing abilities of the central authority. In particular, Rivkin and Siggelkow's (2003) analysis is put forward in four steps: First, the authors investigate the effects that an active central authority has on the search process and on performance. They find that, in line with conventional wisdom, central authority is not helpful in the case of low interactions between sub-units' decisions but for moderate levels of interaction, a central authority appears to increase organizational performance. However, contrary to conventional wisdom, if interactions are dense, centralization turns out to be harmful since the central authority tends to lead the organization to one of the many bad local optima in which the organization is then likely to be trapped. In the second step, the effects of the sub-units' managers' capabilities for a broad search of solutions are investigated. The results show that, contrary to conventional wisdom, centralization is more valuable if managers are highly capable of excessive searching and interactions are dense since then the central authority has a stabilizing effect. This corresponds to the results of Dosi et al. (2003) as reported in Sect. 3.3. The third step of analysis reveals some results that run contrary to intuition of the "differentiation versus integration" tension: Intuition suggests that central authority (i.e. refraining from delegation) and firm-wide incentives (i.e. increasing integration) could serve as substitutes to each other; however, results indicate that they are rather complements: firm-wide incentives can coordinate the *intentions* of sub-units to act in the firm's best interests (integration) but do not necessarily coordinate decentralized *choices*: "Capable subordinates can engage in aggressive, well-intentioned search that results in mutually destructive 'improvement́" (Rivkin and Siggelkow 2003, p. 306). The fourth step of analysis confirms conventional wisdom that centralization provides no additional benefit if no interactions between sub-units' decisions exist; however, decomposing the overall organizational task in such a way that some interactions remain, induces additional search efforts on the sub-units' site which could be beneficially exploited by a capable central authority.

Another question of organizational structure that might be particularly relevant for innovation is raised by Siggelkow and Rivkin (2006): Does extensive searching at lower levels of an organization increase exploration? Building on the framework of NK-landscapes, the overall N-dimensional decision problem of the organization is split into two parts of equal size with each of this partitions assigned to one of two subunits. In this structure, the subunits' capability for exploration is captured by the number of alternatives that each subunit is able to evaluate (and this, in particular, is given by the number of single decisions in the subunits' decisional vectors which could be changed at once). Siggelkow and Rivkin (2006) find that extensive decentralized exploration does not universally increase exploration at firm level. In particular, if cross-departmental interactions exist, departmental managers tend to screen out those solutions that are not in line with their preferences. In consequence, innovative and preferable solutions from the firm's perspective might remain unknown at the company level. Marengo and Dosi (2005), as well as Rivkin and Siggelkow (2006), also apply agent-based simulations to come to similar conclusions.

In the models sketched so far, the structural settings of the organizations are kept stable over time. Siggelkow and Levinthal (2003) investigate whether it might be useful to temporarily change the organizational form, i.e. to transiently modify the configuration of differentiation and integration. In particular, the authors compare a permanently centralized organization (all decisions of an N-dimensional binary decision-problem are made by a central authority without any delegation) and a permanently decentralized organization (the firm's decisions are decomposed into two parts of equal size and delegated to two subunits) with an organization which starts as a decentralized structure and after a certain time becomes reintegrated into a centralized one. In non-decomposable settings (meaning that decisions assigned to one subunit also affect the outcome of decisions of another subunit), the reintegrated form outperforms the permanently decentralized and the permanently centralized structure. With respect to the decentralized form, this is caused by two patterns in the search process: firstly, cyclic "self-perturbance" may occur when each sub-unit modifies its decisions for improving performance and, because of cross-unit interactions, affects the performance of the other unit, which then starts modifying its choices and so on. In this situation, reintegration could stop the cycling behavior. The second pattern which might occur is that the sub-units have found the optimal solution given the choices of the other mutually dependent department, and, hence, sub-units might have found a Nash equilibrium which might, however, be low-performing with respect to firm performance. Then, reintegration could "disturb" the situation and lead to higher levels of overall performance. Moreover, the study of Siggelkow and Levinthal (2003) views the "differentiation versus integration" tension from an angle of environmental dynamics by asking which organizational structure is able to achieve high levels of performance after it has gone through an external shock. Then, a centralized organization with rather a large "distance" to the optimal solution is likely to stick to an inferior local maximum, especially when the distance between the initial point and the optimal solution is high. Compared to that, starting with a decentralized search allowing for local exploration and switching to a centralized organization after some periods allowing for refinement and improvement (exploitation), leads to a higher long-term performance on average. The more general conclusion from this is that organizations facing a highly complex decision-making problem could be centralized in a steady state but should temporarily turn to a decentralized form if they go through major environmental changes. Hence, in the temporarily decentralized organization the tension between exploration and exploitation, is "resolved" into a sequence in time, i.e. local exploration first and then global exploitation, and for each of these phases the appropriate balance between differentiation and integration is implemented.

4 ABM in management accounting research: firm-wide versus business unit-related performance measures in the compensation of business unit managers

In the previous sections we gave an exemplary overview of how agent-based modeling contributed to research on two fundamental issues ("tensions") of managerial science. In this section, by employing an example related to the "differentiation versus integration" tension, we seek to illustrate how agent-based simulation could contribute to research in the domain of management accounting.

There is some evidence that simulation as a research method is still only of minor relevance in the domain of management accounting. Hesford et al. (2007) analyzed 916 articles published from 1981 to 2000 in the ten most influential journals in management accounting with respect to research topic and method applied, and only three of the 916 papers were built on a simulative approach.[9] Even though, since then, some further simulation-based studies have been conducted (e.g. Labro and Vanhoucke 2007; Leitner 2014), the dissemination of simulation and agent-based simulation, in particular, in the domain of management accounting research, appears rather low.

Against this background, the purpose of this section is to illustrate the potential benefits as well as the possible shortcomings of ABM in the domain of management accounting research. For this, we proceed as follows: As an illustration we refer to the study by Bushman et al. (1995), which analyzes whether interactions between business units affect the (optimal) incentive system of business unit managers, in particular, when compensation is based on firm performance or on the performance of business units.

First, the relation of this topic to the "differentiation versus integration" tension as discussed in Sects. 3.3 and 3.4 merits a comment: The tension occurs in the question of how the reward structure, inevitably based on noisy performance measures, as a way of integration should be designed in face of different levels of interdependencies between business units resulting from differentiation.

For our purpose, the Bushman et al. study is of particular interest since it applies a twofold research method: In the first part a closed-form model is introduced and afterwards the results of an empirical study are presented. Hence, the idea behind our procedure is to provide some indication as to how agent-based simulation models could contribute to filling the "sweet spot" (p. 497) between analytical modeling and empirical studies in the area of management accounting, as Davis et al. (2007) expects simulation techniques to do so.

Subsequently, we briefly report on the analytical and empirical part of the Bushman et al. study (Sect. 4.1). In Sect. 4.2 we introduce an agent-based simulation model which takes up major aspects of the closed-form model by Bushman et al. (1995). Section 4.3 presents and discusses the results of our agent-based model. In Sect. 4.4 we discuss the agent-based approach as applied to our exemplary topic in comparison to the two research approaches employed by Bushman et al.

[9] Hesford et al. find that in the field of management accounting research, four research methods predominate. These are analytical studies, surveys and experiments as well as what the authors call "frameworks", i.e., the development of new conceptual frameworks providing new perspectives, drawing from, and combining, "multiple perspectives and information sources such as empirical facts, theoretical or practical observations, prior literature (in other areas or disciplines), supplemented with the authors' own synthesis and perspectives" (Hesford et al. 2007, p. 7).

4.1 Study by Bushman et al. (1995)

4.1.1 Theoretical part

By means of a principal-agent model, Bushman et al. "show that the use of aggregate performance measures is an increasing function of intra-firm interdependencies" (1995, p. 101). The model considers the contracts between a risk-neutral firm (principal) employing a number m of risk-averse business unit managers k as agents (each with a negative exponential utility function). For mapping cross-unit interdependencies, manager k's effort not only affects the performance of this manager's own business unit D_k but also the performance of other units. In particular, the performance of unit k is given by an additive function as

$$D_k = \sum_{l=1}^{m} f_{kl} e_l + \tilde{\theta}_k, \quad k = 1, \ldots, m \tag{1}$$

with $f_{kl} \geq 0$ denoting the marginal product of a manager l's effort e_l on unit k's performance, $f_{kk} > 0$ for all $k = 1, \ldots, m$ and with θ_k being a normally distributed random variable with mean zero, variance σ_k, and covariance $(\theta_k, \theta_l) = \sigma_{kl}$. It is worth mentioning that, due to $f_{kl} \geq 0$, only positive but no negative side effects on other business units are incorporated in the model. As a measure for the possibilities for spillover effects caused by manager k, the authors define the set $M_k = \{l | f_{kl} > 0 \text{ for any } l \neq k\}$. Then $|M_k| = m - 1$ means that manager k can affect the performance of all other business units, while with $|M_k| = 0$ the manager can merely influence the performance of the own unit. The performance of the firm is given as

$$A = \sum_{k=1}^{m} D_k. \tag{2}$$

The model considers a linear incentive scheme with compensation w_i given by

$$w_k = a_k + \beta_k D_k + \gamma_k A. \tag{3}$$

Hence, given the components of interdependencies and incentives, the model is set up from the "familiar ingredients" of principal-agent models, i.e. the principal maximizing his/her utility function in terms of the difference between overall performance A and the sum of compensation w_k subject to opportunity wage constraints and the rational action choice constraints of business unit managers (e.g. Lambert 2001). The solution of the model leads to the following findings (Bushman et al. 1995, pp. 108):

(1) The relative use $[\gamma_k/(\gamma_k + \beta_k)]$ of the aggregate performance measure A in the optimal incentive system for manager k increases

- with the increasing possibilities $|M_k|$ of the manager to affect the performance of other units
- for $|M_k| \geq 1$ given, with an increasing marginal impact f_{kl} on other units
- for $|M_k| \geq 1$ given, with a decreasing number of business units m

(2) The ratio γ_k/β_k of the relative weights of the business units' and the aggregate performance in the optimal contract depends

- on the correlation between business unit k and the rest of the firm: In particular, if the units' performances are correlated with each other, noise could be filtered out of the manager's contract by putting more weight on the "non-k" performance measures
- on the noise of the overall performance A: With increasing noise related to A its relative weight γ_k decreases

4.1.2 Empirical part

The empirical part of Bushman et al.'s study is based on a sample of 246 firms which participated in a survey on compensation plans. However, with respect to the explanatory variables, it is worth mentioning here that the authors do not examine the second part of their theoretical findings, i.e. those related to the information quality (noise) of the performance measures, due to the unavailability of appropriate data.

To measure the level of intra-firm interdependencies, Bushman et al. (1995) use firm-wide characteristics like diversification or intersegment sales. In particular, high diversification across product lines is assumed to lead to business units that are rather independent from each other. The authors distinguish between related diversification (within an industry) and unrelated diversification (sales distributed across unrelated industries). Accordingly, they hypothesize that the use of aggregate performance measures is negatively related to product-line diversification—with an even stronger negative relation to unrelated diversification. The same is predicted for geographical diversification, which is assumed to be negatively related to the use of aggregated performance measures in compensation plans. Furthermore, intra-firm sales are regarded as a proxy for intra-company interdependencies since they could occur if the output of one unit serves as the input of other units. Consequently, it is hypothesized that the use of aggregate performance measures is positively related with intra-firm sales.

To empirically capture the use of aggregate versus business unit performance measures, Bushman et al. (1995) determine two distinct aspects, first, the hierarchical level a manager is assigned to, and, second, the levels of aggregation of performance measures. For the first aspect, on the basis of the underlying empirical survey, Bushman et al. distinguish four hierarchical levels in terms of "Corporate CEO", "Group CEO", "Division CEO" and "Plant Manager"; accordingly, for the second aspect, i.e. the aggregation of performance measures, the authors differentiate between corporate, group, division, and plant performance. The data available from the underlying survey reflect the relative weights that firms give to these performance measures for each managerial level. This allows the weights to be summed up of those performance measures used in the annual bonus plans of a certain hierarchical level that are "more aggregate" than the organizational level of the respective manager. With respect to long-term incentives, Bushman et al. analyze the extent to which incentives like stock options are tied to performance measures above the organizational level of the managers.

The empirical part of Bushman et al.'s (1995) study is more differentiated than the theoretical part with regard to, at least, two aspects: the number of hierarchical levels (i.e. four vs. two levels) and the time structure of the incentives (annual and long-term incentives vs. not determined time-horizon). However, a general finding of the theoretical part—namely that with increasing cross-unit interactions, all else equal, it is more useful to base compensation on aggregate performance measures—is broadly supported by the empirical results. In particular, intra-firm sales and geographical diversification, serving as proxies for intra-firm interdependencies, turn out to be highly relevant for the *annual bonuses* in the predicted manner. In contrast, product-line diversification appears to be marginally relevant for the annual compensation plans, and even the differentiation between related and unrelated product-line diversification does not improve the explanatory power. The general finding of the theoretical part is also supported with respect to the long-term incentives which turned out to be nearly entirely tied on corporate performance (i.e. tied to an aggregate performance measure): they are positively associated with intra-firm sales and negatively associated with product-line and geographic diversification. While the general finding of Bushman et al.'s theoretical part also holds for the different hierarchical levels captured in the empirical part, the proxies for intra-firm interactions turn out to have different explanatory power at different hierarchical levels.

