

Individual and organizational conditions for the emergence and evolution of bandwagons

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Published online: 13 October 2015

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Abstract What makes employees adopt a particular innovation, practice, or idea? And what makes it more likely for adoption to spread wide in an organization? This paper presents an agent-based model that simulates interactions among employees to analyze the spread of bandwagons. Agents are subject to conformity and peer pressure as well as to a two-level organizational hierarchy. In the model, perceptions of the surrounding environment depend on individual cognitive attitudes (or ‘tolerance’ to bandwagons), the level of ambiguity attached to social relationships, and organization size. Findings show that the probability of widespread diffusion (i.e., bandwagon) is dependent more on organizational size, conformity, and interactions than ambiguity and individual attitudes.

Keywords Bandwagon · Cultural conformity · Organizational culture · Social relationships · Collective mindlessness · Agent-based model

1 Introduction

Much of the literature on diffusion processes focuses on the adoption of innovation among a population of organizations (e.g., Maienhofer and Finholt 2001; Rosenkopf and Abrahamson 1999). These studies use a significant array of different analytical and/or theoretical methodologies, ranging from network analysis and event studies

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to differential equations (e.g., Abrahamson and Rosenkopf 1997; Green 2004; Strang and Tuma 1993; Valente 1996). Conditions under which something is adopted are often the focus of the analysis (Rogers 2003). Some studies provide a range of theoretical tools to better understand procedures, conditions, and determinants under which an idea or a practice spreads in a social community (e.g., Strang and Tuma 1993), why this happens at a given point in time (e.g., Rogers 2003; Rosenkopf and Abrahamson 1999), and how it evolves (e.g., Chiang 2007). The study of diffusion processes within organizations is overlooked in the literature although its understanding may bring organizations to prevent potentially damaging ideas and practices from spreading, and/or facilitate the adoption of effective procedures, ideas, and behaviors. This is the case, for example, of employees discarding ethical issues when they arise, of the rise of discriminatory practices, of the acceptance of illegal or de-motivational practices in a subsidiary of a large multinational, or of the spread of ineffective analytical diagnostic practices among workers of a consultancy firm. The diffusion process is usually referred to as ‘bandwagon’ when the tendency of individuals and organizations to adopt a technique, innovation, behavior, idea, process, or attitude is a function of what the sheer number of peers is doing (Abrahamson and Rosenkopf 1993, 1997; Rosenkopf and Abrahamson 1999). The study of bandwagons in organizational contexts aims at defining the conditions under which the organization’s management can achieve a better understanding of organizational dynamics, thus limiting the spread of potentially damaging practices, ideas, processes, or else.

This study examines how bandwagon-like processes emerge and diffuse. First, it addresses the overlooked interaction between (a) individual attitudes towards adoption and (b) organizational culture, relationships, and other elements of an organization’s social structure. Second, the study of bandwagons as they happen *within* organizations requires modeling efforts that are tied specifically to organizational behavior (e.g., Fiol and O’Connor 2003), such as the analysis of how practices, routines, habits, and ideas spread. Third, the paper uses an agent-based model (ABM) to analyze bandwagons. ABMs are particularly useful to simulate complex phenomena where emergent patterns are likely to manifest from agent interactions (Drogoul and Ferber 1994; Gilbert 2008; Goldstone and Janssen 2005; Secchi 2015b). The use of agent-based computational models is on the rise in organization studies (Anderson et al. 1999; Axelrod and Cohen 1999; Carley 2009; Carley and Svoboda 1996; Levinthal 1997; Miller et al. 2012; Miller and Lin 2010; Siggelkow and Rivkin 2005) but, as far as our knowledge is concerned, ABM is used here for the first time to study intra-organizational bandwagons. Fourth, bandwagon processes are modeled as passive cognitive mechanisms that are explained using the distributed cognition paradigm (Hutchins 1995) and equated to passive versions of what Simon called ‘docility’ (1993)—i.e., the attitude to make decisions based on recommendations, advice, and information coming from social channels.

Computer simulations are not new to the study of bandwagons and diffusion processes (especially diffusion of innovation, see, Kiesling et al. 2012). For example, Abrahamson and Rosenkopf (1997) studied the impact of social networks structure on bandwagon-like processes and found that structural idiosyncrasies

facilitate the spread of information and affect bandwagon significantly. Another example is Chiang (2007), who designed two computational experiments to address agents' heterogeneous attitudes to join the bandwagon (i.e., thresholds; Abrahamson and Rosenkopf 1997; Maienhofer and Finholt 2001) showing that their distribution amongst neighboring agents affects adoption and the shape of diffusion. Most of the simulation studies emphasize the impact that the diffusion process has for structural or *macro* aspects of the system. The current research takes a different approach in that it studies bandwagons as they emerge from interactions of autonomous agents. It models actor characteristics such as threshold levels, imitation biases, social relationships, in line with environmental characteristics such as organizational size and organizational culture, to observe and analyze under what circumstances a bandwagon is more likely to emerge.

In the following sections we provide a rationale for the study, then explain the model, present simulation results, and introduce propositions that may be tested in future works.

2 Rationale and theoretical perspective

2.1 A brief definition of bandwagon processes

There are four conceptual elements used in the literature to characterize the bandwagon as a diffusion process. They are (a) the different kinds of pressures (e.g., social, psychological), (b) the main actor (i.e., individuals or organizations), (c) the sheer number of adopters otherwise labelled "popularity," and (d) the process. These elements are reviewed briefly below with the objective to provide the reader with a better understanding of how the bandwagon is interpreted in the present study. At the same time, this allows us to outline the constituents on which our model is based.

2.1.1 Pressure

This can be described as the conditioning and influence that external variables put on potential adopters so that they feel compelled, and sometimes forced, to adopt the practice, behavior, idea, technology, or else (Abrahamson and Rosenkopf 1993; David and Strang 2006; Fiol and O'Connor 2003). This element has been framed in terms of social pressure that materializes when decision makers feel required to adopt because of "price, perceived efficiency, or legitimacy" (Abrahamson and Rosenkopf 1997, p. 293). Other pressures can come from competition, where companies may feel obliged to adopt because all other firms in the same industry have already adopted (Rosenkopf and Abrahamson 1999).

2.1.2 Actors

The second element usually associated with bandwagons is the characterization of the principal *actor*. The decision maker can be an individual (e.g., Banerjee 1992;

Corneo and Jeanne 1997; van Herpen et al. 2009; Strang and Macy 2001; Terlaak and King 2007), an organization (e.g., Abrahamson and Rosenkopf 1993; Angst et al. 2010; Xia et al. 2008), or a mix of both (e.g., Abrahamson and Rosenkopf 1997; David and Strang 2006; Staw and Epstein 2000). Adoption can be based on a rational evaluation of its advantages and disadvantages (Rosenkopf and Abrahamson 1999) or on more trivial and less conscious evaluations (Fiol and O'Connor 2003). In a study on fashion, Esposito (2011) argues that in the case of the spread of something fashionable rational choice becomes something close to the “rationality of irrational” (p. 604).

2.1.3 Popularity

Another element is that a bandwagon is usually defined through *popularity*, i.e. potential adopters are triggered by the number of people that already adopted (e.g., Angst et al. 2010; Pangarkar 2000; Pangarkar and Klein 1998; Staw and Epstein 2000). The number of those that are already in the bandwagon is sometimes referred to as the sheer number of peers (Angst et al. 2010; Pangarkar and Klein 1998) to highlight the fact that there should be some similarities among actors that are exposed (and join) a given practice, idea, or behavior (Strang and Meyer 1993; Burt 1987). This does not imply that diffusion is conditional on the fact that people (or organizations) exposed should be similar in status and/or other characteristics, but the presence of similarities would boost the number of adoptions.

2.1.4 Process

This leads us to the last, but not least, element used to define bandwagons: the fact that it is often studied as a *process* (Abrahamson and Rosenkopf 1993, 1997; Fiol and O'Connor 2003; Pangarkar 2000). This aspect is usually implicit in most of the research and puts the bandwagon dependent on time. One of the consequences of adding time to the process is that the timing of adoption is sometimes crucial to fully understand how it spreads (Abrahamson and Rosenkopf 1997; Rogers 2003). Less studied, but still important, is to understand the timing of the adopted practice, idea, behavior fading out and disappearing (David and Strang 2006). It is worth noting that some authors refer to the process and its consequences as the bandwagon *effect* (Corneo and Jeanne 1997; Chiang 2007; Granovetter 1978; van Herpen et al. 2009; Leibenstein 1950; Rohlfs 2003).

It is interesting to notice that popularity may be related to the degree of pressure that potential adopters perceive. However, this is not always the case; pressure is the interpretation that an actor makes of a popular phenomenon, given environmental constraints. This means that a phenomenon can be popular although the pressure on actors to adopt is relatively low (i.e., there are little/no repercussions for non adopting). This would be the case of buying a certain brand of pasta at the supermarket while it is certainly not the case when it comes to choose which school is good for your kids. Given these four elements, for the purpose of the present study we refer to a bandwagon as a process of diffusion of an idea, behavior, process, practice, or any imitable characteristic amongst individuals who adopt it because of

its increasing popularity. In the following we detail how elements of this definition are interpreted in the making of the model.

2.2 The organizational being

The underlying assumptions on decision makers involved in a diffusion process have varied over the years depending on the literature (Rosenkopf and Abrahamson 1999). We maintain that all actors operating in an organization, whether they are employees or managers, are subject to bounded rationality (March and Simon 1958; Simon 1955, 1997). This connection to bounded rationality can be seen as somehow implicit in the studies reviewed above. We address this shortcoming and attempt to make it more apparent. In the face of bandwagon processes, this reflects on at least two issues.

First, bounded rationality has been indicated as one of the factors affecting organizational learning (March 1991), and used to justify biased judgment (Bazerman 1994; Kahneman 2003; Kahneman and Tversky 1979). Mostly to overcome the limits of bounded rationality, Simon suggested that individuals are ‘docile’ (Simon 1993, 1997). This is the attitude to lean on recommendations, advice, and information coming from social channels while making decisions (Knudsen 2003; Simon 1993). It is a safety net for human cognition that tries and finds resources outside of one’s brain to make appropriate or workable decisions (Bardone 2011). When docility is described this way, it then becomes very close to those approaches to cognition that claim it is *distributed* (e.g., Clark 2003, 2008; Hutchins 1995). According to these perspectives cognition is not limited to one’s brain but it can only be understood and analyzed in connection with the external tools used to facilitate the process itself (Clark and Chalmers 1998; Hutchins 1991). Among these external resources are other human beings, i.e., ‘social’ or ‘organizational’ resources (Michel 2007). This approach to cognition can be interpreted as an extension of bounded rationality (Gavetti et al. 2007; Secchi 2011) and it seems to explain some of the mechanisms underneath bandwagons.

Second, some scholars (Abrahamson 1991, 1996; Fiol and O’Connor 2003) point out that bandwagons happen when individuals are not using their cognitive capabilities to their fullest extent. *Mindlessness* (Langer 1989) is often used to describe this status and has been defined as the individual switching to an ‘automatic pilot’ to indicate that there are low degrees of determination and presence (Langer 1989; Levinthal and Rerup 2006; Weick et al. 1999). A great deal of attention has been channeled through the study of how managers maintain a vigilant and active status of mind, thus avoiding phenomena such as bandwagons (e.g., Fiol and O’Connor 2003; Levinthal and Rerup 2006).

Following this line of thinking, with bandwagons there is a mindless use of external social resources that makes it not sound (i.e., a fallacy, Woods 2004). We suggest this happens when these otherwise powerful cognitive mechanisms are used “passively,” via simple observation of what others are doing. The idea of the bandwagon as a *passive process* refers to the fact that there is no need for the individual to assess the idea, thought, behavior, or anything that is adopted. The only assessment made is that the adoption is spreading all around. When the attitude

towards docility is particularly low—meaning it is mostly passive—, there may be that individuals are only passively getting information from social channels and their decision making remains somehow mechanical (March 1978, 1994; Miller et al. 2012). We are postulating that this characteristic of the individual (i.e., docility) varies in its intensity (Thomsen 2015) depending on contextual and internal elements and it assumes high or low values (Secchi 2015a; Secchi and Bardone 2009). Low docility is mostly characterized by passive attitudes rather than interaction and exchange of information—i.e., a mix of passive and active—because this is a so-called survival condition, where someone needs information from others to make his/her way in the organization. However, the individual is not particularly attuned to the ways communication is handled in the organization or does not feel she/he can trust the others (Ossola 2013). As docility levels rise, we can observe more interaction and a sort of “giving back.” The more value the individual provides to others when giving back information—i.e., active docility—the higher the standards of the interactions (Secchi and Bardone 2009).

The active-passive mechanism in docile attitudes is one and cannot be easily split. However, the active needs the passive to be carried out. Providing information to social channels means that this information is meaningful to those who receive it. The meaningful effort of sharing information with others implies that some information has been gathered at the same time or before the time of sharing. Take the example of a new hire. This individual does not know much about social dynamics in the group/department/division or organization. He/she does not know much about the jargon or the formalities of communicating with others. He/she does not have a sense of community and his/her identity is not tied to the group/department/division or organization, yet. For these reasons, there may be active-passive docile interactions—and useful ones, if the new hire has a genuine willingness to learn and get accepted by the group/department/division—but the new hire will find it relatively difficult to tune in and find the right channels for communicating. Some individuals never find these “right” channels and some organizations do not favor “active” docile behavior, being more preoccupied of preserving the facade of communication (this is an aspect of what Argyris called “defensive routines,” Argyris 1986, 2004). In different words, listening is a key (passive) element of docile individuals, and the more advanced active docility builds on it.

Threshold models of bandwagons have been particularly popular so far (Chiang 2007; Strang and Meyer 1993; Strang and Soule 1998) because they are relatively easy to deal with and bring immediate descriptive and normative results. This study provides a particular interpretation of individual thresholds in that they lean on docility and distributed cognition. Individual characteristics are modeled as attitudes towards adoption of something that is popular in the organization at a given point in time. Given the assumptions above, when individuals have a particularly low level of docility—which means there is a mindless attitude and scarce exploitation of distributed cognitive mechanisms—then their threshold level is also low, i.e. they are more likely to adopt if a relatively low number of individuals have already joined. When docility is high, a corresponding mindfulness and a high potential to

exploit distributed cognitive mechanisms, then the threshold level is high, i.e. individuals are less likely to adopt blindly.

