How groups can foster consensus:
The case of local cultures

Patrick Groeber, Frank Schweitzer, Kerstin Press
Chair of Systems Design, ETH Zurich, Kreuzplatz 5, 8032 Zurich, Switzerland
{pgroeber,fschweitzer,kpress}@ethz.ch

Abstract

A local culture denotes a commonly shared behaviour within a cluster of firms. Similar to social norms or conventions, it is an emergent feature resulting from the firms’ interaction in an economic network. To model these dynamics, we consider a distributed agent population, representing e.g. firms or individuals. Further, we build on a continuous opinion dynamics model with bounded confidence ($\epsilon$), which assumes that two agents only interact if differences in their behaviour are less than $\epsilon$. Interaction results in more similarity of behaviour, i.e. convergence towards a common mean. This framework is extended by two major concepts: (i) The agent’s in-group consisting of acquainted interaction partners is explicitly taken into account. This leads to an effective agent behaviour reflecting that agents try to continue to interact with past partners and thus to keep sufficiently close to them. (ii) The in-group network structure changes over time, as agents can form new links to other agents with sufficiently close effective behaviour or delete links to agents no longer close in behaviour. Thus, our model provides a feedback mechanism between the agents’ behaviour and their in-group structure. Studying its consequences by means of agent-based computer simulations, we find that for narrow-minded agents (low $\epsilon$) the additional feedback helps to find consensus more often, whereas for open-minded agents (high $\epsilon$) this does not hold. This counterintuitive result is explained by simulations of the network evolution.

Keywords: Social Norms, Conventions, Bounded Confidence, Dynamic Networks

1 Introduction

Since the early 1990s, economic theory and policy has dedicated a lot of attention to the causes and effects of clusters, i.e. spatial concentrations of firms in one or a few related industries (Ellison and Glaeser, 1997). Driven by their impressive prosperity, the factors underlying cluster success were extensively studied in the hope of replicating areas like the Silicon Valley or London. Locating in a cluster provides several benefits for firms. However, the existence of these benefits hinges on a set of rules on acceptable business practice – the cluster’s ‘local culture’. For instance, there is a rule among banks located in Frankfurt that they should not hire personnel away from competitors. In the Silicon Valley, the local culture is such that firms openly exchange ideas even with direct competitors. In order to partake in the cluster and its dynamics, firms need to respect these rules, which has made it difficult for outside companies (e.g. multinational enterprises) to tap into the cluster through subsidiaries. While some work has been conducted to determine the
nature and enforcement of such local cultures, their emergence remains far from understood. So far, anecdotal evidence suggests that it depends on agreement about the nature of desirable business practice.

To shed light on the emergence of local cultures, the present paper studies the emergence of the initial consensus. It argues that cluster firms have to interact with each other. As these interactions are not cost-free, they give rise to changes in firm behaviour and different inter-firm networks that affect the future behaviour of constituent firms. Both mechanisms can lead to convergent or divergent behaviour. Those cases finding converging behaviour among all or a majority of cluster firms constitute situations in which the basis for a local culture emerges. This is also important for the emergence of clustering benefits and therefore the economic viability of the cluster. To study the emergence of converging behaviour (i.e. the first step towards a local culture), this paper develops an opinion dynamics model with bounded confidence and group-influence as both aspects are required to mimic the dynamics of inter-firm interaction in clusters.

In doing so, the paper proceeds as follows. Section 2 describes the case under study. The emergence and effect of local cultures is found to be similar to that of norms and conventions as both are means to solve co-ordination and cooperation problems. However, the costliness of inter-firm interactions requires some amendments to existing models (section 3). In particular, it justifies the application of a bounded confidence model introduced in section 4. Agents (= firms) will only interact if they are sufficiently close in their behaviour as the risk of a costly transaction going wrong are too high otherwise. Moreover, agents are linked by ties stemming from previous interactions. Thanks to costly interaction, agents try to maintain these ‘in-groups’ and modify their behaviour accordingly. Section 5 then presents the findings regarding the conditions for consensual behaviour among all or a majority of agents. It is found that the existence and influence of in-groups fosters consensus, especially if agents would only interact with behaviourally similar actors. As a result, the nature of inter-firm interactions in clusters is conducive to consensus and thereby the emergence of a local culture.

2 Defining local cultures

In economic geography, local cultures with rules like "do not hire from competitors", "exchange ideas freely" or "deliver only the highest quality" are a phenomenon characterising clusters like Silicon Valley (IT), London (financial services) or Prato, Italy (textiles). The existence of clusters is tied to that of local cultures because the benefits to clustering are subject to various co-ordination and co-operation issues that are solved by the rules in the local culture.