4.2 An agent-based simulation model

In this section, we describe an agent-based model which reflects major features of the Bushman et al.'s (1995) principal-agent model as there are interdependencies between business units, linear additive incentive schemes based on the business unit or more aggregate performance measures and linear additive errors related to performance measures. However, given the characteristic properties of agents in ABM (see Sect. 2.1), there are also major differences compared to Bushman et al.'s formal model like, for example, the "solution strategy" of the unit managers (i.e. stepwise improvement rather than maximization) due to limited information about the solution space.

The central issue of our illustrative subject of investigation is the intersection of interdependencies between business units on the one hand and performance measures used in the incentive scheme for business unit managers on the other. Hence, the simulation model has to allow for the representation of different structures of interdependencies. For this, the concept of NK fitness landscapes (Kauffman 1993; Kauffman and Levin 1987, see Sect. 2.2) provides an appropriate simulation approach (Davis et al. 2007) as it allows interactions between attributes to be mapped in a highly flexible and controllable way.

In our model, artificial organizations, consisting of business units and a central office, including an accounting department, search for solutions providing superior levels of organizational performance for an N-dimensional decision problem. In particular, at each time step t ($t = 1, \ldots, T$) in the observation period, our artificial organizations face an N-dimensional decision problem $d_{!t}$, d_{2t}, …, d_{Nt}. Corresponding to the formal platform of the NK model, the N single decisions are binary decisions, i.e. $d_{it} \in \{0, 1\}, (i = 1, \ldots, N)$. With that, over all configurations of the N single decisions, the search space at each time step consists of 2^N different binary vectors $\mathbf{d}_t \equiv (d_{1t}, \ldots, d_{Nt})$. Each of the two states $d_{it} \in \{0; 1\}$ makes a certain contribution C_{it} (with $0 \leq C_{it} \leq 1$) to the overall performance V_t of the organization. However, in accordance with the NK framework, the contribution C_{it} to overall performance may not only depend on the single choice d_{it}; moreover, C_{it} may also be affected by K other decisions, $K \in \{0, 1, \ldots, N - 1\}$. Hence, parameter K reflects the level of interactions, i.e. the number of other choices d_{jt}, $j \neq i$ which also affect the performance contribution of decision d_{it}. For simplicity's sake, it is assumed that the level of interactions K is the same for all decisions i and stable over observation time T. More formally, contribution C_{it} is a function c_i of choice d_{it} and of K other decisions:

$$C_{it} = c_i(d_{it}, d_{it}^1, \ldots, d_{it}^K) \tag{4}$$

In line with the NK model, for each possible vector (d_i, d_i^1, …, d_i^K) the contribution function c_i randomly draws a value from a uniform distribution over the unit interval, i.e. U [0, 1]. The contribution function c_i is stable over time. Given Eq. 4, whenever one of the choices d_{it}, d_{ti}^1, …, d_{it}^K is altered, another (randomly chosen) contribution C_{it} becomes effective. The overall performance $V(\mathbf{d}_t)$ of a configuration $\mathbf{d}_t$ of choices is represented as the normalized sum[10] of contributions C_{it}, which results in

$$V_t = V(\mathbf{d}_t) = \frac{1}{N} \sum_{i=1}^{N} c_i\left(d_{it}, d_{it}^1, \ldots, d_{it}^K\right). \tag{5}$$

Vice versa, depending on the interaction structure, altering d_{it} might not only affect C_{it}, but also the contribution of $C_{jt, j \neq i}$ to "other" decisions $j \neq i$. Hence, altering d_{it} could provide further positive or negative contributions (i.e. spillover effects) to overall performance V_t. In the most simple case, no interactions between the single choices d_{it} exist, i.e. $K = 0$, and the performance landscape has a single peak. In contrast, a situation with $K = N - 1$ for all i reflects the maximum level of interactions, and the performance landscape would be maximally rugged (e.g. Altenberg 1997; Rivkin and Siggelkow 2007).

So far, the model describes interactions between decisions but not between business units. For this, we assume that decisions i are delegated to business units. In particular, our organizations have M business units indexed by $r = 1, \ldots, M$. Let each business unit r have primary control over a subset with N^r decisions of the N

[10] Due to normalization by N and since C_{it} is drawn from an interval [0; 1], the overall performance $V(d_t)$ ranges between 0 and 1.

decisions with the units' subsets being disjoint so that $\sum_{r=1}^{M} N^r = N$. The overall organizational N-dimensional decision problem $\mathbf{d}_t \equiv (d_{1t}, \ldots, d_{Nt})$ can then also be expressed by the combination of "partial" decision problems as $\mathbf{d}_t = [\mathbf{d}_t^1 \ldots \mathbf{d}_t^r \ldots \mathbf{d}_t^M]$ with each unit's decisions related only to its own partial decision problem $\mathbf{d}_\mathbf{t}^r \equiv (d_{1t}^r, \ldots, d_{N^r t}^r)$.

According to the basic behavioral assumptions of agent-based models as sketched in Sect. 2, our decision-making units do not have the cognitive capabilities to survey the whole solution space, i.e. the entire performance landscape, at once. Rather they are limited to exploring the performance landscape stepwise. As familiar in ABM, this is reflected in our model by a form of *local search* combined with a *hill-climbing algorithm* (e.g. Levinthal 1997; Chang and Harrington 2006; Levinthal and Posen 2007). In every period, each of the business units makes a choice out of three options: keeping the status quo, i.e. the choice $\mathbf{d}_{t-1}^{r*}$ made by the department r in the last period, or opting for one of two adjacent alternatives discovered randomly. These alternatives are "neighbors" of $\mathbf{d}_{t-1}^{r*}$, i.e. the status quo of the partial configuration, where "neighborhood" is specified in terms of the *Hamming distance*, i.e. the number of dimensions in which two vectors differ. In particular, each department randomly discovers one alternative $\mathbf{d}_t^{r1}$ which differs with respect to *one* of the single decisions that unit r is responsible for and which has a *Hamming distance h* equal to 1 with $h(\mathbf{d}_{t-1}^{r*}, \mathbf{d}_t^{r1}) = \sum_{i=1}^{N^r} \left| d_{i,t-1}^{r*} - d_{i,t}^{r1} \right| = 1$. A second option $\mathbf{d}_t^{r2}$ is discovered in which *two* bits are altered compared to the (partial) status quo configuration, i.e. with $h(\mathbf{d}_{t-1}^{r*}, \mathbf{d}_t^{r2}) = \sum_{i=1}^{N^r} \left| d_{i,t-1}^{r*} - d_{i,t}^{r2} \right| = 2$. From the three options, $\mathbf{d}_{t-1}^{r*}$, $\mathbf{d}_t^{r1}$ and $\mathbf{d}_t^{r2}$, each unit's manager seeks to identify the best configuration while assuming that the other units q do not change their prior sub-configuration $\mathbf{d}_{t-1}^{q*}, q \neq r, q = 1, \ldots, M$.

Which configuration is most preferable from a unit head's perspective is determined by her/his preferences. We assume that managers are interested in increasing their compensation compared to the status quo salary according to the incentive scheme given. The compensation in each period t is based on a *linear additive* function with possibly two components: First, the rewards depend on the normalized sum B_t^{rOWN} of those contributions C_{it} resulting from the subset $\mathbf{d}_t^r$ of decisions delegated to the unit and this reflects unit r's "own" performance contribution—corresponding to a unit's performances in Bushman et al. (1995):

$$B_t^{rOWN}(\mathbf{d}_t^r) = \frac{1}{N} \cdot \sum_{i=1+p}^{N^r} C_{it} \text{ with } p = \sum_{s=1}^{r-1} N^s \text{ for } r > 1 \text{ and } p = 0 \text{ for } r = 1. \quad (6)$$

Second, to harmonize the interests of head of unit r with the organization's performance, the performances achieved through the subset of decisions $\mathbf{d}_t^q$ assigned to other units $q \neq r$ could be part of the value base of compensation of unit r. Hence, similar to Bushman et al. (1995), the compensation might also depend on the firm's performance as given by

$$V_t = V_t(\mathbf{d}_t) = \sum_{r=1}^{M} B_t^{rOWN} \tag{7}$$

which leads to the overall basis for compensating business unit r's head

$$B_t^r(\mathbf{d}_t) = \alpha \cdot B_t^{rOWN}(\mathbf{d}_t^r) + \beta \cdot V_t(\mathbf{d}_t) \tag{8}$$

Thus, similar to Bushman et al.'s (1995) model, it depends on the values of α and β to which extent unit r's performance and/or firm performance—as an aggregate performance measure in terms of Bushman et al.—is rewarded.

Our baseline model allows for one mode of coordination, which reflects most purely the form of coordination applied in Bushman et al.'s (1995) model: In a fairly decentralized mode, in each period each unit's head chooses one of the three optional partial vectors $\mathbf{d}_{t-1}^{r*}$, $\mathbf{d}_t^{r1}$ and $\mathbf{d}_t^{r2}$ related to the decisions the unit head is in charge of, and the overall configuration $\mathbf{d}_t$ results as a combination of these decentralized decisions—without any intervention from central office or any consultation with the other unit (for this and further modes of coordination, see Siggelkow and Rivkin (2005) and Dosi et al. (2003)). Hence, similar to Bushman et al. (1995), only the incentive system is at work for coordination, and the role of central office is confined to ex post evaluation of the performance of choices made by the unit managers.

Ex post evaluation of the unit managers' choices is supported by an accounting department which provides the central office and the units with performance information about the choices made, i.e. about the status quo configurations. In particular, at the end of period $t-1$ and before making the decision in period t, the unit managers receive the compensation for period $t-1$ according to the incentive scheme, and in the course of being rewarded they are informed about the $\mathbf{d}_{t-1}^{r*}$ s' performances as measured by the accounting department. However, the accounting department is not able to measure $\mathbf{d}_{t-1}^{r*}$ s' performances perfectly. Instead, the accounting department makes measurement errors $y(\mathbf{d}_{t-1}^{r*})$, which we assume to be independent and normally distributed random variables—each with mean zero, variance σ^r and stable within the observation period T. Hence, the measured value base for unit r's "own" performance contribution to their status quo option—in deviation from Eq. 6—is given by

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

which principally corresponds to Bushman et al.'s (1995) model (see Eq. 1). Accordingly, firm performance and the overall value base for compensation resulting from the status quo configuration, as measured by the accounting department are afflicted by errors. Thus, $V_t(\mathbf{d}_{t-1}^{r*})$ and $B_t^r(\mathbf{d}_{t-1}^{r*})$ are modified to $\tilde{V}_t(\mathbf{d}_{t-1}^{r*})$ and $\tilde{B}_t^r(\mathbf{d}_{t-1}^{r*})$, respectively, corresponding to Eqs. 7, 8 and 9.

Hence, we assume that the unit managers in a period t, when choosing one out of options $\mathbf{d}_{t-1}^{r*}$, $\mathbf{d}_t^{r1}$ and $\mathbf{d}_t^{r2}$, remember the compensation they received in the last period $t-1$ and, from that, infer the value base $\tilde{B}_t^r(\mathbf{d}_{t-1}^{r*})$ for the compensation of

$\mathbf{d}_{t-1}^{r*}$ as imperfectly measured by the accounting department. Additionally, our managers have some memorial capacities: Whenever, in the course of the search process, an option $\mathbf{d}_t^{r1}$ or $\mathbf{d}_t^{r2}$ is discovered which had already been chosen in periods $\leq t-2$, each unit manager remembers the compensation received for that period and, thus, the imperfectly measured value base for the compensation based on that configuration.

Let us summarize the information structure captured in the agent-based model: In the search process, the decision-making agents, i.e. the unit heads, stepwise discover the space of configurations $\mathbf{d}$ and the performances related to those configurations. Further, the heads of unit r stepwise learn about the measurement errors which the accounting numbers are afflicted with in relation to each configuration that has been implemented.[11] Moreover, the unit heads remember these (potentially imperfectly) measured performance numbers which are assumed to be stable in time. However, the unit heads have limited knowledge of each other's actions. In particular, they assume that the other units stay with the status quo of their partial decisions.

4.3 Results and discussion

4.3.1 Simulation experiments and parameter settings

In the simulation experiments, artificial organizations are randomly "thrown" somewhere in the performance landscape and observed while searching for superior levels of performance in a given observation time. In order to be clear and concise, we find it helpful to conduct the simulation experiments in three steps: First, we investigate some baseline scenarios for parameter settings (Sect. 4.3.2) before a robustness analysis is carried out with respect to the cross-unit complexity of interactions and the level of accounting errors (Sect. 4.3.3). Finally, we discuss some model extensions and present results standing for a more intense coordination mode (Sect. 4.3.4).

The simulation experiments are carried out for parameter settings as summarized in Table 1. Our parameter settings deserve some further explanations which we seek to give subsequently.

The organizations we simulate face a ten-dimensional binary decision vector, i.e. $N = 10$. The organizations consist of two business units at the first level under the central office (i.e. $M = 2$) where the business units are of equal size in terms of scope of single decisions d_i delegated to them. We decided for this organizational configuration for the sake of simplicity: Focusing on this most simple configuration allows to concentrate on decisional interactions, incentives and accounting errors, which are in the center of this analysis without having the results being mixed with

[11] In a way, given the behavioral ideas incorporated in ABM, this comes closest to the information structure as assumed in Bushman et al.'s (1995) principal-agent model: In that model the business unit managers know in advance about the true performance and the distribution of measurement errors that their choices will be afflicted with. In our agent-based model, the agents neither know the solution space in advance nor the measurement errors but they have some capabilities for memorizing. This allows unit managers to remember the "historic" accounting numbers once a certain configuration has been implemented at least once within the observation period.