Everything described so far does not happen *in vacuum*. One of the characteristics of the organizational environment is that it provides the conditions for individual interactions. Some of these conditions are more likely to affect the emergence of bandwagons. This study analyzes which organizational characteristics lead individuals with different levels of docility (or thresholds, as defined above) to join the bandwagon. According to the literature, these conditions may be referred back to (a) organizational culture, (b) hierarchy, (c) ambiguity, and (d) proximity. The sociology-based literature on diffusion has emphasized the role of culture (Strang and Meyer 1993; Strang and Soule 1998) in the adoption of innovation or any other practice, thought, behavior, or else. In particular, it has been argued that the degree of formalization affects the progress of a diffusion process (Burns and Stalker 1961; Strang and Soule 1998). This may be also relevant for hierarchical levels and how role models or leaders (e.g., Bandura 1977; Gibson 2003) may affect the diffusion process (Abrahamson and Rosenkopf 1997). In addition to this, some scholars have pointed out that higher degrees of *ambiguity*—defined as a condition where either one or all amongst the range of alternatives, outcomes, and probabilities are unclear (Rosenkopf and Abrahamson 1999)—affect the likelihood of adoption of new ideas (Carley 1995). Lastly, spatial proximity becomes relevant when what is going to be diffused is intellectually cheap (Strang and Soule 1998).

As some of the simulation and modeling literature suggests, ABMs are one of the most appropriate tools available to bring together these aspects at the individual level as well as the broader environmental conditions (e.g., Carley 2009; Drogoul and Ferber 1994; Fioretti 2013; Gilbert 2008; Gilbert and Terna 2000; Goldstone and Janssen 2005; Kiesling et al. 2012; Meyer et al. 2011; Miller et al. 2012; Miller and Lin 2010). In the following, we describe how these elements are modeled, how the data is derived and analyzed, then implications are discussed.

3 Model specification

Models and computer simulation of social systems always face a trade-off between simplicity and realism (Coen 2009a, b; Lave and March 1975). One of the reasons why many social scientists have embraced ABMs is their ability to model complexity in social systems even with a relatively limited number of parameters (Van Dam et al. 2013; Fioretti 2013). The purpose of the simulation is to unveil how the organization's social structure and individual characteristics affect and are affected by bandwagons. Agents are modeled so that their perception of the organization is given by both their location in the three-dimensional space and their threshold levels (i.e., active or passive docility and ability to exploit distributed cognition mechanisms). In the following, we detail how agents (employees) and environments (organizations) are created in the model. Table 1 provides a summary of conditions and parameter specifications.

Table 1 Parameter notations and values

Parameter	Values	Description
N	100, 200, 500, 1000	Number of employees in a given organization
Ambiguity	On/off	When switched on, ambiguity is modeled as random movement of all agents, with (socially) 'close' ones moving together
Management	On/off	When switched on, managers are 10 % of the total number of individuals in the organization; it represents a two-level organizational hierarchy or power structure
Proximity (v)	4, 5, 6	The area in which individuals interact with their peers and with management (if this condition is prompted)
K	0, 0.1, 0.5, 1	Conformity as an aspect of organizational culture; values close to 0 indicate poor conformity whereas values close to 1 indicate high levels of conformity for agents in the organization
k	$\mathcal{D}(0.5, 0.25)$	Docility attitudes of the agent that is allocated to each agent at time $T = 0$; it leads the process of adaptation for individual thresholds due to internal and external conditions (i.e., position, peers, individual threshold level). All values below 0 and above 1 are respectively 0 and 1
α	0.25	Threshold constant used to allocate individual characteristics as initial conditions
t_a	$\mathcal{D}(\mu, \sigma)$	Threshold of agents; μ is given by the total number of employees in a given organization, N , times the threshold constant, α , and σ is defined as N times $0.6 \cdot \alpha$

3.1 Employees

Every agent (employee or manager) is defined with its unique characteristics and this gives it a distinctive view of the world. This not only implies that every agent is different but that also their perception of what happens around them is slightly different from their peers. The model characterizes each agent using random or pseudo-random (as defined in Miller 2015) techniques and rules of attribution. In the following, we detail how this is achieved.

In our model, each and every individual has a *threshold* level t —i.e., the degree the agent can tolerate to adopt or not to adopt (Abrahamson and Rosenkopf 1997; Granovetter 1978)—that is initially assigned to each agent on the basis of a random-normal distribution $t \sim \mathcal{D}(\mu, \sigma)$.¹ The mean μ is given by the total number of employees in a given organization, N , multiplied by a discount factor, α (0.25), and σ is defined as $N \times 0.6\alpha$. These values for the distribution were set up after several trial runs of the simulation to preserve enough variability among employees. Too many low values would have led to the spread of bandwagons whereas too many high values would have led to very little occurrences. When thresholds are anchored to the total number of employees in an organization, it means that their initial allocation is a function of the social system in which agents operate. This is to say

¹ We use the letter \mathcal{D} to indicate the normal distribution so that it does not conflict with our use of the letter N to indicate sample size.

that the attitude towards joining the latest trend in the use of a particular financial indicator, for example, has to depend on conditions of the organization where this trend occurs. The simulation takes the total number of employees in an organization as the upper abstract reference point on which to allocate thresholds. It serves as the anchor on which any social phenomenon within the organization happens. It is important to notice that thresholds are allocated as general attitudinal mechanisms that are tied to the organization but they are activated by the particular conditions each agent is exposed to. Written differently, the mechanism of threshold allocation is ‘general’ while the way it is activated is ‘local.’ This has two implications. First, thresholds can be higher than the total number of peers, but they are anchored to that number. This allows us to make the so-called “snob effects” (Leibenstein 1950)—i.e. individuals that would never join the bandwagon because they move the opposite way the crowd moves (the opposite of the bandwagon effect)—possible although highly improbable. It also allows us to simulate individuals who would join the bandwagon independent of circumstances around them; again, this is possible but highly improbable. Second, employees’ behavior is also anchored to what happens in the organization, to what management and their peers do and think, and to what surrounds them. This both defines the organization as context of shared meaning among its participants and is consistent with previous uses of ABM in the field (e.g., Miller and Lin 2010). These initial thresholds are the starting point for each simulation run. Agents thresholds adapt and vary as the simulation goes on to mimic social dynamics with a logic that is fully explained below.

A second characteristic of each agent is set by their *docility*, k (Simon 1993). Each agent has a different attitude that is assigned using a random-normal distribution $k \sim \mathcal{D}(0.5, 0.25)$. This allows agents to be more or less prone to see other agents as source of useful information, i.e. of exploiting social channels as resources for their cognition (Secchi 2011; Clark 2004). However, we implemented this mechanism in the model (see Eqs. 1 and 2 below) to mimic a *passive* attitude towards gathering information more than re-distributing it (Secchi and Bardone 2009; Secchi 2011). The lower the value of k is, the more likely it is that agents take whatever is coming from the environment and align to it, thus increasing the probability of joining the bandwagon. Instead, agents with higher levels of docility k are less likely to join the bandwagon. This operates as a changing mechanism to the agent’s threshold, as detailed in the equations below. This resembles low k individuals to the unintelligent docile and high k as intelligent docile of a model proposed by Simon (1993). To model this particular aspect of bounded rationality on the ABM, we reviewed some of the existing attempts available in the literature (in particular, Dal Forno and Merlone 2002; Miller and Lin 2010).

Another feature of the agent is that each one of them has a limited perspective on the organization. Each agent can only observe and deal with a limited number of peers on a parameter that is the same for every agent/employee and that is labeled *proximity* or v (Strang and Soule 1998) and can be framed as one of the aspects of bounded rationality. The parameter does not indicate the number of peers every agent interacts with but it sets an area of interaction in the organizational space. Given the random allocation of agents in the organizational space, this allows for variability in the number of peers each agent interacts with. The values of this

parameter are v [4, 5, 6] (Table 1). From pilot tests of the model we found that for numbers greater than 6, the likelihood of a bandwagon becomes very high, therefore, this study does not take them into consideration. On the other hand, for proximity lower than 4, there is an insufficient number of relationships and (especially when $N \leq 200$) it is very unlikely that a bandwagon emerges. A spin-off effect of these parameter values is that the model sets the conditions for *ambiguity* over how, and under what circumstances, bandwagons may emerge or not.

The parameter *vicinity* is better understood in relation to the set of conditions for *ambiguity* (Carley 1995; Rosenkopf and Abrahamson 1999). This is facilitated by employees positioning in the three-dimensional organizational space is random and takes the form of (x_i, y_i, z_i) where i is the i -th agent. In addition to that, and to reiterate ambiguous conditions as time goes by, agents move on the three-dimensional space. Their movements are rather limited and are based on an algorithm (Fruchterman and Reingold 1991)—that is one of the standard options for movement available in NetLogo, the software we used—that brings agents away from their initial random position, with a force that is partially repulsive to each other and partially attractive to the mutual relationship established. This mechanism is done to mimic how individuals interact dynamically with both the environment and their peers (Gilbert and Terna 2000).

Given its importance in this model, *ambiguity* needs to be specified further. We defined it above as a condition where either one or all amongst the range of alternatives, outcomes, and probabilities are unclear (Rosenkopf and Abrahamson 1999) but we believe this only points at general conditions that have to be met and lacks of specificity. A way to tie ambiguity to the organizational context can be found in Cohen and March (1974, Ch. 9) as it relates to goals/tasks, perception, and power. In the model, agents do not see the whole range of alternatives, i.e. what is happening in the entire organization, because their location is determined by what is in their immediate range of action. This implies that the agent has some difficulties to forecast what is about to happen at time t_1 , because this depends on its location, interactions, and observations of others. A bandwagon can be thought of as an ambiguous task/goal, since there is no statement of why it is there for, nor to what extent it is going to benefit the individual or the organization. Individual conditions are relative to the agent's perception of the organizational environment and of the relations with other surrounding agents. This setting adds more uncertainty to the fact that the goal/task (i.e., bandwagon) is not specific nor clear in its formulation, hence contributing to add ambiguity (Cohen and March 1974). Finally, there is also ambiguity related to power, and that comes in with the introduction of hierarchical levels (what we call 'management' in the simulation). If the agent-employee gets in contact with an agent-manager, the movement of its threshold is significantly influenced by that of the agent-manager. The reasons for this effect are not necessarily rational and can be due to the ambiguity that power exercises to others. The responsibility of which (Cohen and March 1974) discuss and that comes with power derives from this fundamental ambiguity. Others (employees) may take what comes from management without thinking too much, hence taking their attitudes towards bandwagons as something that may eventually lead others to align.

This stylized view of ambiguity (of tasks, perception, and power) is obtained in the simulation with the random allocation and smooth movements in the three-dimensional space. These movements contribute to make interactions uncertain in such a way that every step of the simulation can bring something new so that what happens at time t_1 is hard for the agent (and the observer) to forecast when at time t_0 . There are two conditions in the simulation, one where ambiguity is high and another where it is low. In the latter case, agents are allowed to move smoothly around the three-dimensional space although they can establish relations with others (in the form of links). In the former condition, agents are connected to each other (based on *proximity*), they do not move around, and tend to interact with each other for the time of the simulation. The first case is more unpredictable and agents are subject to more extemporaneous interactions, hence making the perception of goals/tasks as well as the relation with hierarchical power more uncertain. The second case mimics a more stable (probably formal) environment where relationships are more certain and there is a clearer perception of the goal or task that is implicitly represented by a bandwagon.

3.2 Organizations

We model organizations on a three-dimensional space where employees and managers interact. The position in the space is supposed to be more the opportunity that agents have to interact and this opportunity may be caused by the fact that simulated employees work together in a department or that they are more likely to get along. This resembles a socio-cognitive vicinity rather than a physical proximity.

Structure is defined by a two-layer hierarchy, with employees on the one hand and managers on the other. Managers are set at 10 % of the total number of agents in the system and have characteristics that are similar to employees. The only difference is that their impact on employees' threshold—from time 1 on—is much higher, when they are in range of *proximity*. If that is the case, then the threshold of employees takes the form

$$t_{e,T+1} = t_{e,T} - K \cdot (t_{e,T} - \bar{t}_{m,T,v}), \quad (1)$$

where $t_{e,T+1}$ is the threshold of an employee at time $T + 1$, $t_{e,T}$ is the value of the threshold at time T , K is a value for culture (more on this below), and $\bar{t}_{m,T,v}$ is the average of managers' thresholds at time T in the radius v . Managers have higher likelihood of affecting other employees that get in contact with them, with a factor that is proportional to the number of links with employees (see below). The characteristics of the individual together with their position in the organization—figuratively indicated by their location and hierarchical level—can be considered as elements of bounded rationality (Carley et al. 1998; Carley and Newell 1994). Moreover, we acknowledge that management thinking or behavior may have a stronger impact on employees compared to that of peers, due to position, leadership, line of command.

Social relationships among agents are represented by a link, a connection, that becomes apparent between two or more agents that are in the radius v . This is done for each employee and for each manager. The result is that, given the random initial location on the organizational space and the semi-random movement of each agent, new links may appear at every step. These represent working, personal, or any other kind of relationship amongst employees in the organization. These links spread over co-workers and managers and do not break until the end of the simulation. New links can be added under the high ambiguity condition while there is no change under the low ambiguity condition.