Usually, cluster benefits relate to scale and specialisation effects as well as positive externalities. The former (scale and specialisation) emerge since companies in a cluster usually divide the production process. Rather than having all firms manufacture shoes, one specialises in soles
while other provide laces, tops, linings and so on (Pyke et al., 1990). This division of labour leads to scale and specialisation benefits as firms can achieve a greater output with a limited budget and become more efficient in their activities (Smith, 2003). Second, companies conduct competing and complementary activities under identical local conditions in the cluster. This leads to positive externalities in the diffusion of ideas and the availability of skilled labour.

To generate these benefits, cluster firms have to overcome several dilemmas. For a division of labour to emerge, suppliers need a fair price and a sufficient market (Smith, 2003, p. 27). Moreover, the quantities provided by different firms have to be aligned. Positive externalities in knowledge and personnel are tied to respective investments in research and training. This is only viable if deflection (free-riding) is limited. Akin to famous cooperation problems like the Kula Ring (Ziegler, 2007) or the Chicago diamond market (Coleman, 1990), the cluster literature argues, that these dilemmas are solved by rules on acceptable business practice that make up the local culture. While some work has determined what local cultures look like (e.g. Porter, 1990; Pyke et al., 1990; Saxenian, 1994) and how their enforcement can be ensured (Holländer, 1990; Kandel and Lazear, 1992) their emergence is far less understood.

It is usually suggested that firms learn about successful behaviour when interacting with others. Successful past behaviour is then repeated and possibly copied among firms in the cluster, which implies that gradually, this behaviour spreads in the population. Once established, such a consensus on "good" behaviour creates expectation about others' future behaviour, thereby reducing frictions in interaction. Specific rules making up a local culture can finally emerge to foster and enforce this consensual behaviour by monitoring and punishment of defecting agents (Maskell, 2001, p. 926). The first step towards a local culture is thus a behaviour that is viewed as desirable enough to become the basis of rule-making. We argue that a good candidate for viable rules is a behaviour already prevalent in the cluster, i.e. a behaviour that is shared by (a majority of) local firms. As a result, consensus on a certain behaviour constitutes the necessary condition for rule-making, rule enforcing and the emergence of local cultures. This paper investigates how a consensus on a specific behaviour emerges in a cluster. In doing so, the paper argues that the division of labour in clusters requires interaction between firms to manufacture the product. As interactions are not cost free (Coase, 1937; Williamson, 1975), two mechanisms come into play.

First, interaction costs increase with the difference in firm behaviour. Firms with similar behaviour are likely to respond similarly to future developments. This makes it unnecessary to specify all possible scenarios in a contract thereby reducing the cost of interaction. If all interactions are equally beneficial, the increasing cost of interaction implies that (a) firms will not

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1 Competitors experiment with different strategies under identical conditions. This allows for direct comparisons of performance and selection of best practice. In addition, firms tackling the same or related problems may exchange knowledge through various mechanisms (Allen, 1983). Both aspects contribute to knowledge spillovers. Finally, many firms in a cluster increase the quality of the local labour pool by training activity and immigration of skilled people.

2 Investment research and training requires an understanding that allows firms to capitalise on it, i.e. no exploitation of others' efforts or hiring away of personnel trained elsewhere.
interact with all possible partners and (b) the partners to an interaction modify their behaviour
to become more similar. Second, costly interactions make it beneficial to maintain links with
existing partners. Firms therefore become more embedded in networks emerging from their in-
teraction history. Moreover, the desire to maintain these networks may constrain their behaviour
as firms seek to remain sufficiently similar to existing partners.

The consensus resulting from these mechanisms (if any) can take very different forms. It can
reside with a behaviour that is very co-operative, i.e. every firm strongly invests in activities
subject to externalities and supplier-buyer relations are characterised by fairness. Such a situa-
tion provides high incentives to free-ride implying that this behaviour is not self-enforcing. In
other instances, consensus can reside with very defective behaviour where all firms try to exploit
one another as much as possible and do not investment in activities with externalities. This
situation would provide no incentive for deviation (at least not to an individual firm), i.e. the
local culture is self-enforcing.