Table 1 Parameter settings

Parameter	Meaning	Values/types
Number of decisions	Number of single decisions the organizations have to make, i.e. dimensions of the binary decision problem of the organizations	$N = 10$
Number of business units	Number of business units at the second managerial level, i.e. at the first level under central office in the organizations	$M = 2$ with unit 1 in charge of partial vector $\mathbf{d}^1 = (d_1, \ldots, d_5)$ and unit 2 in charge of partial vector $\mathbf{d}^2 = (d_6, \ldots, d_{10})$
Interaction structure	Number of decisions assigned to a business unit which are affected by other units	Baseline scenarios: SELF: $K^* = 0$ FULL: $K^* = 5$ Robustness analysis: K^* varied from 0 to 5 in steps of 1
Incentive structure	Ratio at which units' performance contribution and firm performance are rewarded	Units' performance rewarded only: $\alpha = 1$ and $\beta = 0$ Firm performance rewarded: $\alpha = 0$ and $\beta = 1$
Level of accounting error	(In)Accuracy of accounting information about units' performance contributions in terms of standard deviation σ^r (with mean zero)	Baseline scenarios: $\sigma^r \in \{0; 0.05; 0.1\}$ Robustness analysis: σ^r varied from 0 to 0.1 in 0.01 steps
Coordination mode	Mode in which decisions of the business units are coordinated among units and central office	Baseline scenarios: DECENTRALIZED Model extension in Sect. 4.3.4: CENTRAL
Observation period	Number of time steps given to the organizations for improving firm performance, i.e. length of the search process	$T = 250$

the number and size of departments. However, it is worth mentioning that this is not a principle point related to ABM; on the contrary, it would be a natural extension to the results presented here to additionally investigate the effect of the number and size of departments.

Since even relatively small numbers N of single decisions can lead to a vast space of interaction structures,[12] it is useful to focus the analysis on significant interaction structures which apparently have empirical relevance (Rivkin and Siggelkow 2007) and which are particularly relevant for the aspect under investigation. As such, in the baseline scenarios we distinguish between two types of interaction structures as

[12] With $N = 10$ decisions as in our simulation experiments, an interaction matrix has 100 entries, of which those on the main diagonal are always set to x. Therefore, 90 other elements remain, each of which could be filled or not, and, hence, with $N = 10$ principally $2^{90} = 1.2379 \times 10^{27}$ different interaction structures are possible.

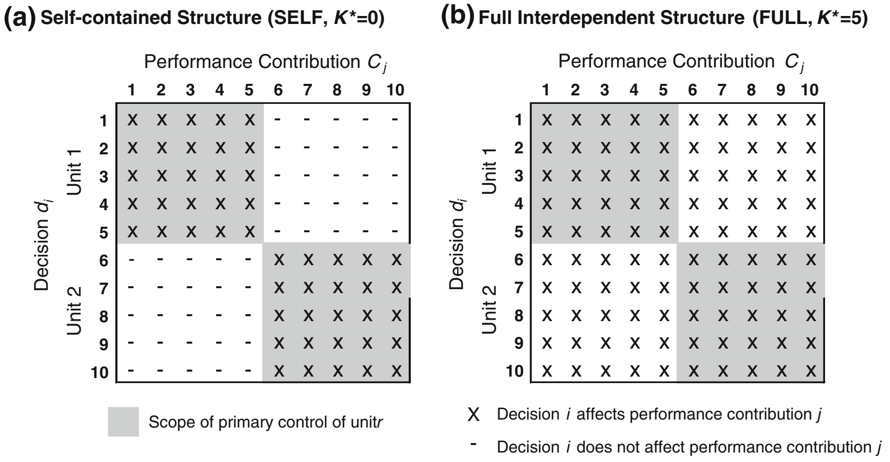


Fig. 1 Interaction structures in the baseline scenarios

indicated in Fig. 1a, b which are of particular relevance in the literature of organizational design.

The interaction structure in Fig. 1a shows two groups of decisions d_i and contributions C_i with highly intense intra-unit interactions, but without inter-group interactions. Hence, Fig. 1a represents a decomposable decision problem, and the choices of one unit do not affect the performance contributions the other business unit has primary control over. We denote the level of *cross-unit* interactions by K^*, which in the case of Fig. 1a is equal to zero. This type of interaction appears as a "block-diagonal" (Rivkin and Siggelkow 2007; Chang and Harrington 2006). However, the specific aspect indicated in Fig. 1a results from the combination with the delegation to business units (i.e. differentiation in terms of Lawrence and Lorsch (1967)): Not only, that it is possible to decompose the decision problem into two disjoint partial problems; these partial problems are each delegated to a distinct business unit. This combination of decisional structure and delegation corresponds to a "self-contained" organization structure (Galbraith 1974) and comes close to a pooled interdependence (Thompson 1967; Malone and Crowstone 1994). Self-contained structures are feasible, in particular, for organizations pursuing strategies of geographical diversification or which create their units according to products in terms of product divisions and the coordination need across the units is limited (Galbraith 1973). Subsequently, this structure is named SELF for short.

While Fig. 1a could represent a structure where an organization's overall task is differentiated (Lawrence and Lorsch 1967) according to products or geographical areas, the structure in Fig. 1b could stand for an organization with functional specialization with its typical high level of interrelations between units and, in consequence, high level of coordination need (Galbraith 1973, p. 41) (i.e. need for integration in terms of Lawrence and Lorsch (1967)). In this sense, Fig. 1b represents the extreme case where all decisions affect the performance contributions of all other decisions and this situation comes closest to reciprocal interdependence according to Thompson's classification of interdependencies in organizations (Thompson 1967; Malone and Crowstone 1994). Hence, in this situation, decisional interdependence is raised to a maximum and, in particular, the cross-unit interference is raised to a maximum, i.e. $K^* = 5$. This structure is named FULL for short. However, it is to be mentioned that we restrict our analysis in the baseline scenarios to the SELF and FULL structure in order to be concise in the presentation of the main results—and not due to a shortcoming of ABM as might become obvious by the robustness analysis (Sect. 4.3.3) where we simulate further interaction structures (see Table 1).

With respect to the incentive schemes, we restrict the presentation of results to two distinct parameter settings[13]: In the case of $\alpha = 1$ and $\beta = 0$ only units' performance is rewarded while in the case of $\alpha = 0$ and $\beta = 1$ firm performance as an aggregate performance measure in terms of Bushman et al. is compensated. We chose these two incentive schemes for the detailed presentation of results for the following reason: As illustrated in Sect. 3, ABM is particularly helpful for investigating situations in which a certain tension is efficient and this gave reason for these parameter settings. With the two interaction structures selected for the baseline scenarios (i.e. SELF and FULL) and the delegation of decisions to business units (differentiation), the cross-unit coordination *need* is specified and the two incentives schemes simulated might be regarded as two means for integration which most purely direct managers' attention either merely towards intra-unit coordination or broaden it towards cross-unit interactions. Hence, in a way, in these parameter settings for the baseline scenarios the tension between differentiation and integration is captured in a rather polarizing set-up.[14]

After thrown randomly somewhere in the performance landscape, the organizations are observed for $T = 250$ periods in searching for higher levels of organizational performance. The main reason for choosing this observation time results from the main purpose of this part of the paper, i.e. to exemplary compare an ABM to the two methodical approaches (theoretical and empirical) of the Bushman et al. (1995) paper. The major theoretical finding of Bushman et al. is that in the equilibrium, achieved by the contracting parties in the principal-agent model, with increasing (decreasing) cross-unit interactions—all else equal—it becomes more (less) useful with respect to firm performance (i.e. the principal's performance in the principal-agent model) to base compensation on aggregate performance measures. In order to see whether this finding, in principle, is reproduced in the agent-based model we seek to give the simulated search processes "enough time"—particularly, since our model implies that our decision-makers show some kind of learning of the measurement errors made by the accounting system, in order to make our model even more comparable to the fairly gifted decisions-makers of Bushman et al.'s (1995) principal-agent model. We chose an observation time of 250 periods with respect to the results in the FULL interaction structure for *perfect* accounting

[13] However, it is to be mentioned that the simulations were also carried out for further intermediate incentive schemes which is mentioned briefly in Sect. 4.3 within note 17.

[14] The simulations were also carried out for further levels of cross-unit interactions which is reported in Sects. 4.3.3 and 4.3.4.

information: In $t = 250$, the two incentive systems lead to approximately similar levels of performance. For the other scenarios we find that the performance levels achieved appear to be rather stable even before $t = 250$.

(Agent-based) Simulations have the potential to reveal characteristics of the processes by which, for example, adjustments take place or higher levels of performance are achieved (e.g. Davis et al. 2007). Hence, in our analysis of the simulation experiments, we apply some measures which are mainly directed towards procedural aspects (see also Tables 2 and 3):

Final_Perf reports the final performance achieved in the last period of the observation time, $T = 250$. *Avg_Perf* denotes the averaged performance level during the observation time. The difference between *Final_Perf* and *Avg_Perf* might be regarded as a condensed indicator for the speed of performance enhancement. *Final_Perf* and *Avg_Perf* are relative, i.e. they are given in relation to the global maximum of the respective performance landscapes (otherwise the results could not be compared across performance landscapes). *Speed_*t_5 gives the increase in performance gained in the first five time steps of the search process and measures speed, without being "mingled" with search effects, in a rather pure manner (Rivkin and Siggelkow 2002). *Freq_GlobMax* reports how often the global maximum is found in the final observation period relative to the total number of simulation experiments with the same parameter settings. A problem in adaptive search processes is that they may stick to local maxima since no configurations with a higher performance can be found in the neighborhood of a local peak (Rivkin and Siggelkow 2002). Therefore, an interesting measure is how many alterations of the decisional vector **d** are realized within the search process. *Freq_AltConf* gives the ratio of periods in which an altered configuration of the decisional vector **d** is realized to the total number of observation periods (averaged over all simulations with identical parameter settings). Hence, in a way, this measure might serve as an indicator for the diversity of the search process. With respect to imperfect accounting information, an interesting aspect is how many of the alterations are directed towards "false positive" configurations, i.e. moves in favor of an alternative which, in fact, does not increase but rather decreases overall performance compared to the status quo. *Ratio_FalsePos* gives the ratio of false positive alterations to the number of alterations (also averaged over all simulation runs with the same parameter settings).

4.3.2 Analysis of baseline scenarios

We analyze the results as displayed in Table 2 in three steps: We present the results for each of the two interaction structures separately, and afterwards we discuss the major findings in more detail and with respect to the results of Bushman et al. (1995).

4.3.2.1 Results in the case of no cross-unit interactions (Self) Comparing the results for the two incentive schemes reveals that—besides the case of perfect accounting numbers (*Acc_err* = 0)—the final and average performance is higher if only unit performance is rewarded. Moreover, with increasing levels of accounting

Table 2 Condensed results for the baseline scenarios

Level of Acc_error	*Final_Perf*	*CI*[a] *of Final_Perf*	*Avg_Perf*	*CI*[a] *of Avg_Perf*	*Speed_t_5*	*Freq_GlobMax* (%)	*Freq_AltConf* (%)	*Ratio_FalsePos* (%)
(a) Interaction structure SELF $(K^* = 0)$								
(a1) Units' performance rewarded only ($\alpha = 1$, $\beta = 0$)								
0	0.96854	±0.00181	0.96478	±0.00178	0.25115	38.02	1.59	0.00
0.05	0.93742	±0.00254	0.93370	±0.00243	0.22108	14.58	2.65	33.02
0.1	0.88890	±0.00367	0.88563	±0.00353	0.17896	6.94	2.89	39.11
(a2) Firm performance rewarded only ($\alpha = 0$, $\beta = 1$)								
0	0.96865	±0.00187	0.96468	±0.00184	0.24758	40.42	1.61	0.00
0.05	0.90635	±0.00370	0.90361	±0.00362	0.20092	10.58	1.53	25.39
0.1	0.83082	±0.00521	0.82918	±0.00513	0.14520	3.46	1.12	29.95
(b) Interaction structure FULL $(K^* = 5)$								
(b1) Units' performance rewarded only ($\alpha = 1$, $\beta = 0$)								
0	0.88991	±0.00479	0.84155	±0.00356	0.09424	11.30	30.88	50.53
0.05	0.86160	±0.00390	0.83187	±0.00333	0.09223	5.70	16.88	49.39
0.1	0.79698	±0.00458	0.78732	±0.00419	0.08441	1.88	7.32	47.89
(b2) Firm performance rewarded ($\alpha = 0$, $\beta = 1$)								
0	0.89388	±0.00264	0.88892	±0.00256	0.16924	5.48	1.75	15.22
0.05	0.85297	±0.00362	0.84918	±0.00351	0.14940	3.14	1.69	32.54
0.1	0.79746	±0.00497	0.79480	±0.00484	0.11118	1.78	1.37	37.22

[a] Confidence intervals (CIs) at a confidence level of 0.001. Common parameter for all organizations: coordination mode DECENTRALIZED (see Table 1 for further explanatory remarks). Each row represents the results of 5,000 adaptive walks: 1,000 distinct performance landscapes with five adaptive walks on each

error the differences between the two incentive structures increase. Furthermore, when rewarding unit performance rather than firm performance, the search processes with noisy accounting numbers are apparently more effective: the speed of performance enhancements in the early search periods is higher, the global maximum in the solution space is found more often. Obviously, the organization makes more movements in the sense that more configurations are implemented (*Freq_AltConf*) although the ratio of false positive movements is higher than when firm performance is rewarded. To sum up:

> Without cross-unit interactions it appears more appropriate to reward unit managers for their particular unit's performance rather than according to firm performance and this is more advantageous the higher the accounting errors.