The parameter K identifies one aspect of organizational cultural identity that is particularly close to bandwagons. This can take four values (0, 0.1, 0.5, and 1) and it is a measure of *conformity*, where 0 is no conformity and 1 is complete conformity. The parameter impacts on individual thresholds in a way similar to what already shown above in the case for management. When social relationships are in place, then the threshold of employees modifies according to the following algorithm

$$t_{e,T+1} = t_{e,T} - (K/2) \cdot (t_{e,T} - \bar{t}_{e,T,v}) \quad (2)$$

where $t_{e,T+1}$ is employee's threshold at time $T + 1$ and $t_{e,T}$ is employee's threshold at time T , K is the conformity factor, $\bar{t}_{e,T,v}$ is the average of thresholds of surrounding employees that are in the v radius at time T . When this cultural "rule" is down to zero then individuals only lean on their docility attitudes k . This means that an initial value for docility $k \sim \mathcal{D}(0.50, 0.25)$, substitutes organizational cultural conformity K in the equations. When organizations are subjected to the rule of cultural conformity then the effect of docility can be thought of as implicitly reflected on the threshold distributions. Instead, when there is no clear cultural conformity rule in the organization, individual docility plays an independent role on the agents, affecting thresholds more explicitly. The former case reflects a more formal while the latter a more informal social structure (Scott 2003). Both conditions (k and K) fill in the given initial threshold level depending on position, social relationships with peers, hierarchical relation with management, and personal attitudes. A key study for the modeling of culture in computer simulation is that of Axelrod (1997); our approach to modeling culture in ABMs has taken some hints from that pioneering study. In summary, while Eq. (1) refers to the way employee thresholds change in the presence of management, Eq. (2) is the more general rule for threshold change, given different levels of cultural conformity (or docility, when this is down to zero).

When management is contemplated in the simulation, we do not specify that there is a "direction" in the diffusion of bandwagons, we only postulate that there is some sort of organizational "contagion" that operates through thresholds that modify according to proximity of agents. The only specification we give to the agents is that, when one of the surrounding agents is a manager, then its influence is greater than that coming from non-managers. Hence, while we do not necessarily indicate a point of origination for the bandwagon (whether it is from management or employees) we do acknowledge the likelihood that something coming from management is more likely to spread. On the one hand and to some extent, this

means that there is a higher likelihood that management-originated bandwagons have better chances to spread. On the other hand, this means that we do not preclude that employee-originated bandwagons would not spread or would spread less effectively. In fact, these employee-originated bandwagons can spread all around, independent of the type of agents. As specified above, the threshold level for each agent is originally attributed using a random-normal distribution and this means that a manager as well as an employee may start the simulation being “in the bandwagon” already. Management thresholds adapt following the same rules of the agent-employees. The bottom up “permeability” of management allows for the emergence of *autonomous* trends within organizations, in the sense of (Burgelman 1983a, b) and the simulation aims at reflecting these occurrences.² Of course, we do not know whether these phenomena—that we call bandwagons in this paper—have further impacts on organizational strategy, but it is likely that some would, once acknowledged and taken on board by managers.

The simulation works at a high level of abstraction in the sense that we do not specify *what* is being adopted (what diffuses) within the organization but we postulate that it is a phenomenon that represents the characteristics of a mindless bandwagon.

Organizational *size* is modeled as the number of agents (employees) included in a given round of the simulation. This number is N [100, 200, 500, 1000] (Table 1), and identifies small, small mid-sized, large mid-sized, and large organizations. Bandwagons emerge as a function of agent thresholds. The initial number of agents that adopted a given practice, idea, innovation, behavior are the *initiators* of what may become a trend or a widespread adoption (Rogers 2003). These individuals have been randomly attributed threshold of 0. In the simulated organizational space, these agents take the red color as opposed to ‘regular’ agents that are green colored. At every step, a bandwagon spreads if the threshold for each agent is lower than the proportion (percentage) of red-colored agents in the surroundings.

Finally, it is worth noting that organization size is stable over the entire period of the simulation. This means that the number of employees in a given organization does not change for the entire time of the simulation. In practice, this can be interpreted as absence of hiring or firing in the period considered. However, this does not mean that agents in the simulated organization have all the same experience or that they react to treatment conditions the same way. For example, agents with particularly low level of cultural *conformity* can be thought of representing mostly new hires—i.e., employees who are not yet acquainted with the organization’s social structure, even if a given Person-Organization fit (Edwards 2008) was high at the time of hiring. At the same time, newcomers are more likely to show the attitude to lean on others to make decisions. To say it differently, they are probably more lenient on their passive *docility* attitudes and tend to take other people’s recommendations, suggestions, advice. Cultural conformity and docility together—one affecting the bandwagon negatively and the other positively—probably indicate what is the state of new hires in the organizations considered in the simulation. It is interesting to notice that we do not have a clear linear effect

² We thank one of the anonymous reviewers for this intuition.

here, but a complex set of two parameters that operate on thresholds to identify the probability that a new hire would join the bandwagon.

3.3 Simulation procedures

The simulation was performed plotting agents on a three-dimensional area and have them move according to a given time scale. Every run of the simulation is obtained having one only parameter change its value, all other parameters being equal. This allows to mimic experimental design and to unveil the effect of each parameter on to the spread of bandwagons. From Table 1 it becomes apparent that data from the ABM follows a factorial design of $2 \times 2 \times 3 \times 4 \times 4$.

The procedure to determine how many runs were needed is based on power analysis (Cohen 1988, 1992; Hallahan and Rosenthal 1996), adapted from (Ritter et al. 2011). The range of power levels that are considered acceptable for simulations is $\geq .90$ (Ritter et al. 2011) and some authors indicate 0.99 as the ultimate threshold (Secchi 2014). Simulation runs in our model stop automatically whenever the number of agents joining the bandwagon is more than 90 % of the total organizational population or when time $t = 300$.³ For the first round of simulation, every run (r) have been repeated 50 times. The model produced 9600 (50×192) bandwagon procedures with the parameters settings defined above, for a total of 32 days 19 h and 33 min of computational machine-time. The total machine-time for the process tended to be expensive for higher values of the parameters. Therefore, to compute the optimal number of runs—required to avoid Type II error—we required that all runs met the basic 0.90 criteria. For example, for the run defined by $N = 100$, $v = 4$, $K = 0.1$, no hierarchy (i.e., management switched to ‘off’), and low ambiguity (i.e., switched to ‘off’ position), we performed a power analysis for one-way ANOVA, to check runs needed to unveil differences among covariates. Overall, with the experiment design set at 50 runs, 300 steps per each parameter configuration, derived the effect size, and set $\alpha = 0.05$, power ranged between 0.98 and 0.99. This means that the simulation model is clearly beyond 0.90 and close enough to the upper end of 0.99, making Type II error unlikely to occur.

In compiling the information above and specifying results of this model, we have attempted to cover as many aspects as possible of the adapted Overview, Design concepts and Details (ODD) protocol (Polhill et al. 2008; Polhill 2010) and to the broader systematic Design of Experiments (DOE) (Lorscheid et al. 2012).

4 Analyses and results

The model and its procedures were implemented using NetLogo 3D 4.1.3, an open source software for simulations of artificial societies (Wilensky 1999). We compiled the code to run this software using an incremental, trial and error approach. That is, we ran several pilot tests that were used to improve the initial programming and the

³ We harmonized time to fit 100 scale—x axis—in all the figures.

model before running the one presented in this paper. Pilot-testing took approximately 1 year; the final model is available, together with codes and software specifications, on the online platform “OpenABM” (<https://www.openabm.org/model/4716/version/1>, Secchi 2015c).

Data is coded 1 or 0 for each time period if the agent either joined the bandwagon or not. This information is then weighted on the basis of how many agents joined as compared to the total number of individuals ‘at risk.’ The procedure let the data assume a configuration that appears to be suitable for survival analysis (Selvin 2008), consistent with some existing models on diffusion (Strang and Meyer 1993; Strang and Macy 2001; Strang and Tuma 1993).

Results are analyzed using cumulative events plots, equal to the reverse of survival curves (i.e., $1 - S(t)$). Robustness checks were conducted running Cox proportional-hazards regression models (Cox 1972); results are reported in the “Appendix”. The cumulative events curves are plotted below and show the probability an employee would join the bandwagon over time (Selvin 2008). The probability $1 - S(t)$ is related to the cumulative hazard rate in so that $S(t) = \exp(-H(t))$. While results of the Cox regressions (Appendix) show how different values of a given parameter increase or decrease the likelihood of bandwagons presenting relative proportional coefficients, cumulative events curves unveil the probability that an employee would join bandwagons and how these probabilities (curves) evolve over time. The difference is that in the regression the initial benchmark is not given (in fact it is set to 1.00) while the plots provide a map of all conditions. We believe it is more intuitive to look at cumulative events curves to show how strong is the effect of parameters on the probability of employees to join the bandwagon. As the curve goes up and reaches the value of 1, it is more likely that individuals will be part of the bandwagon (i.e., they won’t stay immune to bandwagons). Every curve starts at value 0 and time 0 ($S(t_0) = 0$) and changes over time given the conditions described above.

In a more operational fashion, a bandwagon effect is usually identified by an s-shaped curve (e.g., Rosenkopf and Abrahamson 1999) that defines a non-linear diffusion process within the organization. There are several ways of operationalizing the idealized bandwagon curve and we refer to a function of thresholds that can be represented by $p = (u/N)^q$, where p is the probability to join the bandwagon at a given time, equivalent to $1 - S(t)$, u varies with time as well $u(t)$ and it is the number of individuals that join the bandwagon, N is the total number of individuals in the system, and q is a parameter for the distribution of thresholds (the curvature) (Chiang 2007). This curve may take from more to less skewed distributions. While analyzing results from our simulation, we consider a curve to be representative of a bandwagon if it can be expressed using a function similar to the one reported above: it is not linear, and carries on at least 50 % of the population, i.e. $1 - S(t) \geq 0.50$.

Computations are made using an estimate of all simulation runs for each condition, all other parameters being equal. Hence figures below follow an incremental logic, going from the smallest to the largest number of conditions. This allows us to isolate the impact of a parameter relative to all conditions. Survival data

are analyzed using the *survival* package for *R*, version 2.15.3, a computational statistics software (R Development Core Team 2012).

4.1 Cultural conformity and proximity

We started our analysis with the simplest combination of parameters. Figure 1 shows the impact of very low ($K = 0.1$), middle ($K = 0.5$), and high ($K = 1$) cultural conformity rule given the range of interactions ($v[4, 5, 6]$) on different organizational sizes. Figure 1a presents probability curves for the small organization and shows that their variation is below 10 %. This means that a bandwagon is unlikely to materialize when organizations have a limited number of employees, independent of *proximity* and cultural conformity. There is a slight increase when employees are given the opportunity to interact more ($v = 6$) and when there is higher cultural conformity ($K = 1$). However, no bandwagon can be detected.

The smallest of the two mid-sized organizations ($N = 200$) does not differ from the small organization. Figure 1b shows that there is a slight variation among conditions here although the probability to join the bandwagon is never more than 40 %. As employees make clearer steps towards conformity to organizational culture ($K = 1$), probability to adopt similar practices, behaviors, or ideas increases. Also, wider opportunities to establish relationships ($v[5, 6]$) bring to a larger variation of probabilities due to the impact of cultural conformity. This is consistent to the fact that more interactions among individuals increase the likelihood that exchanges of information (and of any other kind) happen and diffuse. However, it is hard to see proper bandwagons (i.e., s-shaped curves) from Fig. 1b.

Under the same conditions analyzed above, increasing the number of employees to $N = 500$ and to $N = 1000$ leads to different results. First, unlike previous findings, Fig. 1c, d show curves that spread over the full range of probabilities. Second, when cultural conformity is low ($K = 0.1$), probabilities to join the bandwagon are lower as potential relationships among employees are higher ($v = 6$). The mechanism behind this result is simply the multiplication effect (amplification) that culture has on larger organization. It is somehow expected that weaker cultures have limited impact on imitative behaviors such as bandwagons. The largest organization type ($N = 1000$) is more likely to show bandwagon-like behavior when cultural conformity is stronger ($K = 1$). Bandwagons spread more quickly when the range of interactions is wider ($v = 6$) and Fig. 1d shows that high cultural conformity ($K = 1$) cuts in half the time needed for the bandwagon to spread as opposed to the time needed with mid-range conformity ($K = 0.5$).