4.3.2.2 Results in the case of maximum cross-unit interactions (Full) To a certain extent things seem to be different in the case of maximum cross-unit interactions. Interestingly, we find that the final performance achieved is—more or less—the same (0.797) for the two incentive schemes under investigation for a high level of accounting errors (i.e. $\sigma^r = 0.1$ for all r). However, the search processes obviously differ substantially with the two incentive systems and, in particular, the search processes when firm performance is rewarded are more effective: The average performance is higher, although differences between the two incentive systems decrease with an increasing level of accounting error. Moreover, when firm performance is rewarded, the speed of performance improvements in the early periods of the search process is remarkably higher, the search processes require fewer alterations to achieve the final performance and go less frequently in a false positive direction. However, the global maximum is found even less frequently in the case of firm performance being rewarded. We summarize these findings as follows:

> In the case of maximum cross-unit interactions, rewarding unit managers for firm performance rather than on the basis of their particular unit's performance leads to more effective search processes although the advantages decrease with increasing accounting errors.

4.3.2.3 Discussion Both conventional wisdom and prior research suggest using aggregate performance measures rather than unit-related measures for compensating unit managers in the case of intense cross-unit interactions (Bushman et al. 1995; Eisenhardt 1989; Siggelkow and Rivkin 2005). The reason is that departmental incentives would not encourage decision makers to consider the external effects of decisions on the rest of the organization (Siggelkow 2002). In this sense the incentive system itself can be a source of "misperception" since it might create "ignorance" or "myopia" where a broad perspective is required (Siggelkow 2002; Siggelkow and Rivkin 2005). Transferred to our model, this suggests the following: With cross-unit interactions (Full) and unit performance rewarded, units *ignore* the external (negative or positive) effects of their choices, and, reasonably, this slows down performance enhancement (scenario b1 in Table 2 shows that 50 % of the alterations made even with perfect accounting information are false positive ones).

Using aggregate performance measures as a basis for compensation would ensure that unit heads consider the external effects of their decisions on the rest of the organization; due to the firm-wide incentives, unit heads have no conflicting interests and this should lead to fast performance enhancements. In contrast, without cross-unit interactions (Self), no externalities exist for departmental decisions, and, therefore, it does not matter whether firm-wide incentives are given or not. The results provide broad support for this intuition since all measures reported in Table 2 for the Self structure (blocks a1 and a2) and *perfect* accounting numbers show similar values—regardless of the incentive scheme.

However, with increasing levels of accounting error, final and average performances decline for all combinations of interaction structure and incentive structure, which is in line with intuition, but not generally in line with prior research. Moreover, it appears worthwhile commenting that in three of the four scenarios with noisy accounting numbers, the frequency of alterations, i.e. the diversity of the search, decreases with increasing error level. In a way this may be regarded as counterintuitive and also contradicts other findings indicating that errors, especially forecasting errors, increase the diversity of search processes, and as such might even lead to better results than with perfect information (Levitan and Kauffman 1995; Knudsen and Levinthal 2007; Wall 2010). To explain this effect we argue that in our model the accounting numbers stepwise replace the actual performance numbers in the unit managers' perception: For time period *t*-1 the unit managers receive compensation that, due to accounting errors, might be too low or too high with respect to the actual performance their choices produced, and which our unit managers know. In case the compensation was too low, this probably makes the alternatives $\mathbf{d}_t^{r1}$ and $\mathbf{d}_t^{r2}$ discovered in period t even more attractive than staying at status quo $\mathbf{d}_{t-1}^{r*}$ and this might lead to false positive decisions in favor of $\mathbf{d}_t^{r1}$ and $\mathbf{d}_t^{r2}$. (This is broadly reflected in the high ratios of false positive decisions in Table 2 in the case of imperfect accounting numbers.[15]) However, in case the compensation for status quo $\mathbf{d}_{t-1}^{r*}$ was too high compared to the actual performance, this probably makes it attractive for unit managers to retain the status quo. In the course of the search process, the unit managers learn more and more about the landscape of the *rewarded performance* (which is a combination of the actual performance plus accounting errors; see Eq. 9). The landscape of *rewarded* performance is more rugged the higher the level of accounting errors—and it is well known that the more rugged the landscape, the more likely it is to stick to local peaks (e.g. Altenberg 1997; Rivkin and Siggelkow 2007), which reduces the frequency of alterations.

Hence, we argue that accounting errors related to performance measures used for compensation reduce the actual performance achieved in two ways: First, these accounting errors make it more likely that choices are made which are advantageous from the unit managers' perspective in terms of compensation but which might actually reduce performance ("false positive decisions"); second, accounting errors

[15] For perfect accounting numbers in the Full interaction structure combined with an incentive system which rewards unit performance only, we also find a high level of false positive decisions: This is due to myopia or ignorance of spillover effects on the part of the unit managers induced by the inappropriate incentive structure—and not due to accounting errors.

make it more likely that the search process sticks to a (local) *maximum of compensation* which, in particular, does not necessarily coincide with a (local) maximum of *actual* organizational performance, and this "inertia" prevents what would actually be superior solutions from being implemented.

4.3.3 Robustness analysis

In the baseline scenarios two rather extreme structures of cross-unit interactions are analyzed: Either the units do not affect each other at all (SELF, $K^* = 0$) or the interactions are maximal (FULL, $K* = 5$), meaning that each decision of unit r affects the outcome of every decision of the other unit. Hence, it is interesting to see to what extent the findings could be generalized for "intermediate" levels of cross-unit interactions. In order to gain some indications on this aspect, we ran further simulations for all intermediate levels of interactions (i.e. for $K^* = 1, \ldots, 4$), each with the two incentive structures under investigation (units versus firm performance rewarded). Moreover, we simulated further levels of accounting errors (from 0 to 0.1 in steps of 0.01). For each of the 132 scenarios[16] (see also Table 1 for the parameter settings) we simulated 5,000 adaptive walks (5 walks on 1,000 distinct landscapes).

To compare the two alternative incentive structures against each other comprehensively (i.e. rewarding the units' versus firm's performance), we compute the difference in average performance *Avg_Perf* achieved in the observation time under the two incentive structures. In particular, for each level of accounting error given and for each level of cross-unit interactions, the *difference in the average performance achieved in the observation period for rewarding company performance minus the units' performance* is computed. Figure 2 shows the three-dimensional structure of the results: values on the vertical axis greater (lower) than zero indicate that it is advantageous (detrimental) to compensate unit managers based on the firm performance rather than on the basis of the relevant units' performances.

The results displayed in Fig. 2 suggest that rewarding unit managers according to their units' performance is advantageous not only in the case of $K^* = 0$, i.e. when no cross-unit interactions exist. Rather, the results indicate that even with higher levels of cross-unit interactions, it may be beneficial to rely on units' performance for compensation or—to put it bluntly—to generate ignorance on the part of the unit managers relating to the external effects of their decisions; in particular, according to the simulation results for levels of cross-unit interactions $K^* = 1$ and $K^* = 2$, it depends on the level of accounting error as to whether to use the units' or firm performance as value base for compensation. For levels of cross-unit interaction $K^* \geq 3$, it is advantageous to reward according to firm performance for all levels of accounting errors simulated. However, it appears worthwhile to notice that the advantage of using aggregate performance measures seems to decline with

[16] For the robustness analysis, 132 scenarios were simulated resulting from 6 levels K^* of cross-unit interactions, 11 levels of accounting errors and 2 incentive structures.

increasing levels of accounting errors.[17] This corresponds to findings of the principal-agent model in Bushman et al. (1995, p. 108), suggesting that with increasing noise in the performance measures related to the rest of the organization, it becomes less useful to base compensation on aggregate rather than unit performance.[18]

Hence, this lets us summarize the findings as follows: *With lower levels of cross-unit interactions it is more appropriate to base unit managers' compensation on units' performance. For higher levels of cross-unit interactions it becomes advantageous to reward according to firm performance; however, advantages of rewarding firm performance could be (over-)compensated by negative effects of increasing levels of noise in the accounting numbers.*

4.3.4 Intensifying coordination and further potential extensions of the model

So far, the only coordination mechanism our artificial organizations apply is the incentive system: once the business units have decided on their preferences among the three optional vectors $\mathbf{d}_{t-1}^{r*}$, $\mathbf{d}_t^{r1}$ and $\mathbf{d}_t^{r2}$ each manager implements that option which corresponds with the manager's preferences at the best and without any further coordination. While this complies with the coordination mode mapped in the principal-agent model in Bushman et al. (1995), obviously, the coordination could be more intense, and various other forms of coordination are feasible (e.g. Christensen and Knudsen 2010; Sah and Stiglitz 1986; Siggelkow and Rivkin 2005)—or in other words: the tension between differentiation and integration could be balanced in favor of a higher level of integration.

For example, our organizations could employ a rather centralized mode of coordination (subsequently named "Central" for short): In every period each unit is allowed to propose an ordered list with entries of the two most preferred partial configurations of the three optional vectors $\mathbf{d}_{t-1}^{r*}$, $\mathbf{d}_t^{r1}$ and $\mathbf{d}_t^{r2}$. The central office combines these partial configurations to an overall configuration and selects the combination which promises the highest aggregate performance V. Hence, in this mode of coordination, the units shape the search space for central office by making

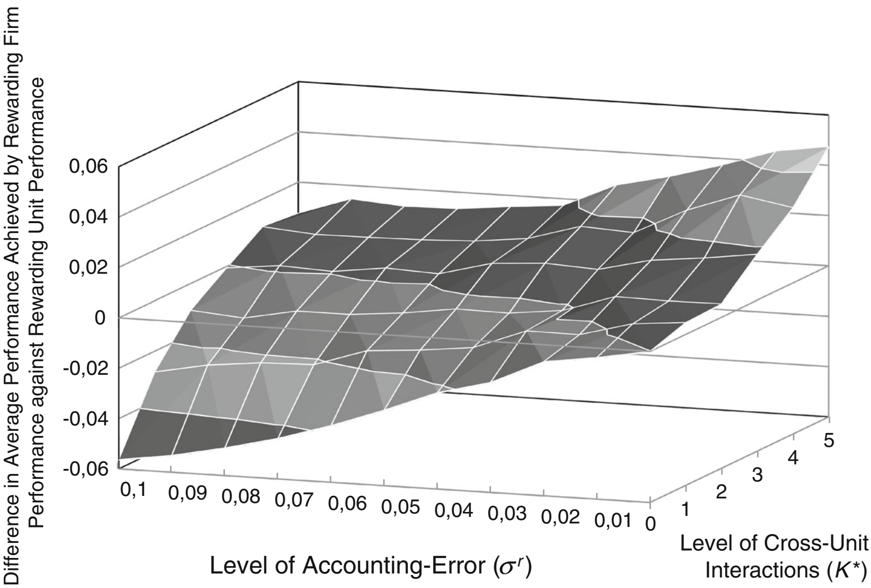
[17] Further simulations were carried out for intermediate forms of the incentive schemes compared to the two schemes reported above. In particular, for each level of accounting error σ^r and each level of cross-unit interactions K^*, additionally, three further incentive schemes were simulated with combinations of α and β of (1; 0.5), (1; 1) and (0.5; 1). We compared the results for each of these incentive structures with the reward structure of $\alpha = 1$ and $\beta = 0$ similar to the analysis introduced in Fig. 2 done for the setting of $\alpha = 1$ and $\beta = 1$. This means that for each of the three intermediate reward structures we computed the difference of average performance achieved against compensating unit performance only. The principle results regarding the effects of level of cross-unit interactions and noise are in line with those presented in Fig. 2 and the related text. Moreover, we compared the results across the four incentive schemes where firm performance is rewarded (i.e. where $\beta > 0$): We find that with increasing relative use of firm performance in the reward structure and increasing levels of accounting error, the higher the loss against rewarding merely unit performance—or put in terms of the graph in Fig. 2: with increasing relative weight put on firm performance in the incentives system the three-dimensional structure becomes steeper.

[18] In Sect. 4.4 we go more into detail regarding the comparison between the optimizing approach in the theoretical part of Bushman et al. (1995) and the simulation experiments.

Table 3 Condensed results for the "central" mode of coordination

Level of Acc_error	*Final_Perf*	*CI*[a] *of Final_Perf*	*Avg_Perf*	*CI*[a] *of Avg_Perf*	*Speed_t_5*	*Freq_GlobMax*	*Freq_AltConf*	*Ratio_FalsePos*
(a) Interaction structure Self $(K^* = 0)$								
(a1) Units' performance rewarded only $(\alpha = 1, \beta = 0)$								
0	0.96976	±0.00178	0.96584	±0.00175	0.25045	40.28	1.60	0.00
0.05	0.91450	±0.00337	0.91101	±0.00330	0.21304	11.86	1.28	19.99
0.1	0.84865	±0.00493	0.84604	±0.00485	0.15878	5.24	0.96	26.32
(a2) Firm performance rewarded only $(\alpha = 0, \beta = 1)$								
0	0.96794	±0.00190	0.96414	±0.00187	0.24948	38.58	1.56	0.00
0.05	0.90850	±0.00355	0.90587	±0.00347	0.20498	11.16	1.49	25.17
0.1	0.83784	±0.00526	0.83618	±0.00518	0.15392	4.54	1.09	28.88
(b) Interaction structure Full $(K^* = 5)$								
(b1) Units' performance rewarded only $(\alpha = 1, \beta = 0)$								
0	0.88380	±0.00285	0.87908	±0.00276	0.17930	3.68	1.08	0.00
0.05	0.84732	±0.00363	0.84370	±0.00353	0.15743	2.56	1.07	23.02
0.1	0.79956	±0.00461	0.79724	±0.00450	0.12547	1.86	0.94	30.58
(b2) Firm performance rewarded $(\alpha = 0, \beta = 1)$								
0	0.89340	±0.00269	0.88956	±0.00261	0.19426	4.92	1.32	0.00
0.05	0.85663	±0.00356	0.85387	±0.00346	0.17278	3.50	1.30	26.17
0.1	0.80899	±0.00459	0.80699	±0.00448	0.13850	2.38	1.09	31.78

[a] Confidence intervals (CIs) at a confidence level of 0.001. Common parameter for all organizations: coordination mode CENTRAL (see Table 1 for further explanatory remarks). Each row represents the results of 5,000 adaptive walks: 1,000 distinct performance landscapes with five adaptive walks on each



Notes: Common parameter for all organizations: coordination mode DECENTRALIZED (see Table 2 for further explanatory remarks). For each combination of incentive structure, level of cross-unit interactions and level of accounting error 5,000 adaptive walks (1,000 distinct performance landscapes with 5 adaptive walks on each) were simulated

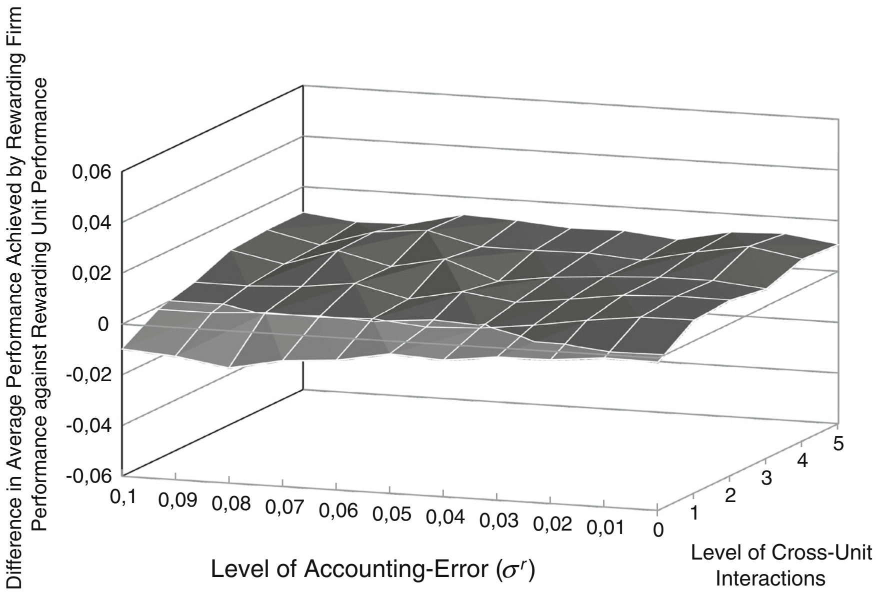
Fig. 2 Wins and losses in average firm performance resulting from rewarding firm performance instead of the units' performances in the decentralized coordination mode

their proposals and, in doing so, affect the configuration finally chosen. However, each proposal is evaluated by the central office, which makes the final choice.

Table 3 reports the condensed results for the SELF and the FULL interaction structure and Fig. 3 indicates the differences in average performance for the two reward structures for different levels of accounting error and cross-unit interactions—corresponding to Fig. 2.

The results for CENTRAL coordination confirm the general findings as proposed for the decentralized coordination mode and as stated by Bushman et al. (1995) in their formal analysis: compensating according to units' performances is more appropriate in the case of low levels of cross-unit interactions while rewarding firm performance becomes advantageous with increasing levels of interactions. This finding seems to be rather robust against different coordination modes. Moreover, this robustness may contribute to explaining why Bushman et al. (1995) confirm their major finding (the higher the level of intra-firm interactions, the more aggregate performance measures should be used) in their empirical study without controlling for the coordination mechanisms applied beyond the incentive system.

However, Fig. 3 suggests that in the case of CENTRAL coordination, the choice of the appropriate incentive structure is less relevant than for the DECENTRALIZED mode (the wins and losses reported on the vertical axis in Fig. 3 are rather low—or, in other words, the three-dimensional structure is remarkably flat compared to Fig. 2).



Notes: Common parameter for all organizations: coordination mode CENTRAL (see Table 2 for further explanatory remarks). For each combination of incentive structure, level of cross-unit interactions and level of accounting error 5,000 adaptive walks (1,000 distinct performance landscapes with 5 adaptive walks on each) were simulated

Fig. 3 Wins and losses in average firm performance from rewarding firm performance instead of units' performance in the "Central" mode of coordination

In this sense, the configuration "FULL; unit's performance rewarded only" (scenario b1 in Tables 2 and 3) is rather interesting: In this case the incentive structure leads to each units' ignorance of the rest of the organization, although external effects should be taken into account—inducing a rather low average performance. However, with the central office involved in decision making, each (potentially myopic) proposal from the units is evaluated by a second instance, which takes an organization-wide perspective. Hence, in a way the central coordination mode might be regarded as a substitute for the inappropriate incentive system.

Moreover, involving the central office in decision making apparently changes the search processes, as characterized by the frequency of alterations and the ratio of false positive alterations and, in a way, seems to widely immunize organizations against noisy accounting information. Comparing the respective numbers in Table 3 to those in Table 2 shows that with central coordination fewer alterations tend to take place and the ratio of false positive alterations is reduced considerably. This corresponds broadly to findings which Sah and Stiglitz (1986) state in their seminal work on organizations endowed with imperfect information for the evaluation of project alternatives: hierarchies tend to reduce errors in terms of "false positive" decisions (a certain option is only accepted in case it is positively evaluated by each instance involved).

Hence, this aspect leads to further potential extensions of the model. First, it is worth mentioning that—apart from the decentralized and the central mode of coordination as introduced here—various other forms of coordination could be analyzed like, for example, lateral coordination between business units (e.g. Christensen and Knudsen 2010; Sah and Stiglitz 1986; Siggelkow and Rivkin 2005). Hence, it might also be promising to integrate *costs of information processing* and *costs of intra-organizational communication* into the model: The idea behind that is that, while more intense coordination, i.e. more integration, could reduce "false positive" alterations as our simulations exemplarily show, integration usually comes at a price since more communication is required and more instances "work" on the decision-making process.

A further extension could be to integrate the *cost of effort* into the model.[19] A rather "natural" way of doing this could be to regard keeping the status quo $\mathbf{d}_{t-1}^{r*}$ as being associated with no or negligible effort for business unit managers, whereas altering one or even two of the single decisions, i.e. opting for $\mathbf{d}_t^{r1}$ or $\mathbf{d}_t^{r2}$ respectively, increases the effort involved.[20] With respect to the cost of effort induced by alterations, in particular, the potentially beneficial effects of the diversity of the search as mentioned above are put into perspective.

Moreover, in our basic model, "false positive" alterations could occur because of two sources: First, due to ignorance of negative spillover effects induced by the incentive system, and, second because of errors made in *ex post* evaluations of performance which the unit managers "learn" and remember when evaluating a certain option again later on. An additional source of false positive decisions could be imperfect *ex ante* evaluations by unit managers: unlike in Bushman et al.'s (1995) model and as an extension of our basic model, the unit managers might have imperfect knowledge of the "production function" and, hence, the decision-facilitating information (Demski and Feltham 1976) might be erroneous too. In particular, which performance contributions results from configurations $\mathbf{d}_t^{r1}$ or $\mathbf{d}_t^{r2}$ under consideration might be known imperfectly ex ante (Knudsen and Levinthal 2007)—regardless of the errors made by the accounting system in ex post evaluations. Integrating imperfect ex ante evaluations allows for a broad range of further extensions of the model.

Moreover, further dynamics could be captured in the model. As such, for example, it might be interesting to investigate to what extent improving ex post evaluations due to learning capabilities in the accounting department pays off. More broadly, the entire performance landscape could underlie certain dynamics in the sense that the environment is instable, causing the performance contributions of

[19] As is familiar in principal-agent models, business unit managers could be seeking to maximize a utility function where not only the compensation but also the cost of effort is of relevance.

[20] In further simulation experiments we modeled and simulated the cost of effort in such a way that the more single decisions are altered, the higher the cost of effort. In line with intuition, the cost of effort reduces movements in the search process and slows down performance enhancements.

configurations **d** to change over time (e.g. Siggelkow and Rivkin 2005). An interesting aspect, then, is the extent to which the incentive structure, which interferes with the complexity of the interactions structure, allows for fast performance enhancements in dynamic environments, possibly combined with imperfect ex ante and ex post evaluations by the accounting systems.

4.4 Comparing the research approaches

In short, the major result of Bushman et al.'s (1995) paper is that with increasing (decreasing) cross-unit interactions—all other things being equal—it becomes more (less) useful to base compensation on aggregate performance measures. The authors derive this finding from a formal analysis and provide empirical evidence. The agent-based model presented in this paper confirms the main result of the Bushman et al. (1995) paper. Hence, we have three methodological approaches at hand leading, in principle, to the same result. Of course, on the one hand this is good news for the agent-based simulation approach; however, on the other hand the question arises as to whether the agent-based model yields additional insights which are captured neither in the formal analysis nor in the empirical study by Bushman et al. (1995)—or in other words: *What is the marginal contribution of the agent-based model in our illustrative investigation?* This section aims to answer this question by comparing the three research approaches in order to highlight their specific features for our example. In the following, we discuss major aspects on rather a condensed level; additionally Table 4 provides a comparative overview of the components as captured in the three approaches.

Bushman et al.'s (1995) formal analysis, based on a principal-agent model, solves an optimization problem and yields the ratio of weights of aggregate-to-unit performance measures in the *optimal contract* in an *explicit form*. In particular, the weight ratio of performance measures is given as a function of both interactions among business units and (in-)accuracy (noise) related to performance measures as explanatory variables (Bushman et al. 1995, p. 107). From this, the form of how results of the agent-based simulations are given differs substantially: the results are generated by (extensive) numerical experiments and, in this sense, we simulated further parameter settings in order to gain deeper insights into the relation between the relative weights of aggregate-to-unit performance measures, level of intra-firm interactions, accounting error and overall firm performance.[21] However, as Chang and Harrington (2006) put it, simulation results "ultimately are a collection of examples, perhaps many examples… but still noticeably finite" (p. 1277). Nevertheless, results of simulation experiments and extensive sensitivity analyses can be used to derive regression models (Leombruni and Richiardi 2005; Epstein 2006a).

[21] For this, see note 17.

Table 4 Overview of the major components of the three models

Components mapped/controlled for	Principal-agent model in Bushman et al. (2005)	Empirical study by Bushman et al. (2005)	Agent-based model presented in this paper
(1) Organizational levels	Two: firm and unit heads	Four: "corporate CEO", "group CEO", "division CEO" and "plant manager"	Two: central office and unit heads
(2) Interdependencies among business units	Level of cross-unit interactions as number of units whose performance might be affected by a business unit	Product diversification (related and unrelated) and geographical diversification Intra-firm sales; segment disclosures; entropy measures	Level of cross-unit interactions based on single decisions delegated to the units and affecting the performance contributions of other decisions (NK model)
	Intensity of cross-unit interactions as marginal product of unit managers' efforts on (other) units' outcome	(Not controlled for)	Intensity of cross-unit interactions as random variables
	Positive spillover effects only		Positive and negative spillover effects
(3) Performance measures used in the incentive scheme	Continuously scalable ratio of unit performance versus firm performance	Annual compensation plans: four levels of aggregation (corporate, group, division and plant performance) and their averaged weights for each of four managerial levels	Model: continuously scalable ratio of unit performance versus firm performance Results presented: unit performance versus firm performance as two distinct incentive schemes
		Long-term compensation: e.g. stock options	
(4) Coordination mechanisms beyond incentive system	Though not explicitly described, "decentralized" in terms of the agent-based simulation model presented in this paper	(Not controlled for)	"Decentralized": i.e. no coordination between units beyond the incentive system "Central": proposals by units to central office which combines units' proposals and makes final decision
(5) Error/noise related to performance measures in ex post-evaluation	Normally distributed, mean zero, any covariance	(Not controlled for)	Normally distributed, mean zero, covariance zero
	Decision makers informed about properties of errors/noise		Decision makers learn stepwise about measurement errors

With respect to the (in-)accuracy of performance measures, first of all, it should be mentioned that this aspect is not captured in the empirical study of Bushman et al. (1995) due to limitations of data availability (p. 110). On the other side, the principal-agent model of Bushman et al. allows for a detailed analysis of the effects of the measures' (in-)accuracy on the optimal contract: In particular, the authors derive that in the optimal contract the relative weights of aggregate to unit-related performance measures equals the ratio of signal-to-noise-ratios of the aggregate to unit-related measures which, in a way, reproduces the general finding of Banker and Datar (1989) for the optimal weighting of multiple performance measures in linear contracts. In a further case discrimination, Bushman et al. (1995) investigate the situation where the covariance between the performance measures related to the business units is zero and this case corresponds to our agent-based model where the measurement errors related to the measures of units' performance are independent (see also Lambert 2001, p. 22). For this case, Bushman et al. find that, as mentioned before, the relative use of aggregate performance measures in the optimal contract increases if the cross-unit impact of business units increases and the noise in the aggregate performance measures decreases which corresponds to results of our agent-based model. Moreover, Bushman et al.'s principal-agent model allows for further insights for cases where the correlation between units' performance measures is not zero. However, this case is not captured in our agent-based model. Notwithstanding this difference another aspect merits a comment: In the principal-agent model the unit managers are assumed to be well informed about the signal-to-noise-ratios related to the performance measures in advance (i.e. before contracting). In contrast, unit managers in our agent-based model stepwise learn about the measurement errors. These differences in the knowledge about errors related to performance measures in a way also reflect the different assumptions about the decision makers' (bounded) rationality in "traditional" economic modeling versus ABM.