Similarly, Fig. 1c shows that there is higher probability for employees of a large mid-sized organization ($N = 500$) to join the bandwagon when conformity is in its mid-range ($K = 0.5$). The probability reaches 80 % when the opportunity of interactions is higher ($v[5, 6]$) and time ≥ 90 . The probability is also higher than 60 % for higher levels of conformity ($K = 1$) and it remains constant after time 50 when opportunities of interactions are greater ($v = 6$). In this particular case, there is a sudden increase of bandwagons, with a stable equilibrium reached in the organization after time 50. A mid-range cultural conformity parameter ($K = 0.5$)

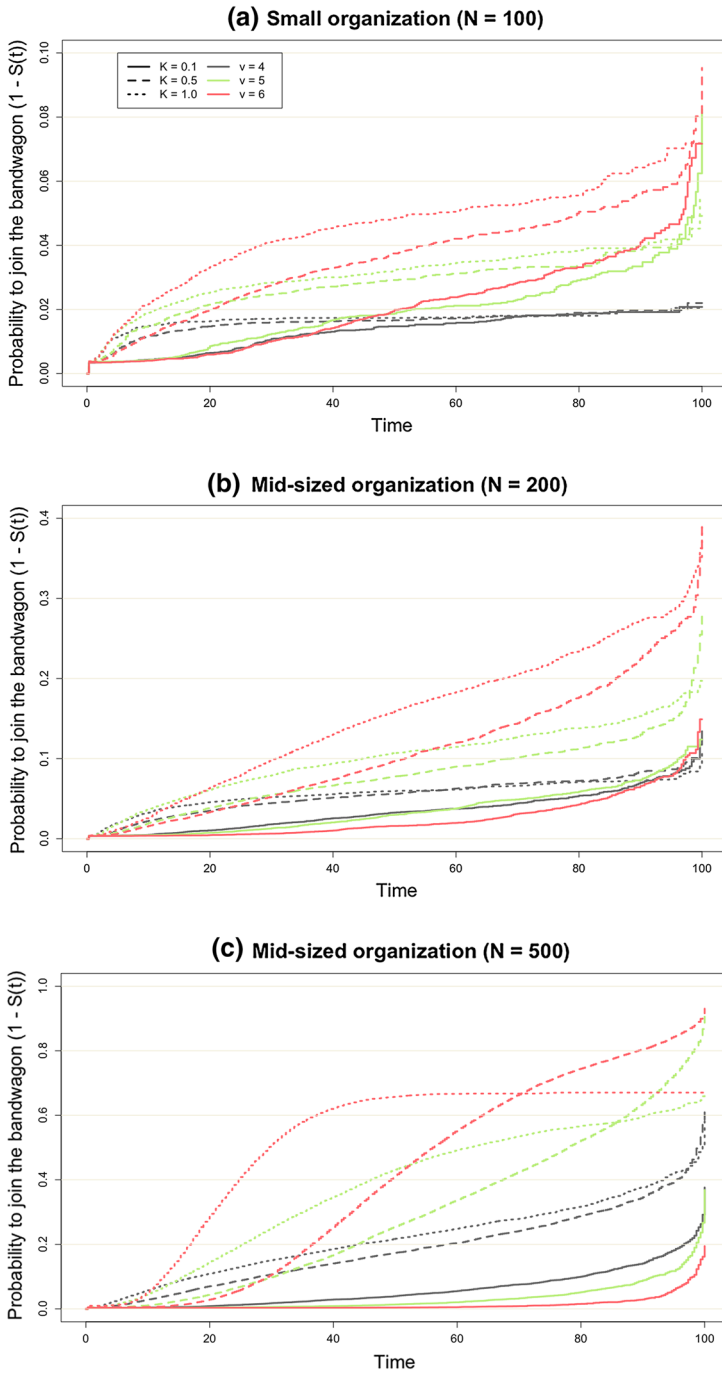


Fig. 1 Probability to join the bandwagon under conformity K and proximity v

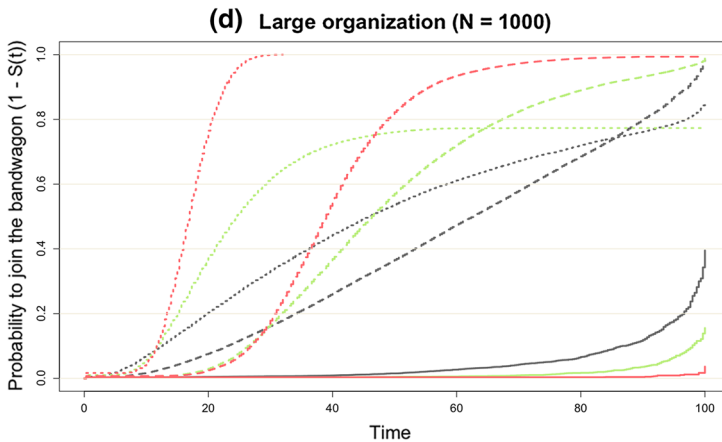


Fig. 1 continued

leads to similar results in both types of organizations with a slightly faster occurrence for the larger organization (Fig. 1d).

The simulation shows that there probably is a cutoff size for organizations, where the bandwagon becomes dependent on conformity and employee range of interaction as the number of employees grows. The environment of the simulation (i.e., the organizational space) is the same in the four cases. This is done to mimic the fact that larger organizations are relatively more crowded than the smaller. Thus employees are more likely to observe and/or meet colleagues. Interestingly enough, different conditions (K and ν) in differently-sized organizations still lead to similar results of no-occurrence when cultural conformity is in the mid- and in the low range ($K[0.1, 0.5]$) and can be seen from Fig. 1. Instead, there are quite significant and varying effects when we compare the high cultural conformity rule across organizational sizes.

4.2 The effect of ambiguity

Surprisingly, adding ambiguity brings limited change to the patterns as far as most conditions are concerned (Fig. 2). In particular, both the the small ($N = 100$) and the smallest mid-sized organization ($N = 200$) do not seem to be affected by high levels of ambiguity. Although there is no pattern that leads to bandwagon-like phenomena, for higher cultural conformity and range of proximity (i.e., $K[0.5, 1]$ and $\nu = 6$) the probability at time 100 increases slightly with high ambiguity (over 15 % and over 40 %; Fig. 2a, b) as compared to low ambiguity (Fig. 1a, b). Most of the other conditions bear very similar effects to those of parameters under low ambiguity.

Figure 2c shows that bandwagons spread in the second mid-sized organization ($N = 500$) only with the highest cultural conformity ($K = 1$) and highest range of interactions ($\nu = 6$). There is a 60 % probability for the milder condition ($K = 0.5$

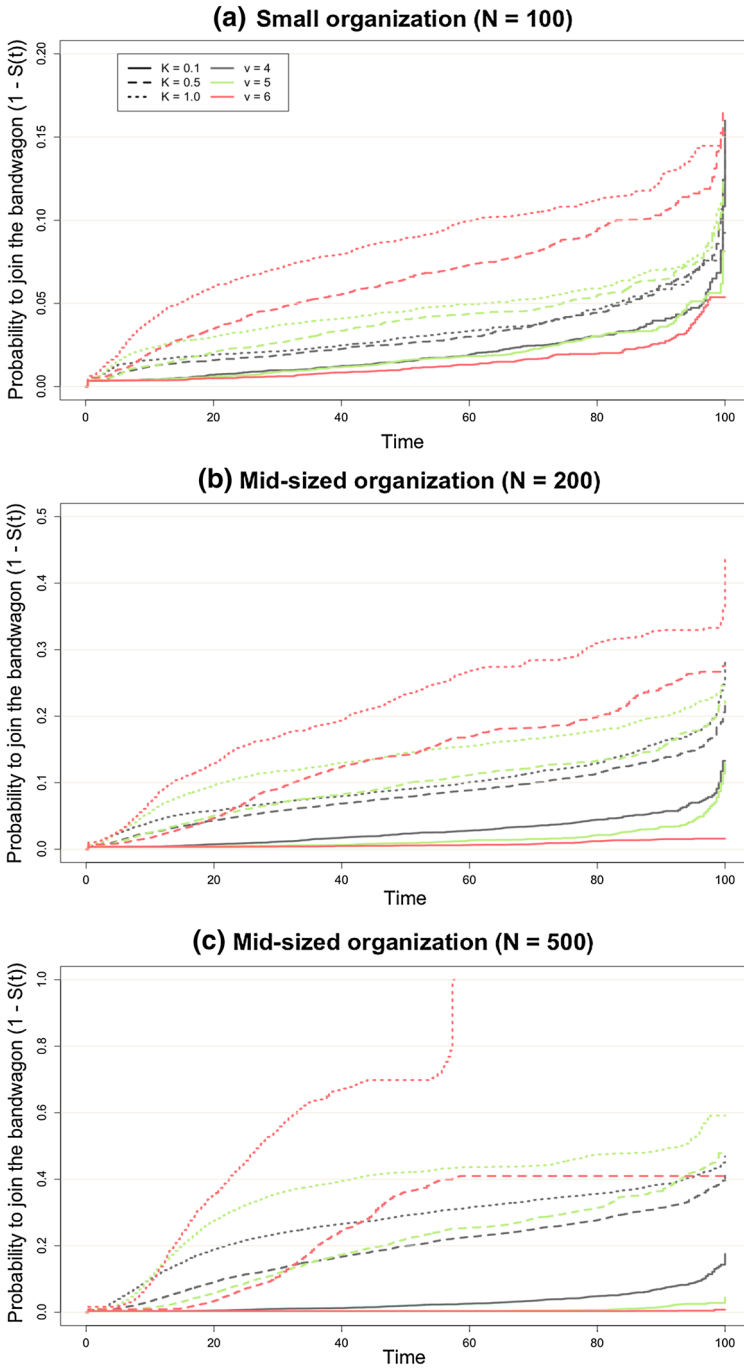


Fig. 2 Probability to join the bandwagon under conformity K , proximity v , ambiguity

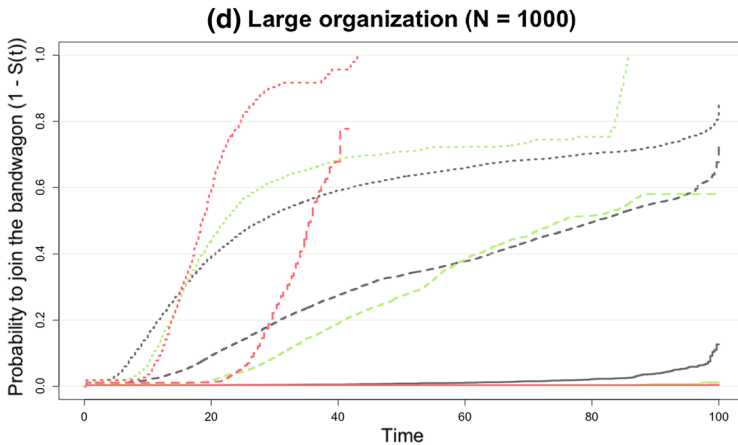


Fig. 2 continued

and $\nu = 5$) while all the other conditions are on or around 40 %. Figure 1d for the largest organization ($N = 1000$) shows, on average, higher probabilities. However, high ambiguity seem to decrease the probability to join the bandwagon or make agents take slightly more time to join. What seems to be constant across conditions is that lower cultural conformity and limited range of interactions ($K = 0.1$ and $\nu = 4$) bear no effect on bandwagons.

The high ambiguity condition is obtained having agents semi-randomly float in the organization space on an attractive-repulsive algorithm. This way, it is impossible for simulated employees to know *ex ante* how their environment looks like as they get ready to the following step of the simulation. Figure 2 shows that this condition decreases the likelihood of bandwagons instead of increasing it. The previous conditions (Fig. 1) see agents/employees interacting with the same agents since the beginning of the simulation and to its end. In the high ambiguity setting, agents start with a selection of other agents just like in the low ambiguity condition. The difference is that the interactions increase its number due to movement. It is worth noting that agents' characteristics are allocated randomly at the beginning of the run and they only change through interactions. The equation shown above allows agents to adapt their threshold to what happens around them. When interactions are stable and with the same simulated employees, there is a group effect that is equated to individuals that align themselves to the group. If relationships increase then group dynamics change and individual thresholds adapt to the new set of interactions.

4.3 Management impact on bandwagons

Figures 3 and 4 present the probabilities that employees join the bandwagon given a two-layered hierarchy in the organization, respectively with low and high ambiguity. The two figures can be considered as add-on to the ones presented above.

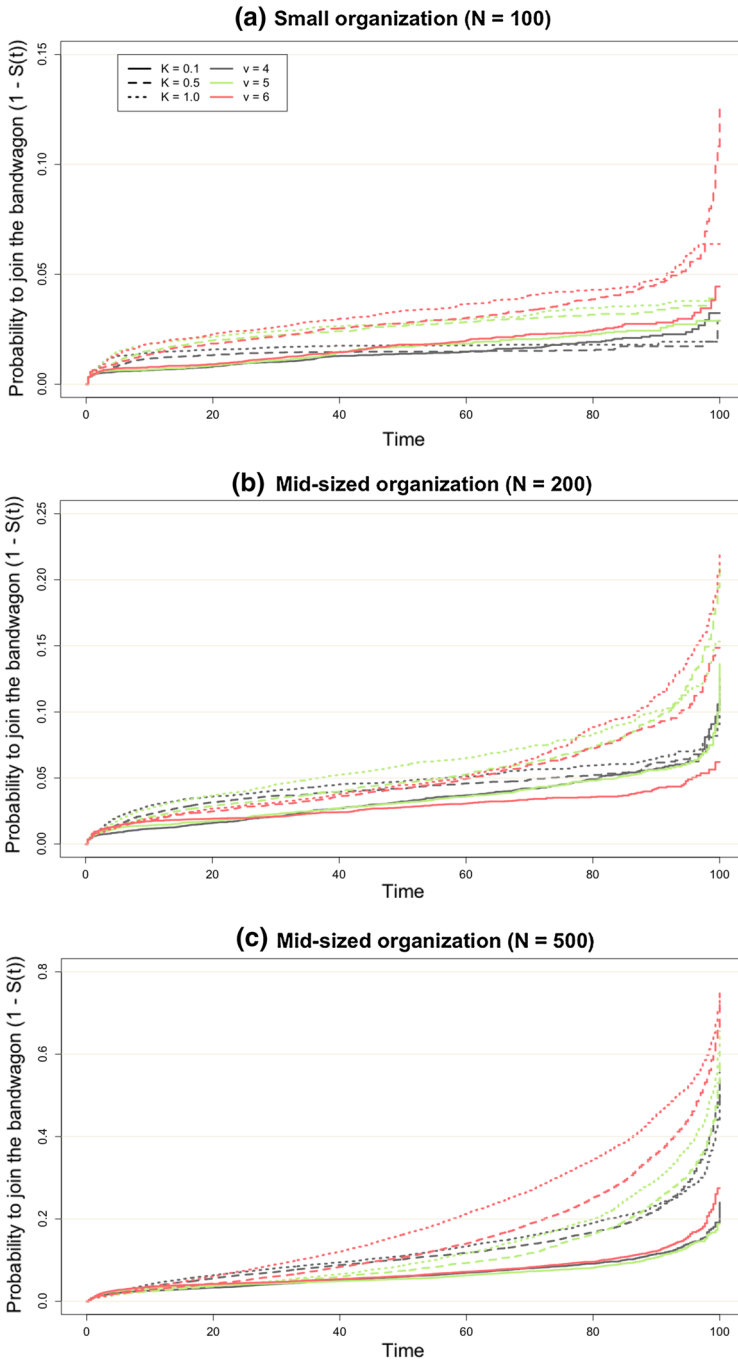


Fig. 3 Probability to join the bandwagon under conformity K , proximity v , and hierarchy

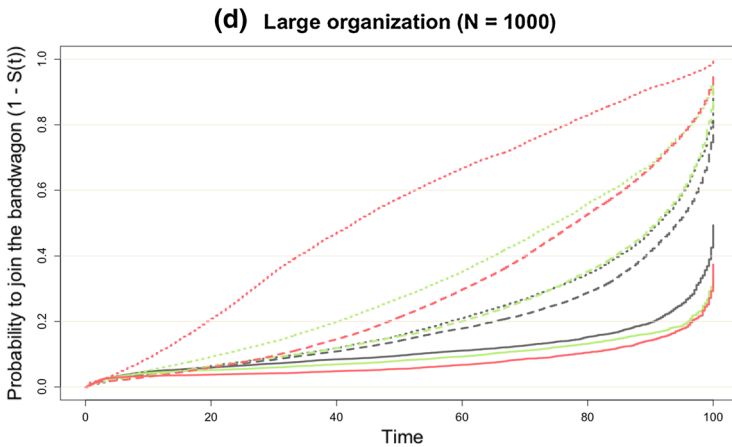


Fig. 3 continued

Overall, the impact of management is that of decreasing the likelihood of bandwagons. Figure 3a, b show that small organizations ($N = 100$ and $N = 200$) are less likely to see employees joining bandwagons. Most of them remain “immune” to the phenomenon, with probabilities always below 15 and 25 % for, respectively, the smallest and the small mid-sized organizations.