To figure out potential further insights yielded by the agent-based approach, we find it useful to furthermore address those aspects which are additionally reflected or controlled for in the model presented here.

The principal-agent model maps a rather reduced form of organizational structure, meaning, in particular, that *no coordination mechanisms other than* incentives are used, which corresponds to the DECENTRALIZED mode in our simulation model. In contrast, the empirical analysis presumably includes companies which apply various mechanisms of coordination—in addition to the incentive systems under investigation—but does not control for these coordination mechanisms. Hence, the fact that the major theoretical insight (i.e. the more cross-unit interactions there are, the more weight there is on aggregate performance measures) is supported by the empirical part may be regarded as an indication that this finding is robust against richer coordinative forms. However, the question arises as to under *which circumstances and to what extent this is the case*. Using an agent-based simulation model allows an explicit analysis of richer organizations with, for example, more sophisticated modes of intra-firm coordination (which might be hardly tractable in formal models). We tried to illustrate this by introducing the CENTRAL mode of coordination. In particular, analyzing the CENTRAL mode indicates that the general finding of Bushman et al.'s paper holds but that, first, the relevance of the incentive system seems to be reduced compared to the DECENTRALIZED mode and, second, the search processes differ substantially too.

The agent-based model allows further insights resulting from the underlying behavioral assumptions compared to those of the principal-agent model in Bushman et al. (1995), who assume a utility-maximizing individual who is able to survey the whole solution space and to identify the individually optimal solution instantaneously. However, when the researcher is interested in how alternative incentive schemes, accounting errors and intra-firm interdependencies affect solutions discovered by less gifted decision makers, an agent-based model, as presented in this paper, could provide some further insights. For example, our model allows an investigation of procedural aspects like the *speed* of performance enhancements, the *frequency* of discovering the global maximum, or how many "wrong" decisions are made during the search process. Findings of this procedural nature are more or less precluded in the principal-agent model and would be particularly difficult to obtain in an empirical analysis (Davis et al. 2007). In particular, when the speed and costs of adaptations are of interest, e.g. due to turbulent environments, these findings may be particularly useful.

In this sense, ABM might also bear the potential to investigate to what extent findings provided by analytical models hold if some of the underlying assumptions are relaxed (e.g. Axtell 2007; Davis et al. 2007; Leitner and Behrens 2013). Our exemplary study might be regarded as an attempt in this direction, since it indicates that a major finding of the related principal-agent model is robust against relaxing assumptions about the cognitive capabilities of the decision-making agent and even holds for rather myopic agents which, however, are equipped with some foresight as to the outcomes of options and memory of accounting numbers.

Hence, against the background of our modeling effort and the extensions as discussed in Sect. 4.3.4, the potential contributions of ABM for research in management accounting could be summarized in five items: (1) Agent-based models allow the investigation of management accounting issues in rich organizational contexts including, for example, various coordination mechanisms, heterogeneous agents, and various forms of intra-organizational complexity. (2) ABM could help to study the effects of different errors in accounting numbers in interaction with each other and with respect to organizational performance. (3) When procedural aspects of management accounting are of interest—be it due to turbulence in the environment, the learning capabilities of the agents or since the development of the management accounting system itself is to be investigated—agent-based models allow us to study the relevant processes into detail. (4) The "micro–macro interaction" as incorporated in agent-based models enables researchers in management accounting to derive consequences for the system's overall performance which result from, for example, the use of accounting techniques on the micro level. (5) ABM might allow us to investigate to what extent findings of, for example, principle-agent models hold if some of the underlying assumptions are relaxed. However, there are various shortcomings of ABM which we subsequently address in a broader perspective.

5 Opportunities and limitations of ABM in managerial science

In the preceding sections we sought to give an overview of core features of ABM and its applications for discovering theory in managerial science. In this section we outline recent criticisms as well as potential contributions of ABM in managerial science from a more general point of view. For this, it is helpful to remember that ABM is a multi-facetted approach which incorporates two aspects to be addressed at this point: First, ABM in its very methodical core means conducting computer experiments by simulation which, in itself, entails certain strengths and weaknesses. Second, ABM incorporates certain concepts (for example, of agents' behavior) which provide interesting opportunities for research but also certain pitfalls.

5.1 ABM as simulation-based research

Agent-based models are "solved" by extensive computational experimentation by means of simulation. Hence, ABM could be regarded in the light of simulation-based research in general as a method for theory development. According to Harrison et al. (2007) simulation modeling allows researchers to capture "complex multilevel, and mathematically intractable phenomena" (p. 1240) by taking prior management theories and empirical data into account within the model and using computational technology; the computational experiments produce data which could bring about new empirical research (not least for validating and testing the simulation model) and new management theories—and these could be subject to further simulation research. Davis et al. (2007) argue that simulation is especially useful "in the 'sweet spot' between theory-creating research using such methods as inductive multiple case studies… and formal modeling…, and theory-testing research using multivariate, statistical analysis" (p. 481), when the research question addresses some fundamental tensions as exemplified in Sect. 3 and in our illustrative study.

Furthermore, simulation-based research is viewed as valuable for revealing the boundary conditions of empirical findings or to investigate longitudinal phenomena, which are often difficult to study empirically due to problems in the availability of data. In this sense, simulation-based research might help to generate empirically relevant data and, as Epstein argues (2006a) with respect to agent-based simulations in particular, could provide ideas of counterintuitive behavior to be analyzed more into detail in laboratory research or could reveal effects on the macro-level resulting from micro-level behavior as investigated in laboratory experiments (p. 21). Moreover, simulation particularly allows non-linear phenomena to be explored like thresholds or tipping points or disaster scenarios.

In any case, since simulation requires putting the system under investigation into a computational form, this also means that the models are precisely formalized (for a further debate on this point see Leombruni and Richiardi 2005; Epstein 2006b; Harrison et al. 2007; Richiardi 2012). However, formalization and computational representation inevitably require finding abstract formulations of the system under investigation. For example, employing the idea of NK fitness landscapes requires that the underlying optimization problem can be appropriately represented in terms of an N-dimensional binary vector optimization problem, which is obviously a strong abstraction of many real-world problems. Hence, a major question of simulation is the extent to which the simplifications and abstraction which are prerequisites of a computational representation may induce a critical lack of external validity (Harrison et al. 2007; Davis et al. 2007).

Simulation-based research is often regarded as suffering from what is called a "black box", meaning that the models and results often suffer from not being comprehensible and transparent to other researchers (Lorscheid et al. 2012; Harrison et al. 2007; Reiss 2011; Barth et al. 2012): Simulation models allow more complex phenomena to be studied than "traditional" formal models, and this, in consequence, would require rather extensive descriptions of data, rules, and parameter settings, etc. However, this is often not done in order to avoid overloading the reader or to meet the publisher's space limitations (Lorscheid et al. 2012). Moreover, the major findings of a simulation study often are to be differentiated with respect to parameter settings within a given study, which makes it even more difficult to be conclusive without providing too many details (Axelrod 1997a). In order to overcome these somewhat "built-in" problems of simulation-based research, there is a strong claim to make use of standardization—be it in the process of simulation modeling, in the data structures or in the algorithms (Richiardi et al. 2006; Lorscheid et al. 2012; Müller et al. 2014).

5.2 Issues specifically related to ABM

While the aforementioned aspects pertain to simulation-based research in general, some issues specifically related to agent-based models require closer attention within this paper. For this, first of all, it should be pointed out that ABM as a research method is not free of criticism, particularly in an economic context (overviews are given in Leombruni and Richiardi 2005; Richiardi 2012; Waldherr and Wijermans 2013). Subsequently, we discuss benefits and criticisms relating to ABM with respect to managerial science, and, in particular, we address aspects resulting from (1) assumptions related to agents as familiar in ABM, (2) the mode of "solving" a model, and (3) the focus of analysis in agent-based models.

As described more into detail in Sect. 2.1, a core feature of agent-based models is to map heterogeneous decision-making agents with richer internal cognitive structures and more complex interactions than conventionally captured in economic models. With these features, ABM bears the potential to flexibly map organizations consisting of diverse agents (e.g. knowledge, capabilities, attitudes towards social norms, preferences) with various communication and coordination patterns, allowing for the investigation of the emergent behavior of the organization as it results from interactions between these heterogeneous agents (Harrison et al. 2007; Midgley et al. 2007). Hence, ABM allows depicting more realistic scenarios than, in particular, those captured in neoclassical economics (Kirman 1992; Chang and Harrington 2006; Axtell 2007).

For managerial science, these features of ABM provide some interesting research opportunities as well as challenges. First, relaxing the assumptions of neoclassical economics on agents' cognitive capabilities provides the opportunity to study to what extent the principal findings of a research effort conducted on the basis of these assumptions are robust in settings with agents showing more cognitive limitations (e.g. Axtell 2007; Davis et al. 2007; Leitner and Behrens 2013). This methodological approach is called "agentization" (Guerrero and Axtell 2011). However, it turns out that it is not difficult to model agents with rather limited cognitive capabilities (e.g. myopia and fairly simple search processes), "but to extend their intelligence to the point where they could make decisions of the same sophistication as is commonplace among people" (Gilbert 2008, p. 16). Second, Chang and Harrington (2006) argue that ABM could provide a trade-off between richness on the one hand and rigor on the other, since, for example, organization theory is traditionally either broad, institutionally rich and vague, or narrow though mathematically precise using formal logic. ABM allows researchers to deal with complex entities while maintaining rigor and formality. Nevertheless, this requires weighing up the complexity and simplicity of an agent-based model (Harrison et al. 2007).

However, the high flexibility incorporated in ABM also causes problems when employing ABM as a research method. In particular, Safarzyńska and van den Bergh (2010) criticize that in agent-based models behavioral rules are often introduced ad hoc due to a lack of empirical data for validating model assumptions, and that the behavioral rules are justified merely by stylized facts. In this sense, Richiardi et al. (2006) argue that the high flexibility which ABM grants to researchers "has often generated in a sort of anarchy… For instance, there is no clear classification of the different ways in which agents can exchange and communicate: every model proposes its own interaction structure" (no. 1.5). In order to overcome this "anarchy" and increase the acceptance of ABM among "traditional" economists, the claim has been made to develop a common framework for ABM (Richiardi et al. 2006; Janssen et al. 2008).

Compared to neoclassical economics, the way of "solving" an agent-based model differs substantially, since not proofs but extensive numerical derivation produces the results (Chang and Harrington 2006). Moreover, agent-based models often incorporate a considerable number of parameters, allowing for the study of various settings of the system under investigation. In doing so, the boundary conditions of certain regularities can be explored, and creative experimentation can be used to fathom regularities. Extensive numerical experimentation allows the identification of non-linear phenomena typical for many agent-based models and the results often provide evidence for multiple optima, suggesting the existence of multiple equilibria rather than a single-peak prediction (Tesfatsion 2006).

However, this could be regarded as a virtue and a pitfall of ABM too. In particular, in conjunction with the aforementioned lack of justification of model assumptions, the results provided by ABM might suffer from low traceability (Richiardi et al. 2006; Leombruni and Richiardi 2005; Chang and Harrington 2006). In particular, while traditional economic modeling is based on formulating equations and produces algebraic solutions (Epstein 2006a), the results of computational models stem from numerical experiments (ideally) "sweeping the parameter space… and conducting extensive sensitivity analysis" (Epstein 2006a, p. 28) allowing for deriving a regression model (Leombruni and Richiardi 2005; Epstein 2006a). However, a scepticism against ABM results from the possibility that the data produced by simulation may not represent all outcomes which the model could produce since it might be possible that for certain configurations of parameters the results change dramatically (Leombruni and Richiardi 2005, p. 107).