The other two larger organizations show a different distribution of probabilities when compared to the absence of hierarchy. First, the distribution is different over time. In both cases, it takes more time for bandwagons to spread. In other words, the probability reaches 60 % and above for large mid-sized organizations ($N = 500$) and 80 % and above for large organizations ($N = 1000$) only at time 100. The effect of hierarchy on bandwagons is that it takes more time to spread. In the one case shown in Fig. 3d, there is a constant and continuous increase in the probabilities, pictured in a curve that seems drawn on the diagonal of the plot ($K = 1$ and $v = 6$). The presence of a two-layer hierarchy decreases the probability that workers join the bandwagon at any given time when we compare Fig. 3 with Fig. 1. However, in the case of larger organizations the outcome seems to be more consistent across conditions in that the structure would, around time 100, make it more likely for ideas, practices, and anything else to spread over the entire organization. Another element that we should consider when management is introduced in the large organization ($N = 1000$) comes from the low cultural conformity parameter ($K = 0.1$; Fig. 3d). The final probability at time 100 for each condition of proximity ($v[4, 5, 6]$) is always higher than what observed in absence of management, i.e. Fig. 1d.

The mechanism that explains the effect of management is due to the fact that simulated employees recognize hierarchy. This element affects threshold levels as employees establish relationships with management and peers. In larger organizations this different factor related to management does not eliminate the “risks” of bandwagons to spread but, as results show, it slows its pace. This process seems to

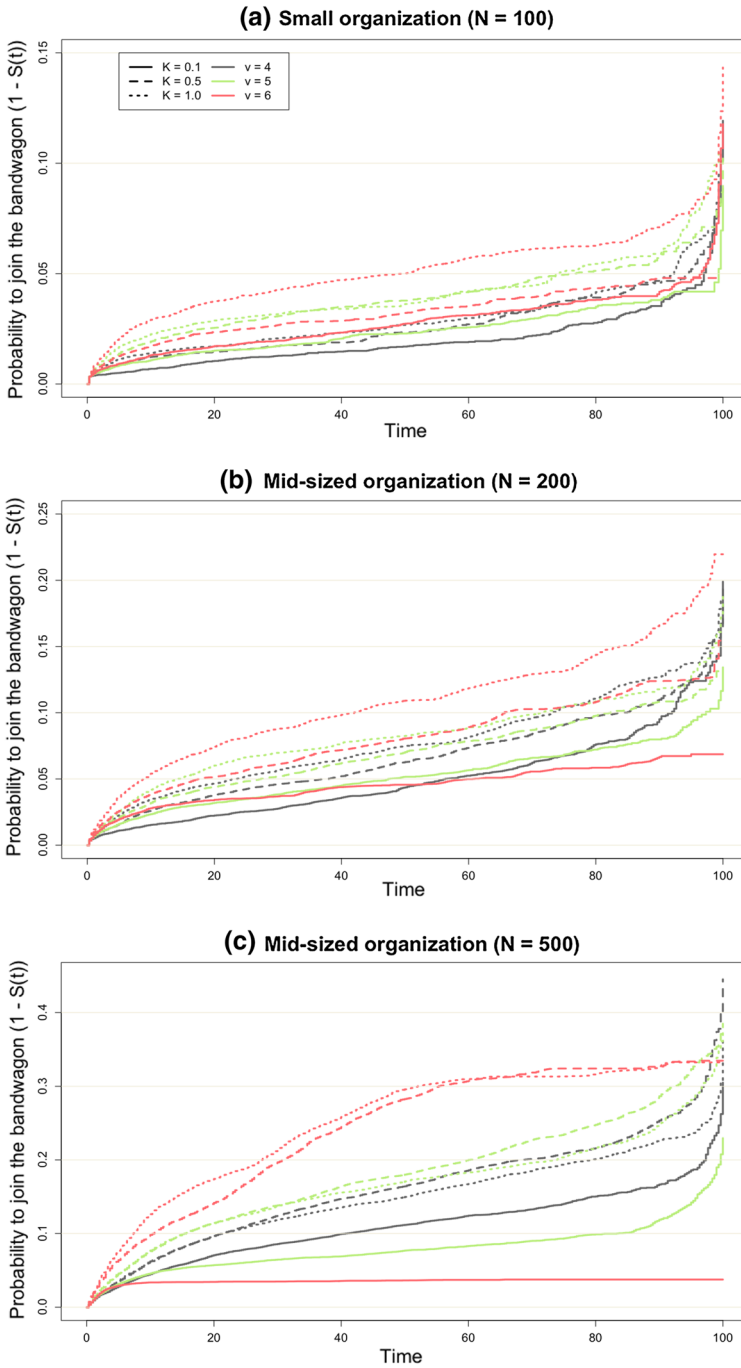


Fig. 4 Probability to join the bandwagon under conformity K , proximity v , hierarchy, and ambiguity

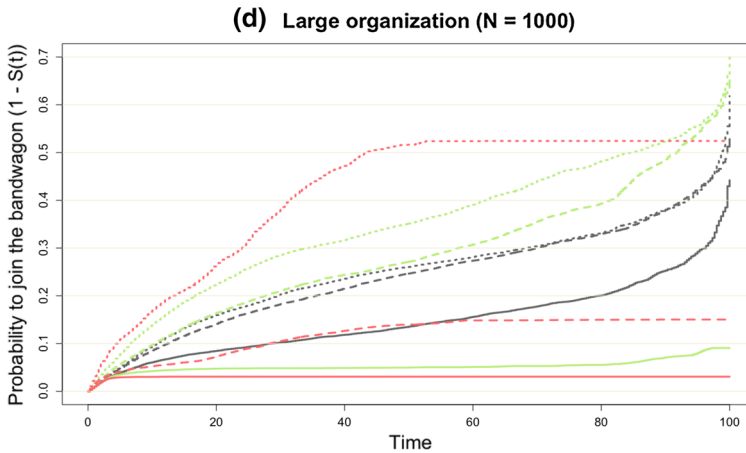


Fig. 4 continued

mimic the presence of departments, teams, or divisions within a given company. Although we do not provide a detailed account of what happens to these micro-clusters within larger organizations, we can confidently state that they look similar to what was recorded in smaller organizations.

Figure 4 presents findings for a two-layer hierarchical structure in presence of high ambiguity. The probability to join the bandwagon for the two smaller organizations ($N = 100$ and $N = 200$) are shown in Fig. 4a, b. These results are very similar to those found in Fig. 3a, b, the only difference being that differences amongst all conditions can be visualized more easily by looking at the figures. However, probabilities are well below 50 % hence there is limited evidence that the phenomenon would occur.

More interesting results appear in Fig. 4c, d for the two larger organizations ($N = 500$ and $N = 1000$). Contrary to what shown in the other conditions for large mid-sized organizations ($N = 500$), probabilities are all below 50 % for all conditions when management is introduced in the model. This points at the fact that the presence of management (even if limited to a two-layer hierarchy) prevents bandwagons from spreading. When cultural conformity is in its mid-range ($K = 0.5$), Fig. 4c shows that probabilities reach their highest (i.e., above 40 %).

Management has a similar effect in larger organizations. Due to the number of agents and to the conditions described above for large organizations ($N = 1000$), the probabilities that appear in Fig. 4d are higher than those of the other organization sizes. There is a steady growth for high cultural conformity ($K = 1$) and higher range of relationships ($v = 6$) until the curve reaches around 55 %, where the system seems to reach an equilibrium. There still is a higher probability for bandwagons to emerge for mild and low cultural conformity ($K[0.5, 0.1]$) and limited range of interactions ($v[4, 5]$). The mechanisms that explains the curves' behavior is the same for large and for large mid-sized organizations. When information from the environment is extremely ambiguous then management seem

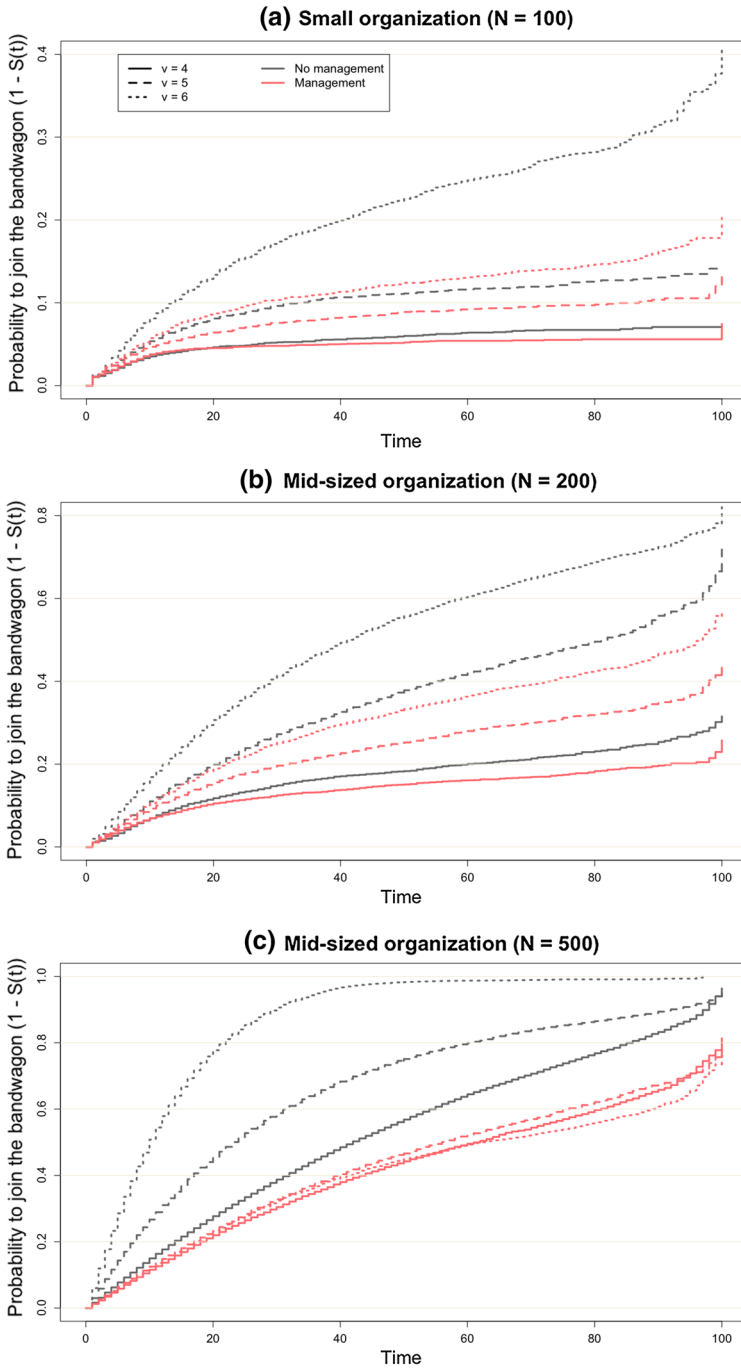


Fig. 5 Probability to join the bandwagon under docility k , proximity v , and hierarchy

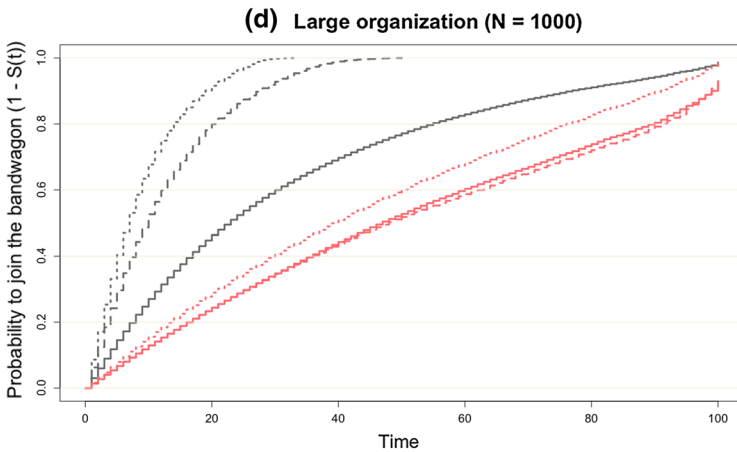


Fig. 5 continued

to serve as a boundary for bandwagons, especially as range of interactions increases. Management is a sort of “filter” used to stabilize organizations when the opportunity to establish relationships is broader and there is a diverse flow of information. Ambiguity and low-range interactions make the role of management a bit more difficult. However, in all conditions, it takes the whole time frame (i.e., $T = 100$) for probabilities to reach a level that actually triggers a bandwagon.

4.4 The surge of passive docility

The next step in the simulation is to check what happens to the four organizations when there is no cultural conformity ($K = 0$) and individuals are left to interact with each other based on their own cognitive characteristics. This may be representative of start-up organizations, or organizations facing an intense crisis, for example. Agents were modeled with “passive docility” attitudes. This is the tendency to take information from others, without engagement or exchange. It is rather different from the active or passive-active mechanism. The assumption here is that a bandwagon is more likely to emerge when employees use passive distributed cognitive mechanisms, i.e. when they don’t think of what they are doing (i.e., they are mindless; Fiol and O’Connor 2003). A passive attitude would be, for example, to observe peers’ behavior and imitate that behavior.