ABM differs from traditional economic modeling with respect to the focus of analysis too. The latter models are usually directed at an analysis of the state of a system when it has converged to an equilibrium which often means that the perspective is rather long-termed and related to a steady state; in contrast, ABM often is directed to the study of medium-run dynamics due to adaptation (Chang and Harrington 2006). In this sense, ABM might be regarded as a more realistic way of modeling since its primary focus is not to analyze—in reality rarely occurring stable—equilibria but processes of adaptation. For example, for high environmental dynamics (e.g. in terms of technological change, competitive situation) ABM might be regarded as an appropriate way of modeling since it allows for investigating how *fast* organizations adapt to the dynamic environment. These aspects also became apparent in our illustrative study: The solution of the principal-agent model in Bushman et al. (1995) consists in the explicit form for the optimal incentive scheme in equilibrium; our agent-based modeling effort provided information about the adaptation processes towards higher levels of organizational performance and the performance achievable in a long-run perspective; moreover, as mentioned before, among the obvious model extensions it would be to study adaptation processes with instable performance landscapes. Therefore, as Tesfatsion (2006) puts it, ABM should be regarded "a complement, not a substitute, for analytical and statistical modeling approaches" (p. 864).

6 Conclusion

The aim of this paper has been to highlight applications of ABM for developing theory in managerial science by way of example and to elaborate the research opportunities as well as the limitations of ABM as a research approach in managerial science. A particular emphasis has been placed on an exemplary study of ABM in the domain of management accounting research—a domain which, so far, has seen few efforts in the spirit of ABM.

Our review of ABM in research on two fundamental trade-offs of managerial science (i.e. "exploration vs. exploitation" and "differentiation vs. integration") reveals that agent-based models have contributed to a multi-facetted understanding of these issues—may it be related to product design, design of the organizational structure or a firm's strategy, to short-term versus long-term effects, to the importance of complexity and turbulence or to the relevance of different modes of decision-making in organizations. Further, we set up an agent-based model for an exemplary question in the domain of management accounting, i.e. whether to use aggregate or business unit performance measures for compensating unit managers in face of intra-company interactions. When comparing the results of our agent-based simulation with those provided by a closed-form model and an empirical study, we found that ABM could provide valuable additional insights which would be hard to gain analytically or empirically. Moreover, a promising application of ABM is studying to what extent the findings of principal-agent models are robust when typical assumptions incorporated in those models, for example relating to agents' information processing capabilities, are relaxed.

While ABM promises interesting research opportunities it is worth mentioning that it also bears certain perils in terms of the traceability and transparency of results. A major cause for these perils is the high flexibility that ABM grants to the researcher when modeling agents, environments and interactions from which the system's behavior under investigation results. In this sense, ABM's flexibility and potential to study micro–macro interactions might be regarded a blessing and a curse at the same time.

Appendix

See Table 5.

Table 5 Overview of articles as reported on in Sects. 3.2–3.4

Study	Journal	Research question	Major tensions	Explanatory/independent variables and parameters	Dependent variables/ simulation output of interest
Baumann and Martignoni (2011)	Schmalen-Bach Business review	Is an pro-innovation bias in order to foster exploration beneficial with respect to firm performance?	Exploration versus exploration: objective evaluation of new options versus pro-innovation biased evaluation; exploitation intended by decision-makers, but, in some settings, exploration happening accidentally	Intensity of a pro-innovation bias, complexity of an organization's environment	Firm performance[a]
Dosi et al. (2003)	Industrial and Corporate Change	How do problem-complexity, delegation of problem-solving tasks, hierarchical power and incentive structure in interrelation with each other effect firm performance?	Differentiation versus integration; problem-solving efficiency versus incentive efficiency	Decomposition of the search for new solutions, mode of selection of new discovered solutions (esp. structure of incentives and veto-power), interactions within the organizational decision problem	Firm performance[a]
Ethiraj and Levinthal (2004)	Management Science	What is the appropriate level of modularization in the design of new products?	Exploration versus exploration as recombination, i.e. substituting one module by another (from within the organization or from copying of another firm); process efficiency versus product efficiency	Level of modularization in design compared to true level of modularity in the design problem	Speed and efficiency gains and losses of modularization
Ethiraj et al. (2008)	Management Science	What is the appropriate level of modularization in the design of new products with respect to imitation by competitors?	Exploration versus exploitation: exploitation as incremental innovation by innovation leader and exploration by copying of imitator; modularity versus complexity; innovation benefits versus imitation deterrence	Modularity of design; accuracy of imitation by competitors	Innovation performance, shield against imitation

Table 5 continued

Study	Journal	Research question	Major tensions	Explanatory/independent variables and parameters	Dependent variables/ simulation output of interest
Gavetti et al. (2005)	Strategic Management Journal	How effective is analogical reasoning with respect to firm performance?	Exploration versus exploitation: exploration as general guidance by analogies versus exploitation as incremental improvement	Effectiveness of distinguishing similar from different settings, bredth and width of managerial experience, complexity of interactions in the industry	Firm performance[a]
Ghemawat and Levinthal (2008)	Management Science	Is a fully articulated strategy required to achieve a high level of firm performance or it is feasible to compensate past strategic mistakes throughtactical adjustments?	Exploration versus exploitation: exploration as strategic guidance ex ante versus exploitation as tactical alignment by stepwise improvement ex post	Balance between ex ante design decisions and ex post adjustment decisions, complexity of interactions within strategic choices	Long-term firm performance[a]
Knudsen and Levinthal (2007)	Organization Science	How do imperfect ex ante evaluations of indivual decision-makers affect performance of the organization?	Differentiation versus integration: decentralized evaluations with potentially discovery of new options by chance as beneficial by-product of noisy evaluations versus multiple evaluations in the hierarchy with high level of accuracy of evaluations and peril of sticking to local peaks	Capabilities of decision-makers to ex ante evaluate alternative options, modes of coordination, interactions within the organizational decision problem	Firm performance[a]
Levinthal (1997)	Management Science	What causes the diversity and persistency of organizational forms?	Exploration versus exploration: exploitation as local adaptation versus exploration of radical change of organizations' characteristics	(Complexity of) starting configuration; (in-)stability of environment	Firm heterogeneity

Table 5 continued

Study	Journal	Research question	Major tensions	Explanatory/independent variables and parameters	Dependent variables/ simulation output of interest
Rivkin (2000)	Management Science	What is the optimal level of strategic complexity?	Exploration versus exploration: exploration as informed copying by competitors versus exploitation as imitation by incremental improvement by competitors; modularity versus complexity	Complexity of a strategy, imitation by competitors	Firm performance[a]
Rivkin and Siggelkow (2003)	Management Science	How to balance the search for good solutions and stability around good solutions in organizations?	Exploration versus exploitation: search for novel options versus exploiting around options already found; differentiation versus integration in terms of location of decision-making and incentives provided	Organizational design elements: (de-) centralization, bredth of search for new solutions by subunits, incentives, information processing capacity of central unit, interactions within the organizational decision problem	Characteristics of search processes; firm performance[a]
Siggelkow and Levinthal (2003)	Organization Science	How should firms organize to achieve superior levels of performance after facing an environmental change?	Differentiation versus integration: short-term decentralization versus long-term stability of the level of (de-) centralization of decisions; exploration versus exploitation, particularly with respect to putting the two in sequence in time	Stability of (de-) centralization of decision-making authority, interactions within the organizational decision problem	Characteristics of search processes; firm performance[a]
Siggelkow and Rivkin (2005)	Organization Science	How do environmental turbulence and complexity affect the appropriate formal design of organizations?	Differentiation versus integration; stability versus turbulence	Stability/turbulence of the environment, modes of coordination among sub-units and central authority (various forms), structure of incentives, interactions within the organizational decision problem	Speed and extent of enhancements in firm performance[a]

Table 5 continued

Study	Journal	Research question	Major tensions	Explanatory/independent variables and parameters	Dependent variables/ simulation output of interest
Siggelkow and Rivkin (2006)	Academy of Management Review	Is it beneficial with respect to firm performance to locate exploration tasks at lower levels in organizations?	Differentiation versus integration in terms of location of exploration; exploration versus exploitation: exploration at lower versus exploration at higher hierachical levels	Organizational level of search for new solutions, subunits' information-processing capabilities for exploration, cross-departmental interactions within the solution space	Firm performance[a]
Sommer and Loch (2004)	Management Science	Which of the fundamental approaches of "selectionism" versus "trial and error learning" is more appropriate in face of complexity and uncertainty?	Exploration versus exploitation: efficiency of parallel search (selectionism) versus efficiency of continuous improvement (trial and error learning)	Quality of testing appropriateness via ex post selections of most appropriate solution, complexity of system to be designed, uncertainty as inability to recognize the relevant influence variables and their functional relationships	Project pay-off

[a] "Firm performance" is used to indicate the overall performance achieved by an organisation or a firm. The term does not refer to a certain accounting-related measure (e.g. firm value, profit); the articles partially use other denominations as, for example, "organizational performance" or "fitness"

References

Altenberg L (1997) Section B2.7.2: NK fitness landscapes. In: Back T, Fogel D, Michalewicz Z (eds) The handbook of evolutionary computation. Oxford University Press, Oxford, pp B2.7:5–B2.7:10

Anderson P (1999) Complexity theory and organization science. Organ Sci 10(3):216–232

Axelrod R (1997a) Advancing the art of simulation in the social sciences. Santa Fe Institute, working paper no. 97-05-048

Axelrod R (1997b) Advancing the art of simulation in the social sciences. Complexity 3(2):16–22

Axelrod R, Cohen MD (1999) Harnessing complexity: organizational implications of a scientific frontier. Free Press, New York

Axtell R (2007) What economic agents do: how cognition and interaction lead to emergence and complexity. Rev Austrian Econ 20(2–3):105–122

Banker RD, Datar SM (1989) Sensitivity, precision, and linear aggregation of signals for performance evaluation. J Acc Res 27(1):21–40

Barth R, Meyer M, Spitzner J (2012) Typical pitfalls of simulation modeling: lessons learned from armed forces and business. JASSS-J Artif Soc Simul 15 (2)

Baumann O, Martignoni D (2011) Evaluating the new: the contingent value of a pro-innovation bias. Schmalenbach Bus Rev 63:393–415

Behrens DA, Berlinger S, Wall F (2014) Phrasing and timing information dissemination in organizations: results of an agent-based simulation. In: Leitner S, Wall F (eds) Artificial economics and self organization. Lecture notes in economics and mathematical systems, vol 669. Springer, Berlin, pp 179–190

Bonabeau E (2002) Agent-based modeling: methods and techniques for simulating human systems. Proc Natl Acad Sci USA 99(3(Suppl)):7280–7287

Bushman RM, Indjejikian RJ, Smith A (1995) Aggregate performance measures in business unit manager compensation: the role of intrafirm interdependencies. J Acc Res 33(Suppl):101–129

Carley KM (1995) Computational and mathematical organization theory: perspective and directions. Comput Math Organ Theor 1(1):39–56

Carley KM (2002) Computational organizational science and organizational engineering. Simul Model Pract Theory 10(5–7):253–269

Carley KM, Gasser L (1999) Computational organization theory. In: Weiss G (ed) Multiagent systems: a modern approach to distributed artificial intelligence. MIT Press, Cambridge, pp 299–330

Carroll T, Burton RM (2000) Organizations and complexity: searching for the edge of chaos. Comput Math Organ Theor 6(4):319–337

Caves RE, Porter ME (1977) From entry barriers to mobility barriers: conjectural decisions and contrived deterrence to new competition. Q J Econ 91(2):241–261

Chang M-H, Harrington JE (2006) Agent-based models of organizations. In: Tesfatsion L, Judd KL (eds) Handbook of computational economics: agent-based computational economics, vol 2. Elsevier, Amsterdam, pp 1273–1337

Christensen M, Knudsen T (2010) Design of decision-making organizations. Manage Sci 56(1):71–89

Christensen CM, Kaufman SP, Shih WC (2008) Innovation killers. Harvard Bus Rev 86(1):98–105

Davis JP, Eisenhardt KM, Bingham CB (2007) Developing theory through simulation methods. Acad Manage Rev 32(2):480–499

Dawid H (2006) Agent-based models of innovation and technological change. In: Tesfatsion L, Judd KL (eds) Handbook of computational economics, vol 2. Elsevier, Amsterdam, pp 1235–1272

Demski JS, Feltham GA (1976) Cost determination: a conceptual approach. Iowa State University Press, Ames

Denrell J, March JG (2001) Adaptation as information restriction: the hot stove effect. Organ Sci 12(5):523–538

Dooley K (2002) Simulation research methods. In: Baum J (ed) Companion to organizations. Blackwell, London, pp 829–848

Dosi G, Malerba F, Marsili O, Orsenigo L (1997) Industrial structures and dynamics: evidence, interpretations and puzzles. Ind Corp Change 6(1):3–24

Dosi G, Levinthal D, Marengo L (2003) Bridging contested terrain: linking incentive-based and learning perspectives on organizational evolution. Ind Corp Change 12(2):413–436