Curves are drawn slightly differently to show these findings since there is no cultural conformity K . Figures 5 and 6 show probability curves for different degrees of *proximity* ($v[4, 5, 6]$) and for the presence of management as well as for its absence. As already done above, the second set of figures—i.e., Fig. 6a–d—adds high ambiguity to the mix.

From Fig. 5 it is possible to highlight two findings that apply to all organization sizes. One is that the impact of management either reduces the probability of bandwagons or it decreases its pace. Another finding is that the absence of any

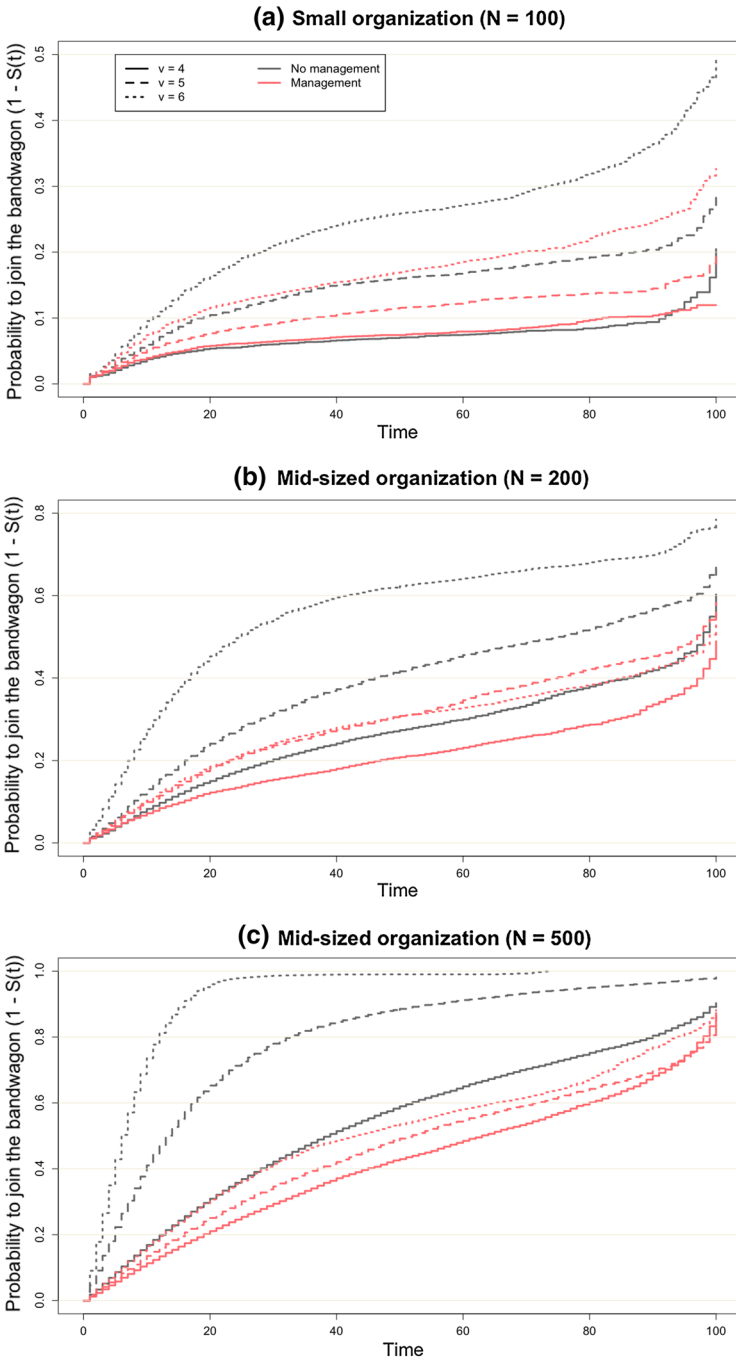


Fig. 6 Probability to join the bandwagon under docility k , proximity v , hierarchy, and ambiguity

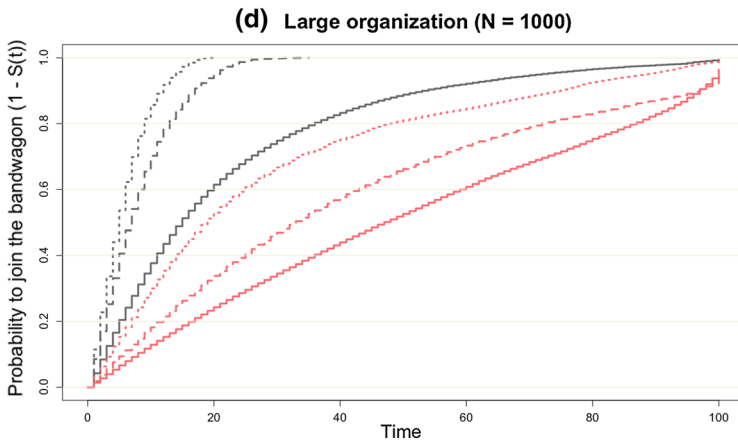


Fig. 6 continued

cultural conformity norm in the organization does increase the likelihood that passive docile cognitive mechanisms have an impact on bandwagons. All probability curves are, on average, hitting higher percentages than those shown in Figs. 1, 2, 3 and 4. The small organization ($N = 100$) in the simulation shows levels of probability for all conditions that are below the bandwagon threshold (i.e., below 50 %). Similarly to what shown above, under most conditions ($v[4, 5, 6]$) probabilities are on or below 20 %. The only exception is for the highest range of interaction ($v = 6$) without a clear management structure. In this latter case the probability goes up to 40 % at time 100.

A different picture comes from Fig. 5b. The small mid-sized organization ($N = 200$) is more subject to bandwagon effects when there is no hierarchy and for higher ranges of interaction ($v[5, 6]$). Probabilities get close to 80 % as time approaches the limit for this simulation ($T = 100$). When a limited range of interactions is allowed ($v = 4$), then bandwagons are always unlikely to happen ($probability \leq 50\%$). With the presence of management, bandwagons may occur only when interactions increase (i.e., $v \geq 5$).

Curves from Fig. 5c, d show similar patterns although the size of the two organizations represented is different, one being double the size of the other. Although with different timing, all conditions bring towards high probability of bandwagons, i.e. on or above 80 %. As already noted above, this happens quickly for structures with no formal management and for the larger organization type ($N = 1000$). Interestingly enough, the impact of management for large organizations (with $v = 6$) is very similar to what found with a high cultural conformity norm ($K = 1$; Fig. 3d). This aspect is particularly interesting in that it points at the fact that the impact of management to curb bandwagons is particularly relevant for large organizations. If we take 80 % as a threshold for bandwagons to spread, we may then observe that large mid-sized organizations ($N = 500$) reach that probability when time is up to 100. Again, management has a strong impact to control, monitor, or simply slow down a given bandwagon effect.

At a first look, Fig. 6 reveals that modeling a more ambiguous environment for the simulated employee does not dramatically change the probabilities for the phenomenon to occur. However, a closer look at the curves shows that ambiguity increases slightly the probabilities and the pace of bandwagon. For all organization sizes, we have that probabilities are higher for low ranges of interactions ($v \in [4, 5]$). The impact of a two-layer hierarchy contributes to slowing the pace of bandwagons, and it shows effects similar to those of the conditions analyzed above.

There are little changes for the small organization ($N = 100$) besides a slight increase of probabilities to join the bandwagon. All curves remain below 50 % with only one getting close to that limit ($v = 6$ with no hierarchy). Findings are different for the small mid-sized organization ($N = 200$) in that most conditions reach or go beyond 50 % at the time limit ($T = 100$). This makes the bandwagon plausible even though still unlikely to occur when interactions are limited ($v = 4$) and there is a formal hierarchy in place. The picture is different for large organizations. Figure 6c, d present probability curves for large size organizations ($N = 500$ and $N = 1000$). In both cases, ambiguity makes bandwagons extremely likely to occur, and increasingly so as we go along the time line. Still, there is an impact of management although probabilities hit 80 % sooner or later down the given time frame. Under all conditions at time 100, these probabilities approach 100 % for large organizations ($N = 1000$) and 90 % for large mid-sized organizations ($N = 500$). When there is no clear organizational cultural reference (or conformity), ambiguity leads large organizations to show higher probabilities for bandwagons to emerge. This may be enough to unveil what seems a stable finding in the analysis.

5 Discussion

This paper presents an agent-based computer simulation with the objective to study what, amongst employee and organizational characteristics, facilitates or hinders the emergence of bandwagons. Findings from the simulation only partly align with previous research. This section elaborates on results, derives theoretical implications, and outlines indications for future research. We derive propositions to better outline these implications and to help future research.

5.1 Redefining threshold attributes

One of the interesting features of this model is that we assume that individual thresholds are not given and static (e.g., Granovetter 1978) but they adapt to the surrounding social environment. In other studies (Abrahamson and Rosenkopf 1997; Rosenkopf and Abrahamson 1999), threshold models characterize the bandwagon itself as an adaptation strategy, since it shows conformity to peers. However, this tendency to conform may vary with time and social pressure (Angst et al. 2010; Strang and Soule 1998). For this reason, our model is a *dynamic* threshold model, where individual attitudes are a function of the self, co-workers, and manager attitudes. Put differently, there is an individual attitude towards joining the bandwagon that modifies itself with increasing opportunities for social relationships

(v), organizational culture (K), hierarchy (*managers*), *ambiguity*, threshold levels (t_e), and docility attitudes (k). The final (behavioral) adaptation—i.e. to join the bandwagon—may be the result of some internal change in individual attitudes, perceptions, or thinking on that idea, practice, behavior, or something else that is being adopted. This brings the *socio-cognitive* perspective in. The model includes this aspect of the working environment and structures it into a cultural element (Strang and Meyer 1993) and a personal socio-cognitive factor (Bardone 2011; Kunda 1999; Michel 2007). The latter is more or less what we just described here while the former can be labeled as a pre-condition to finding common ways to understand each other. Of course, we are just stating that culture constitutes the sharing of values, rules, practices, and beliefs (e.g., Schein 1990, 1996; Scott et al. 2003), and it is not a homogenizing factor per se. However, even those cultures that push towards heterogeneity and diversity start from something that people share to make communication easier and more effective (Strang and Meyer 1993). This is the particular facet of culture that is in the model and that results show it is linked to how bandwagons spread in an organization. Again, what this study does is to model individual attitudes (e.g., thresholds, docility) as dynamic so that they depend on other organizational variables and on interactions amongst employees.

Proposition 1 The initial distribution of thresholds affects the spread of bandwagons less than adaptation due to cultural conformity and docility.

5.2 The mixed effects of management

In this study, organizational structure has a very narrow meaning. It is just the presence of a two-layer hierarchy among workers. In fact, we make a distinction between managers and employees. Threshold levels vary depending on individuals interacting with each other and the distinction between managers and employees helps the model consider aspects such as leadership, role models (e.g., Bandura 1977; Gibson 2003), and other similar factors that power, position, legitimacy, and authority bring to the workplace (Angst et al. 2010). These can all be reframed as a mix of variables X_i that contribute to explain the role of management in curbing bandwagons.

In almost every condition (with some differences and exceptions discussed below) the presence of managers decreases the likelihood of bandwagons (Figs. 3, 4, 5, 6). This effect is larger when there is no cultural conformity (Figs. 5, 6) and slightly larger under high ambiguity (Fig. 6). In every case, the introduction of management brings the probability of bandwagons down especially when a cultural conformity rule is not given. This means that there is a regulating mechanism that structure brings in, especially in larger organizations, where it seems that management has a crucial role in limiting the pace at which bandwagons spread in the organization. These may be the cases of organizations that have been quickly set up or recently founded, where culture (conformity) is yet to emerge. In these cases, creation of a hierarchical structure among workers helps reducing mindless behavior by introducing power, responsibility, and authority. The following proposition seems to fit well with what we are stating:

Proposition 2 Managers can decrease the spread of bandwagons when ambiguity is low and cultural conformity is weak. The effect is larger as organization size increases.

However, there are some nuances in the way management affects the emergence of bandwagons in large organizations ($N = 1000$). When there is a cultural conformity rule in place and under high ambiguity, larger sized organizations do not benefit much from the presence of management. This statement is counterintuitive but, in a scenario of cultural conformity, a behavioral structure is already in place and some of it may be more relevant to employees than just hierarchy.

It is worth noting that the effect of management becomes scarce or almost irrelevant in the case of smaller organizations and it increases the likelihood of bandwagons for larger organizations (Figs. 3d, 4d) when a cultural conformity rule is assumed and proximity is low ($v = 0.1$) as opposed to other conditions (Figs. 1d, 2d). In large organizations, most agent-employees will adopt sooner or later even if cultural conformity is not particularly high (i.e., $K[0.1, 0.5]$), when management is in place. With no hierarchy, the same conditions either fall short of reaching 90 % adoptions or follow a different trend (Figs. 1d, 2d). Even when the curves look similar, the presence of management does not seem to affect the end result. This may be due to the fact that managers of larger organizations are not immune from fads and they are actually more exposed to them (e.g., Abrahamson 1991, 2011; Fiol and O'Connor 2003). When this “exposure” happens, it is more likely that other employees will pick them up in a way similar to inter-organization diffusion processes. Why is this phenomenon related to larger organizations? One explanation may be found in the social relationships that are not so strong and people are more likely to lean on imitation (Strang and Meyer 1993). Indirect relationships (i.e., weak ties Granovetter 1973) can be related to lack of communication, difficulty of mutual understanding, and more passive than active advice giving and taking (Secchi 2011). This may be linked to more imitative behavior on the part of the worker. The phenomenon is likely to increase even more whenever ambiguity is high (usually this is the case when comparing small vs large organizations) and culture is more static and imitation-based.