Duffy J (2006) Agent-based models and human subject experiments. In: Tesfatsion L, Judd KL (eds) Handbook of computational economics: agent-based computational economics, vol 2. Elsevier, Amsterdam, pp 949–1011
Eisenhardt KM (1989) Making fast strategic decisions in high-velocity environments. Acad Manage J 32:543–576
Epstein JM (2006a) Agent-based computational models and generative social science. In: Epstein JM (ed) Generative social science: studies in agent-based computational modeling. Princeton University Press, Princeton, pp 4–46
Epstein JM (2006b) Remarks on the foundations of agent-based generative social science. In: Tesfatsion L, Judd KL (eds) Handbook of agent-based computational economics. Handbook of computational economics, vol 2. Elsevier, Amsterdam, pp 1585–1604
Epstein JM, Axtell R (1996) Growing artificial societies: social science from the bottom up. MIT Press, Cambridge
Ethiraj SK, Levinthal D (2004) Modularity and innovation in complex systems. Manage Sci 50(2):159–173
Ethiraj SK, Levinthal D, Roy RR (2008) The dual role of modularity: innovation and imitation. Manage Sci 54(5):939–955
Fioretti G (2013) Agent-based simulation models in organization science. Organ Res Methods 16(2):227–242
Galbraith JR (1973) Designing complex organizations. Addison-Wesley, Reading
Galbraith JR (1974) Organization design: an information processing view. Interfaces 4(3):28–36
Ganco M, Hoetker G (2009) NK modeling methodology in the strategy literature: bounded search on a rugged landscape. In: Bergh DD, Ketchen DJ (eds) Research methodology in strategy and management. Emerald, Bingley, pp 237–268
Garcia R (2005) Uses of agent-based modeling in innovation/new product development research. J Prod Innov Manag 22(5):380–398
Gavetti G, Levinthal D (2000) Looking forward and looking backward: cognitive and experiential search. Admin Sci Quart 45:113–137
Gavetti G, Levinthal DA, Rivkin JW (2005) Strategy making in novel and complex worlds: the power of analogy. Strateg Manage J 26(8):691–712
Ghemawat P, Levinthal D (2008) Choice interactions and business strategy. Manage Sci 54(9):1638–1651
Gilbert GN (2008) Agent-based models. Quantitative applications in the social sciences, vol 153. Sage, New York
Gilbert N, Troitzsch KG (2005) Simulation for the social scientist, 2nd edn. Open University Press, Buckingham
Guerrero OA, Axtell R (2011) Using agentization for exploring firm and labor dynamics: a methodological tool for theory exploration and validation. In: Osinga S, Hofstede GJ, Verwaart T (eds) Emergent results of artificial economics. Lecture notes on economics and mathematical systems, vol 652. Springer, Berlin, pp 139–150
Gupta AK, Smith KG, Shalley CE (2006) The interplay between exploration and exploitation. Acad Manage J 49(4):693–706
Harrison JR, Zhiang LIN, Carroll GR, Carley KM (2007) Simulation modeling in organizational and management research. Acad Manage Rev 32(4):1229–1245
Hauschild S, Knyphausen-Aufseß D (2013) The resource-based view of diversification success: conceptual issues, methodological flaws, and future directions. Rev Manag Sci 7(3):327–363
Hesford JW, Lee S-HS, Van der Stede WA, Young SM (2007) Management accounting: a bibliographic study. In: Chapman CS, Hoopwood AG, Shields MD (eds) Handbook of management accounting research, vol 1. Elsevier, Amsterdam, pp 3–26
Hilletofth P, Lättilä L (2012) Agent based decision support in the supply chain context. Ind Manage Data Syst 112(8):1217–1235
Hodgson GM, Knudsen T (2010) Darwin's conjecture: the search for general principles of social and economic evolution. The Chicago University Press, Chicago and London
Hommes CH (2006) Heterogeneous agent models in economics and finance. In: Tesfatsion L, Judd KL (eds) Handbook of computational economics: agent-based computational economics, vol 2. Elsevier, Amsterdam, pp 1109–1186
Hutzschenreuter T, Kleindienst I, Schmitt M (2012) Path-related empirical research on M&A-outcome: review and research agenda. Rev Manag Sci 6(4):375–405

Janssen MA, Na'ia Alessa L, Barton M, Bergin S, Lee A (2008) Towards a community framework for agent-based modelling. JASSS-J Artif Soc Simul 11(2):1–6
Kahneman D, Slovic P, Tversky A (1982) Judgment under uncertainty: heuristics and biases. Cambridge University Press, Cambridge
Kauffman SA (1993) The origins of order: self-organization and selection in evolution. Oxford University Press, Oxford
Kauffman SA, Levin S (1987) Towards a general theory of adaptive walks on rugged landscapes. J Theor Biol 128(1):11–45
Kiesling E, Günther M, Stummer C, Wakolbinger L (2012) Agent-based simulation of innovation diffusion: a review. Cent Eur J Oper Res 20(2):183–230
Kirman AP (1992) Whom or what does the representative individual represent? J Econ Perspect 6(2):117–136
Klügl F (2000) Aktivitätsbasierte Verhaltensmodellierung und ihre Unterstützung bei Multiagentensimulationen. Universität Würzburg, Dissertation, Fakultät für Mathematik und Informatik
Knudsen T, Levinthal DA (2007) Two faces of search: alternative generation and alternative evaluation. Organ Sci 18(1):39–54
Labro E, Vanhoucke M (2007) A simulation analysis of interactions among errors in costing systems. Acc Rev 82(4):939–962
Lambert RA (2001) Contracting theory and accounting. J Acc Econ 32:3–87
Law AM (2007) Simulation modeling and analysis, 4th edn. McGraw-Hill, New York
Lawrence PR, Lorsch JW (1967) Differentiation and integration in complex organizations. Admin Sci Quart 12(1):1–47
Leitner S (2014) A simulation analysis of interactions among intended biases in costing systems and their effects on the accuracy of decision-influencing information. Cent Eur J Oper Res 22(1):113–138
Leitner S, Behrens D (2013) On the fault (in)tolerance of coordination mechanisms for distributed investment decisions. Cent Eur J Oper Res 1–28. doi:10.1007/s10100-013-0333-4
Leombruni R, Richiardi MG (2005) Why are economists sceptical about agent-based simulations? Phys A 355:103–109
Levinthal DA (1997) Adaptation on rugged landscapes. Manage Sci 43(7):934–950
Levinthal D, Posen HE (2007) Myopia of selection: Does organizational adaptation limit the efficacy of population selection? Admin Sci Quart 52(4):586–620
Levitan B, Kauffman SA (1995) Adaptive walks with noisy fitness measurements. Mol Divers 1(1):53–68
Lomi A, Larsen ER (1996) Interacting locally and evolving globally: a computational approach to the dynamics of organizational populations. Acad Manage J 39(5):1287–1321
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. Comput Math Organ Theor 18(1):22–62
Malone TW, Crowstone K (1994) The interdisciplinary study of coordination. ACM Comput Surv 26(1):87–119
March JG (1991) Exploration and exploitation in organizational learning. Organ Sci 2(1):71–87
Marengo L, Dosi G (2005) Division of labor, organizational coordination and market mechanisms in collective problem-solving. J Econ Behav Organ 58(2):303–326
Midgley D, Marks R, Kunchamwar D (2007) Building and assurance of agent-based models: an example and challenge to the field. J Bus Res 60:884–893
Müller B, Balbi S, Buchmann CM, de Sousa L, Dressler G, Groeneveld J, Klassert CJ, Le QB, Millington JDA, Nolzen H, Parker DC, Polhill JG, Schlüter M, Schulze J, Schwarz N, Sun Z, Taillandier P, Weise H (2014) Standardised and transparent model descriptions for agent-based models: current status and prospects. Envrion Model Softw 55:156–163
Nikitin M (2013) Can Aristotle help us specify the very nature of management problems? Document de Recherche. http://d.repec.org/n?u=RePEc:hal:wpaper:halshs-01015082&r=bec. Laboratoire d'Economie d'Orléans
Ostrum TM (1988) Computer simulation: the third symbol system. J Exp Soc Psychol 24:381–392
Petticrew M, Roberts H (2006) Systematic reviews in the social sciences. A practical guide. Blackwell, Oxford
Powell TC, Lovallo DAN, Caringal C (2006) Causal ambiguity, management perception, and firm performance. Acad Manage Rev 31(1):175–196

Pyka A, Fagiolo G (2007) Agent-based modelling: a methodology for neo-schumpeterian economics. In: Hanusch H, Pyka A (eds) The Elgar companion to neo-schumpeterian economics. Edward Elgar, Cheltenham, pp 467–492

Reiss J (2011) A plea for (good) simulations: nudging economics toward an experimental science. Simul Games 42(2):243–264

Richiardi MG (2012) Agent-based computational economics: a short introduction. Know Eng Rev 27(Special Issue 02):137–149

Richiardi MG, Leombruni R, Saam N, Sonnessa M (2006) A common protocol for agent-based social simulation. JASSS-J Artif Soc Simul 9(1):1–15

Rivkin JW (2000) Imitation of complex strategies. Manage Sci 46(6):824

Rivkin JW (2001) Reproducing knowledge: replication without imitation at moderate complexity. Organ Sci 12(3):274–293

Rivkin JW, Siggelkow N (2002) Organizational sticking points on NK landscapes. Complexity 7(5):31–43

Rivkin JW, Siggelkow N (2003) Balancing search and stability: Interdependencies among elements of organizational design. Manage Sci 49(3):290–311

Rivkin JW, Siggelkow N (2006) Organizing to strategize in the face of interactions: preventing premature lock-in. Long Range Plan 39(6):591–614

Rivkin JW, Siggelkow N (2007) Patterned interactions in complex systems: implications for exploration. Manage Sci 53:1068–1085

Safarzyńska K, van den Bergh J (2010) Evolutionary models in economics: a survey of methods and building blocks. J Evol Econ 20(3):329–373

Sah RK, Stiglitz JE (1985) Human fallibility and economic organization. Am Econ Rev 75(2):292–297

Sah RK, Stiglitz JE (1986) The architecture of economic systems: hierarchies and polyarchies. Am Econ Rev 76(4):716–727

Sah RK, Stiglitz JE (1988) Committees, hierarchies and polyarchies. Econ Rev 98(June):451–470

Siggelkow N (2002) Misperceiving interactions among complements and substitutes: organizational consequences. Manage Sci 48(7):900–916

Siggelkow N, Levinthal DA (2003) Temporarily divide to conquer: centralized, decentralized, and reintegrated organizational approaches to exploration and adaptation. Organ Sci 14(6):650–669

Siggelkow N, Rivkin JW (2005) Speed and search: designing organizations for turbulence and complexity. Organ Sci 16(2):101–122

Siggelkow N, Rivkin JW (2006) When exploration backfires: unintended consequences of multilevel organizational search. Acad Manage J 49(4):779–795

Silverberg G, Verspagen B (2005) A percolation model of innovation in complex technology spaces. J Econ Dyn Control 29(1–2):225–244

Simon HA (1955) A behavioral model of rational choice. Q J Econ 69:99–118

Smith GF (1995) Classifying managerial problems: an empirical study of definitional content. J Manage Stud 32(5):679–706

Sommer SC, Loch CH (2004) Selectionism and learning in projects with complexity and unforeseeable uncertainty. Manage Sci 50(10):1334–1347

Sorenson O (2002) Interorganizational complexity and computation. In: Baum JAC (ed) Companion to organizations. Blackwell, Oxford, pp 664–685

Squazzoni F (2010) The impact of agent-based models in the social sciences. Hist Econ Ideas 18(2):197–233

Stirling A (2007) A general framework for analysing diversity in science, technology and society. J Roy Soc Interface 4(15):707–719

Tesfatsion L (2001) Introduction to the special issue on agent-based computational economics. J Econ Dyn Control 25:281–293

Tesfatsion L (2006) Agent-based computational economics: a constructive approach to economic theory. In: Tesfatsion L, Judd KL (eds) Handbook of computational economics: agent-based computational economics, vol 2. Elsevier, Amsterdam, pp 831–880

Thompson JD (1967) Organizations in action. Social science bases of administrative theory. McGraw-Hill, New York

Tversky A, Kahneman D (1974) Judgment under uncertainty: heuristics and biases. Science 185(4157):1124–1131

Wakolbinger LM, Stummer C, Günther M (2013) Market introduction and diffusion of new products: recent developments in agent-based modeling. Int J Innov Technol Manag 10(5):1–19

Waldherr A, Wijermans N (2013) Communicating social simulation models to sceptical minds. JASSS-J Artif Soc Simul 16(4):1–13
Walker CC, Dooley KJ (1999) The stability of self-organized rule-following work teams. Comput Math Organ Theor 5(1):5–30
Wall F (2010) The (beneficial) role of informational imperfections in enhancing organizational performance. In: LiCalzi M, Milone L, Pellizzari P (eds) Progress in artificial economics: computational and agent-based models. Springer, Berlin, pp 101–122
Wall F (2011) Diversity of the knowledge base in organizations: results of an agent-based simulation. In: Demezeau Y, Pechoucek M, Cochado JM, Pérez JB (eds) Advances on practical applications of agents and multiagent systems. Advances in intelligent and soft computing, vol 88. Springer, Berlin, pp 13–20
Weiss G (ed) (1999) Multiagent systems: a modern approach to distributed artificial intelligence. MIT Press, Cambridge
Wolfram S (1986) Approaches to complexity engineering. Phys D 22(1–3):385–399
Wooldridge M, Jennings NR (1995) Intelligent agents: theory and practice. Knowl Eng Rev 10(2):115–152
Zenobia B, Weber C, Daim T (2009) Artificial markets: a review and assessment of a new venue for innovation research. Technovation 29(5):338–350