Proposition 3 Managers increase the likelihood of bandwagons in large organizations when cultural conformity is identifiable and when the range of interaction among workers is limited.

Some of the simulation results may appear more clearly looking into the network structures to understand the origination points of the diffusion process. The simulation used a random allocation of thresholds to employees and management, giving an even probability for anyone in the organization to start the bandwagon, be in proximity of others, and move around (in the high ambiguity condition). However, given the higher influence of management, the fact that they are or are not in the bandwagon may reflect significantly to the behavior of the other agents. This implies that analyzing the structure of the network and identifying its evolution may bring in some more insights on results presented in this paper. As already shown in

other studies (e.g., Abrahamson and Rosenkopf 1997; Eguíluz et al. 2005), this is an extremely relevant point and we invite readers to investigate it with our model.⁴

However, in a randomized allocation, the probability that management would or would not be the origination point of—as well as the probability that management would get involved or not involved in—bandwagons are even. On average, independent of the active or passive role of management, the presence of hierarchy affects the emergence and evolution of bandwagons. This is why, although important and interesting, we do not deem there is enough scope to dig into this aspect in the current paper. Although the structure of networks was not within the scope of the current paper, we plan on conducting a follow up study that tackles with this extremely relevant issue.

5.3 The impact of cultural conformity

To further discuss the point in the last proposition, this subsection deals with what we labelled K to represent organizational cultural conformity. Computational and theoretical models simplify real-life phenomena and emphasize only some rather specific aspects (Gilbert and Troitzsch 2005). Although with ABMs it can be argued otherwise (i.e., there are examples of highly descriptive simulations, Edmonds and Moss 2005), the model we present here is no exception (Gilbert and Terna 2000). This is particularly true for the way we modeled culture. As already stated above, we have decided to highlight the shared basis that every culture seem to have as it sets a common ground for agents' behavior (Strang 1991).

The logic behind the model sets a rule for behavior and passive exchange of information (the low docility and low exploitation of distributed cognition mechanisms) that is common and shared among simulated employees in the organization. This affects significantly affects bandwagons probability (hazard rate), and its effects become stronger with the increasing organization size. This may be related to the number of people involved in a larger organization and to the fact that social relations become weaker with the increasing structures and complexity of large organizations. It is safe to state that a culture increasingly based on imitation or conformity ($K = 1$) is more likely to bring bandwagons up. Figures 1, 2, 3 and 4 show cumulative events curves and compares different organization sizes, both when ambiguity is widespread and when it is not. They also show that, for larger organizations, resistance to bandwagons goes down significantly as time goes by. At time $T = 100$, there is little probability of getting “immunity” to bandwagons.

Proposition 4 Stronger as opposed to weaker cultural conformity increases the spread of bandwagons. The effect is more effective in larger organizations when ambiguity is low.

Low ambiguity opens the ground for individuals to lean on each other more often, and this is probably why the effect is larger under these conditions. Also, it is not surprising that large organizations are affected more widely by conformity since

⁴ The model is available on the platform OpenABM (<https://www.openabm.org/model/4716/version/1>, Secchi 2015c).

the perception of culture can differ among diverse aggregations of local agents. These centers may be regarded as “change agents” (Strang and Soule 1998).

Also, and surprisingly, these effects do not change significantly when we add ambiguity to the simulation. This implies that organizational culture or shared behavioral patterns that emerge from cognitive similarities of agents—a sort of imitation mindset—is a very powerful source of bandwagons (and this confirms previous neo-institutional hypotheses such as in, Strang and Meyer 1993), but it is partially opposite to other assumptions (e.g., Carley 1995). Ambiguity is not enough to overcome a strong culture, meaning that certainty, represented by culture, is always preferred to highest uncertainty, represented by ambiguity in our model. Moreover, the larger the organizations, the more individuals decrease the impact of ambiguity on their decision making to find their role in organizational dynamics. In short, our findings support previous research on the influence of institutional variables in the workplace (e.g., Colquitt et al. 2002).

5.4 Strong ties and bandwagons

The parameter social relationships or “proximity” v has a stable impact on bandwagons. A common factor among all organizations can be seen from Figs. 5 and 6, where it becomes apparent that the absence of cultural conformity increases dramatically the probability of bandwagons. This may be counterintuitive and requires further specifications. The presence of culture should allow people to build stronger ties, because they share values, principles, norms, a common environment, and more (in the sense of, Granovetter 1973). However, in the way we have modeled it, cultural conformity K has a rather weak effect on social ties because it operates superficially, on the basis of imitation and not of substantial interaction among agents. Hence, we posit that K is a source of weak rather than strong ties. Instead, the individual attitude to make decisions based on shared information through social channels (i.e., docility k) is likely to generate strong ties, because it creates the conditions for more in-depth social relationships between employees (and management). For this reason, docility is connected to generating strong ties (or ties stronger than in the cultural conformity condition) and these, in turn, lead to an increase of bandwagons. This can be justified by the fact that organizations where an increase in social relationships is quicker than a culture to emerge, may see employees moving together to create that shared culture. In this sense, bandwagons (i.e., moving or sticking together) may be seen as a surrogate of culture:

Proposition 5 When agents are let free to interact on the basis of their docile attitudes only (and cultural conformity is absent) bandwagons are more likely to emerge. The effect increases with organization size.

There is one nuance in the way social relationships affect the spread of bandwagons that relates to large organizations. When large organizations are considered under low ambiguity, it may well be that the impact of social relationships is limited by other parameters/factors. However, when we look at Fig. 5c, d we may realize that the presence of minimal level of social relationships

($v = 4$) already brings the organizations to a situation where there is high occurrence of bandwagons. Modifications do not improve or deteriorate what is already particularly critical.

Simulated employees and managers are characterized by “docility.” This is the tendency to make decisions using social cognitive resources that are external to one’s brain (Simon 1993; Knudsen 2003). The mechanisms of threshold adaptation have been modeled according to this human attitude. When employees are left without a clear rule for organizational cultural conformity (i.e., $K = 0$), it is the distribution of passive docility that spreads and leads to bandwagons more often (Figs. 5, 6). The absence of culture—even if the one aspect that is represented in the simulation is “conformity”—leads individuals to lean on what is called passive (i.e., take-only) docile attitudes (Secchi and Bardone 2009, 2013). The mechanism underlying this phenomenon can be explained with the type of organization that shows no conformity rule. We identified these organizations above as being subject to crisis, start-ups, newly established subsidiaries in foreign countries. There are two hypotheses on how the passive distributed cognitive mechanisms affect bandwagons especially in large organizations. One is that particularly low levels of docility may be associated with a complete passive (or take-only) behavior that is a cheap cognitive mechanism. Imitation can be a successful survival strategy although it can also be associated with what Simon (1993) labelled “unintelligent” docile individuals or with “selfish” non-docile behavior. Both aspects are likely to appear more often when there is no common glue that keeps employees together. In the model, this is mild cultural conformity. In short, it seems that more active (Bardone 2011) and “intelligent” (Simon 1993) distributed cognitive processes are successful when there is a feeling of belongingness and a community to which employees can identify with (Secchi and Bardone 2009). This element needs to be investigated further however, we have isolated some of the aspects that characterized more clearly what is this “mindlessness” that previous works on the bandwagon refer to (Fiol and O’Connor 2003; Secchi and Bardone 2013).

5.5 Limitations and conclusion

There are a few limitations of this study. First, organization structures are not composed of two hierarchical levels, employees and managers. There is a chain of command that is not represented in the model. Moreover, there is a need to better specify what makes the difference between these two levels in terms of decision making and influence. The model is only a first approximation to the complexity of social relationships. Second, culture is modeled through easiness of imitation that may cover some aspects of it, but it certainly does not make justice of the many significant elements defining organizational culture. Once again, the model is designed to isolate what is relevant to bandwagon processes; hence a more complex representation may not turn out to be beneficial. However, it may be a topic for future modifications of this model. An aspect related to this element that can be studied in future research is that of the interaction between a broader concept of culture and bandwagon. Our results suggest that there may be some limited overlap,

under certain conditions. Further research is needed to clarify what exactly the relationship is.

A third limitation is that better fine tuning may be needed to model ambiguity. We defined it as agents that move randomly on a three-dimensional space that represents the organization so that it is a component of the way agents perceive their surroundings, thus affecting their bounded rationality. This simple approximation to ambiguity may be remodeled to include other stochastic components that affect all relevant parameters of the model. This one, again, can be a development for future research although one of the pros of using ABMs is that they are used to model complex emerging problems. Having stated this, we believe a more specific and detailed account of ambiguity can be modeled.

The paper presents a multi-agent model that predicts the likelihood of employees of small and large organizations to join bandwagons. To study the phenomenon, simulation data were generated with threshold levels that let agents adapt to the social environment approximated by organizational culture, proximity, ambiguity, docility, and management-employee relations. Findings show that bandwagons do not depend strictly on the distribution of thresholds in as much as they are affected by strong organizational culture and management-employee relations. Impact of organizational variables also vary with size.

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Appendix

While figures provide a clean representation of our results, statistics support those representations and detail the size of the various effects discussed in the text. We regressed the probability of joining a bandwagon using Cox proportional-hazards regression models (Cox 1972). This statistical technique allows us to estimate the probability for agents to join the bandwagon (i.e., *hazard rate*), comparing two or more covariates. Tables 2, 3, 4, 5, 6 and 7 below are numerical representations of Figs. 1, 2, 3, 4, 5 and 6.

With very few exceptions, results were highly significant mostly because of the large number of observations (reported in the tables with the letter *n*). The following tables present the exponentiated regression coefficients, their *p* values, 95 % confidence intervals, the log-likelihood, and a likelihood-ratio test for goodness-of-fit. The exponentiated coefficients have a direct multiplicative effect on the *hazard rate* (*HR*); e.g., a coefficient of 1.227 for one covariate (Table 2, Model 1, $K = 0.5$) has 22.7 % influence on the *HR* when holding the other covariates constant. The value is relative to the baseline case ($K = 0.1$), so that, when our β is 1.227 for $K = 0.5$, the impact on *HR* is 22.7 % higher than the baseline case. All the models have been run independently, so that the first value (baseline) is set as the benchmark and the other values show an increased ($\exp(\text{coef}) > 1.00$) or a decreased likelihood to join the bandwagon ($\exp(\text{coef}) < 1.00$).

Table 2 Cox proportional hazards regressions for bandwagon affected by conformity K and proximity v

	Small org. (N = 100)		
	Model 1 (v = 4) exp(coef) (.95 Conf. Int.)	Model 2 (v = 5) exp(coef) (.95 Conf. Int.)	Model 3 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.227* (1.009, 1.491)	1.443*** (1.234, 1.688)	1.710*** (1.479, 1.978)
K = 1/0.1	1.291** (1.065, 1.566)	1.603*** (1.374, 1.869)	2.176*** (1.891, 2.505)
Log-likelihood	-6664.944	-10777.127	-13562.030
Likelihood ratio test	7.48*	39.87***	127.6***
	Mid-sized org. (N = 200)		
	Model 4 (v = 4) exp(coef) (.95 Conf. Int.)	Model 5 (v = 5) exp(coef) (.95 Conf. Int.)	Model 6 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.596*** (1.424, 1.789)	2.286*** (2.055, 2.542)	4.520*** (4.030, 5.069)
K = 1/0.1	1.649*** (1.471, 1.848)	2.949*** (2.659, 3.270)	6.578*** (5.880, 7.358)
Log-likelihood	-20,211.744	-28,126.775	-34,267.037
Likelihood ratio test	93.08***	494.4***	1570.0***
	Mid-sized org. (N = 500)		
	Model 7 (v = 4) exp(coef) (.95 Conf. Int.)	Model 8 (v = 5) exp(coef) (.95 Conf. Int.)	Model 9 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	3.392*** (3.145, 3.660)	11.82*** (10.770, 12.98)	44.45*** (38.54, 51.25)
K = 1/0.1	4.077*** (3.784, 4.394)	15.58*** (14.18, 17.11)	72.02*** (62.29, 83.26)
Log-likelihood	-64,666.14	-81,593.37	-52,490.53
Likelihood ratio test	1841.0***	6826.0***	10,527.0***
	Large org. (N = 1000)		
	Model 10 (v = 4) exp(coef) (.95 Conf. Int.)	Model 11 (v = 5) exp(coef) (.95 Conf. Int.)	Model 12 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	13.99*** (12.92, 15.15)	65.93*** (57.34, 75.81)	505.7*** (387.9, 659.2)
K = 1/0.1	17.05*** (15.73, 18.48)	99.72*** (86.54, 114.90)	17,542.4*** (13,118.6, 23,457.9)
Log-likelihood	-12,4584.38	-64,043.57	-27,114.49
Likelihood ratio test	10,825.0***	14,866.0***	17,133.0***

Note: exp(coef) exponential of the coefficient, Conf. Int. confidence interval; n = 45,150

Sig. codes: *** $p < .001$; ** $p < .01$; * $p < .05$; † $p < 0.10$

Table 3 Cox proportional hazards regressions for bandwagon affected by conformity K , proximity v , and ambiguity

	Small org. (N = 100)		
	Model 1 ($v = 4$) $\exp(\text{coef})$ (.95 Conf. Int.)	Model 2 ($v = 5$) $\exp(\text{coef})$ (.95 Conf. Int.)	Model 3 ($v = 6$) $\exp(\text{coef})$ (.95 Conf. Int.)
$K = 0.5/0.1$	1.588*** (1.362, 1.852)	2.155*** (1.846, 2.517)	4.833*** (4.076, 5.731)
$K = 1/0.1$	1.673*** (1.436, 1.948)	2.548*** (2.190, 2.964)	6.717*** (5.688, 7.932)
Log-likelihood	-10,882.79	-12,046.09	-12,266.83
Likelihood ratio test	53.24***	174.4***	705.2***
n	45,150	45,150	43,976
	Mid-sized org. (N = 200)		
	Model 4 ($v = 4$) $\exp(\text{coef})$ (.95 Conf. Int.)	Model 5 ($v = 5$) $\exp(\text{coef})$ (.95 Conf. Int.)	Model 6 ($v = 6$) $\exp(\text{coef})$ (.95 Conf. Int.)
$K = 0.5/0.1$	3.053*** (2.706, 3.443)	6.746*** (5.785, 7.867)	19.83*** (16.01, 24.57)
$K = 1/0.1$	3.678*** (3.269, 4.137)	10.221*** (8.793, 11.880)	38.00*** (30.73, 46.98)
Log-likelihood	-22,755.60	-19,151.88	-12,316.02
Likelihood ratio test	609.8***	1449.0***	2293.0***
n	45,150	44,997	34,831
	Mid-sized org. (N = 500)		
	Model 7 ($v = 4$) $\exp(\text{coef})$ (.95 Conf. Int.)	Model 8 ($v = 5$) $\exp(\text{coef})$ (.95 Conf. Int.)	Model 9 ($v = 6$) $\exp(\text{coef})$ (.95 Conf. Int.)
$K = 0.5/0.1$	7.115*** (6.385, 7.929)	30.51*** (24.77, 37.59)	71.56*** (53.14, 96.36)
$K = 1/0.1$	11.138*** (10.020, 12.380)	80.78*** (65.74, 99.27)	434.78*** (321.80, 587.44)
Log-likelihood	-38,841.302	-19,576.512	-9084.534
Likelihood ratio test	3186.0***	1976.0***	4042.0***
n	45,150	36,973	26,181
	Large org. (N = 1000)		
	Model 10 ($v = 4$) $\exp(\text{coef})$ (.95 Conf. Int.)	Model 11 ($v = 5$) $\exp(\text{coef})$ (.95 Conf. Int.)	Model 12 ($v = 6$) $\exp(\text{coef})$ (.95 Conf. Int.)
$K = 0.5/0.1$	25.00*** (21.73, 28.75)	75.28*** (56.84, 99.72)	124.4*** (89.78, 172.5)
$K = 1/0.1$	67.68*** (58.86, 77.83)	514.53*** (388.20, 681.97)	1537.6*** (1106.50, 2136.8)
Log-likelihood	-39,400.033	-15,014.340	-6895.439

Table 3 continued

	Large org. (N = 1000)		
	Model 10 (v = 4) exp(coef) (.95 Conf. Int.)	Model 11 (v = 5) exp(coef) (.95 Conf. Int.)	Model 12 (v = 6) exp(coef) (.95 Conf. Int.)
Likelihood ratio test	8394.0***	6277.0***	4514.0***
n	40,794	31,205	23,858

Note: exp(coef) exponential of the coefficient, Conf. Int. confidence interval

Sig. codes: *** $p < .001$; ** $p < .01$; * $p < .05$; † $p < 0.10$

Table 4 Cox proportional hazards regressions for bandwagon affected by conformity *K*, proximity *v* and hierarchy

	Small org. (N = 100)		
	Model 1 (v = 4) exp(coef) (.95 Conf. Int.)	Model 2 (v = 5) exp(coef) (.95 Conf. Int.)	Model 3 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.022 (0.8409, 1.243)	1.571*** (1.330, 1.856)	1.694*** (1.448, 1.982)
K = 1/0.1	1.192† (0.9864, 1.440)	1.703*** (1.445, 2.008)	1.902*** (1.629, 2.220)
Log-likelihood	-6600.811	-9758.798	-11,167.656
Likelihood ratio test	3.96 (n.s.)	46.89***	76.3***
n	45,150	45,150	45,150
	Mid-sized org. (N = 200)		
	Model 4 (v = 4) exp(coef) (.95 Conf. Int.)	Model 5 (v = 5) exp(coef) (.95 Conf. Int.)	Model 6 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.259*** (1.116, 1.420)	1.621*** (1.447, 1.817)	1.768*** (1.566, 1.997)
K = 1/0.1	1.419*** (1.261, 1.597)	1.857*** (1.660, 2.077)	2.041*** (1.811, 2.299)
Log-likelihood	-17,570.78	-20,885.71	-18,922.86
Likelihood ratio test	34.99***	131.0***	156.4***
n	45,150	45,150	45,150
	Mid-sized org. (N = 500)		
	Model 7 (v = 4) exp(coef) (.95 Conf. Int.)	Model 8 (v = 5) exp(coef) (.95 Conf. Int.)	Model 9 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.938*** (1.793, 2.095)	1.830*** (1.690, 1.982)	2.396*** (2.232, 2.573)
K = 1/0.1	2.067*** (1.913, 2.233)	2.254*** (2.085, 2.436)	3.308*** (3.085, 3.548)

Table 4 continued

	Mid-sized org. (N = 500)		
	Model 7 (v = 4) exp(coef) (.95 Conf. Int.)	Model 8 (v = 5) exp(coef) (.95 Conf. Int.)	Model 9 (v = 6) exp(coef) (.95 Conf. Int.)
Log-likelihood	-46,085.03	-44,134.82	-59,807.74
Likelihood ratio test	424.8***	469.1***	1317.0***
n	45,150	45,150	44,936
	Large org. (N = 1000)		
	Model 10 (v = 4) exp(coef) (.95 Conf. Int.)	Model 11 (v = 5) exp(coef) (.95 Conf. Int.)	Model 12 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.874*** (1.768, 1.986)	2.799*** (2.635, 2.973)	5.369*** (5.036, 5.725)
K = 1/0.1	2.245*** (2.121, 2.376)	4.781*** (4.508, 5.070)	14.552*** (13.619, 15.549)
Log-likelihood	-82,892.32	-94,334.35	-89,398.69
Likelihood ratio test	883.8***	3332.0***	8301.0***
n	45,150	44,761	38,773

Note: exp(coef) exponential of the coefficient, Conf. Int. confidence interval

Sig. codes: *** $p < .001$; ** $p < .01$; * $p < .05$; † $p < 0.10$

Table 5 Cox proportional hazards regressions for bandwagon affected by conformity K , proximity v , hierarchy, and ambiguity

	Small org. (N = 100)		
	Model 1 (v = 4) exp(coef) (.95 Conf. Int.)	Model 2 (v = 5) exp(coef) (.95 Conf. Int.)	Model 3 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.329 (1.139, 1.550)	1.612*** (1.405, 1.849)	1.147* (1.001, 1.315)
K = 1/0.1	1.473*** (1.267, 1.713)	1.695*** (1.479, 1.943)	1.843*** (1.626, 2.089)
Log-likelihood	-10,743.50	-14,034.88	-15,246.11
Likelihood ratio test	27.17***	70.31***	108.6***
n	45,150	45,150	45,150
	Mid-sized org. (N = 200)		
	Model 4 (v = 4) exp(coef) (.95 Conf. Int.)	Model 5 (v = 5) exp(coef) (.95 Conf. Int.)	Model 6 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.338*** (1.214, 1.476)	1.349*** (1.225, 1.486)	1.790*** (1.618, 1.980)

Table 5 continued

	Mid-sized org. (N = 200)		
	Model 4 (v = 4) exp(coef) (.95 Conf. Int.)	Model 5 (v = 5) exp(coef) (.95 Conf. Int.)	Model 6 (v = 6) exp(coef) (.95 Conf. Int.)
K = 1/0.1	1.570*** (1.428, 1.727)	1.606*** (1.463, 1.764)	2.472*** (2.242, 2.725)
Log-likelihood	-27,128.06	-28,155.60	-26,802.09
Likelihood ratio test	90.14***	102.3***	354.4***
n	45,150	45,150	42,639
	Mid-sized org. (N = 500)		
	Model 7 (v = 4) exp(coef) (.95 Conf. Int.)	Model 8 (v = 5) exp(coef) (.95 Conf. Int.)	Model 9 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.533*** (1.439, 1.633)	2.434*** (2.267, 2.614)	7.451*** (6.745, 8.231)
K = 1/0.1	1.378*** (1.292, 1.470)	2.216*** (2.061, 2.383)	8.093*** (7.322, 8.946)
Log-likelihood	-61,248.51	-52,141.18	-33,624.70
Likelihood ratio test	189.7***	752.3***	2713.0***
n	45,150	45,009	32,279
	Large org. (N = 1000)		
	Model 10 (v = 4) exp(coef) (.95 Conf. Int.)	Model 11 (v = 5) exp(coef) (.95 Conf. Int.)	Model 12 (v = 6) exp(coef) (.95 Conf. Int.)
K = 0.5/0.1	1.740*** (1.650, 1.835)	6.367*** (5.879, 6.896)	4.07*** (3.633, 4.56)
K = 1/0.1	1.829*** (1.735, 1.929)	8.358*** (7.718, 9.051)	15.71*** (14.092, 17.50)
Log-likelihood	-88,961.38	-58,598.09	-25,447.53
Likelihood ratio test	626.6***	4135.0***	3005.0***
n	45,150	44,761	29,771

Note: exp(coef) exponential of the coefficient, Conf. Int. confidence interval

Sig. codes: *** $p < .001$; ** $p < .01$; * $p < .05$; † $p < 0.10$

Table 6 Cox proportional hazards regressions for bandwagon affected by docility k , proximity v , and hierarchy

	Small org. (N = 100)		
	Model 1 (v = 4) exp(coef) (.95 Conf. Int.)	Model 2 (v = 5) exp(coef) (.95 Conf. Int.)	Model 3 (v = 6) exp(coef) (.95 Conf. Int.)
Hierarchy	0.874 (0.731, 1.044)	0.787*** (0.6867, 0.903)	0.510*** (0.457, 0.568)
Log-likelihood	-4377.752	-7307.699	-11824.570
Likelihood ratio test	2.22 (n.s.)	11.76***	152.9***
n	10,100	10,100	10,100
	Mid-sized org. (N = 200)		
	Model 4 (v = 4) exp(coef) (.95 Conf. Int.)	Model 5 (v = 5) exp(coef) (.95 Conf. Int.)	Model 6 (v = 6) exp(coef) (.95 Conf. Int.)
Hierarchy	0.792*** (0.715, 0.876)	0.599*** (0.554, 0.647)	0.505*** (0.470, 0.544)
Log-likelihood	-13,158.14	-22,357.51	-23,685.40
Likelihood ratio test	20.47***	172.9***	334.4***
n	10,100	10,100	10,100
	Mid-sized org. (N = 500)		
	Model 7 (v = 4) exp(coef) (.95 Conf. Int.)	Model 8 (v = 5) exp(coef) (.95 Conf. Int.)	Model 9 (v = 6) exp(coef) (.95 Conf. Int.)
Hierarchy	0.651*** (0.615, 0.690)	0.469*** (0.438, 0.502)	0.174*** (0.159, 0.190)
Log-likelihood	-37,553.79	-27,871.37	-21,101.38
Likelihood ratio test	211.4***	443.8***	1152.0***
n	10,100	9877	7171
	Large org. (N = 1000)		
	Model 10 (v = 4) exp(coef) (.95 Conf. Int.)	Model 11 (v = 5) exp(coef) (.95 Conf. Int.)	Model 12 (v = 6) exp(coef) (.95 Conf. Int.)
Hierarchy	0.524*** (0.491, 0.558)	0.168*** (0.153, 0.184)	0.143*** (0.128, 0.159)
Log-likelihood	-32,933.74	-25,667.22	-23,364.73
Likelihood ratio test	368.8***	1157.0***	970.0***
n	9867	7056	6490

Note: exp(coef) exponential of the coefficient, Conf. Int. confidence interval

Sig. codes: *** $p < .001$; ** $p < .01$; * $p < .05$; † $p < 0.10$

Table 7 Cox proportional hazards regressions for bandwagon affected by docility k , proximity v , hierarchy, and ambiguity

	Small org. (N = 100)		
	Model 1 ($v = 4$) exp(coef) (.95 Conf. Int.)	Model 2 ($v = 5$) exp(coef) (.95 Conf. Int.)	Model 3 ($v = 6$) exp(coef) (.95 Conf. Int.)
Hierarchy	1.043 (0.897, 1.212)	0.703*** (0.625, 0.791)	0.640*** (0.580, 0.706)
Log-likelihood	-5962.765	-9783.699	-13,400.484
Likelihood ratio test	0.3 (n.s.)	34.81***	79.0***
n	10,100	10,100	10,100
	Mid-sized org. (N = 200)		
	Model 4 ($v = 4$) exp(coef) (.95 Conf. Int.)	Model 5 ($v = 5$) exp(coef) (.95 Conf. Int.)	Model 6 ($v = 6$) exp(coef) (.95 Conf. Int.)
Hierarchy	0.742*** (0.683, 0.806)	0.722*** (0.670, 0.777)	0.39*** (0.358, 0.425)
Log-likelihood	-19,404.53	-23,192.75	-17,247.23
Likelihood ratio test	50.75***	73.82***	432.4***
n	10,100	10,100	8992
	Mid-sized org. (N = 500)		
	Model 7 ($v = 4$) exp(coef) (.95 Conf. Int.)	Model 8 ($v = 5$) exp(coef) (.95 Conf. Int.)	Model 9 ($v = 6$) exp(coef) (.95 Conf. Int.)
Hierarchy	0.669*** (0.630, 0.710)	0.308*** (0.285, 0.334)	0.141*** (0.126, 0.158)
Log-likelihood	-34,532.53	-22,436.44	-15,463.53
Likelihood ratio test	168.5***	717.7***	914.2***
n	10,100	7828	5816
	Large org. (N = 1000)		
	Model 10 ($v = 4$) exp(coef) (.95 Conf. Int.)	Model 11 ($v = 5$) exp(coef) (.95 Conf. Int.)	Model 12 ($v = 6$) exp(coef) (.95 Conf. Int.)
Hierarchy	0.354*** (0.329, 0.380)	0.156*** (0.139, 0.174)	0.193*** (0.169, 0.219)
Log-likelihood	-29,626.58	-18,957.91	-11,569.03
Likelihood ratio test	676.9***	884.9***	530.2***
n	8446	6117	4362

Note: exp(coef) exponential of the coefficient, Conf. Int. confidence interval

Sig. codes: *** $p < .001$; ** $p < .01$; * $p < .05$; † $p < 0.10$

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