3 Local cultures as norms or conventions

Once established, local cultures fulfill the function of social norms or conventions insofar as they
solve co-operation or co-ordination problems. As a result, their emergence mimics that of norms
and conventions, which unfolds as follows: The first stage is build on consensus formation, where
agents reach consensus on a certain behaviour through different mechanisms like optimising
behaviour [Opp, 1982; Weber, 1999], imitating or replicating successful strategies [Asch, 1956;
Sherif, 1973] or through trial and error search [Demsetz, 1967]. Once the consensual behaviour
spreads and remains in the population, it creates expectations about everyone’s future behaviour,
which reduce friction in interactions [Axelrod, 1981; Koford and Miller, 1991; Sugden, 1989].
Depending on whether the behaviour is self-enforcing (convention) or not (norm), the second
stage of the process differs. For conventions, the emergence of consensus is sufficient. In case of
norms behavioural regularities have to result in a sense of “oughtness” [Opp, 2001] that may
eventually lead to an enforceable norm prescribing this behaviour: “Thus, patterns of action
emerge that then become normative [...] Individuals comply with the new norm both for the
original reason that the behaviour was appealing, and also because it is now socially enforced”
[Horne, 2001, p. 6].

Depending on the nature of consensual behaviour (self-enforcing or not), local cultures corre-
respond to conventions or social norms. In either case, the first stage of their emergence process
(consensus building) is identical. This makes models on the emergence of norms or convention
applicable to our case. In the literature, most work on norms and conventions is based on game-
theory with a smaller subset of research studying consensus formation (through voter models or
bounded confidence approaches). The game-theoretic approach to norms and conventions (Fehr
and Fischbacher, 2004; Holländer, 1996; Kandel and Lazear, 1992; Ullmann-Margalit, 1977; Voss,
2001) is not applicable to our case for several reasons. By focussing on the nature of the game
(e.g. payoff structure, repetition) and underlying agent interaction, individual incentives and efficient outcomes are derived. Conventions correspond to situations where the optimal outcome is a non-unique Nash equilibrium. Depending on the underlying mechanisms, different equilibria may be selected (see e.g. Pujol et al., 2005; Shoham and Tennenholtz, 1992). Norms instead emerge in situations where the optimal solution is not an equilibrium outcome. The norm is viewed as the solution to the problems preventing a better outcome in that particular game.

The focus on payoffs and incentives implies that there is a known optimal behaviour. In other words, agents know the consequences of their actions, anticipate the choices of others and are thereby able to determine, what kind of behaviour leads to efficient outcomes. In the Prisoner’s Dilemma situation, cooperation is the ex-ante optimal behaviour when jointly maximising the players’ outcome. Moreover, game theory is less concerned with the emergence of a particular norm or convention but rather with its effect for the game’s equilibrium outcomes. Since we cannot determine ex-ante payoff values for business strategy and our concern resides more with the emergence than the effect of local cultures, game-theoretic models are not suited for our research question. We therefore focus on an approach that does not assume an ‘optimal’ behaviour but where the value of an agent’s behaviour only depends on the number of agents adhering to it and on that behaviour’s compliance with the predominant behaviour in the agent’s personal network. In this sense, any consensus among all agents is ‘good’ - regardless of the nature of consensual behaviour.

There are several models studying the emergence of consensus from agent interaction (Axelrod, 1997; Deffuant et al., 2000; DeGroot, 1974; Hegselmann and Krause, 2002; Lehrer and Wagner, 1981). They fall into two main classes: Voter models and bounded confidence models. In voter models, agents are characterised by a discrete opinion (a binary variable in most cases) and are embedded in a network of given topology. They may adopt other opinions according to their frequency in the agent’s neighborhood. In linear voter models, the transition towards a given opinion is directly proportional its local frequency. In non-linear voter models other types of frequency dependent behaviour are possible (Schweitzer, 2007). While consensus is always reached in linear voter models, non-linear responses to the local frequency of an opinion may prevent (Schweitzer and Behrens, 2009) or accelerate (Stark et al., 2008a,b) consensus.

Another class of consensus models deals with continuous opinions $x_i$ represented as a real number between 0 and 1 (Deffuant et al., 2000). Two agents $i$ and $j$, randomly chosen at each
timestep, can only interact if the difference in their opinion does not exceed a threshold value $\varepsilon$. Rather than taking place on a predefined network, agent interactions are randomised and conditional here. This mechanism of ‘bounded confidence’ is applied by Hegselmann and Krause (2002) where all possible interactions take place simultaneously. As investigated by means of several approaches (e.g. Ben-Naim et al., 2003; Lorenz, 2006) consensus then largely depends on the value of the key parameter $\varepsilon$.

Our model, formalized in the following section, builds on the bounded confidence approach, but combines it with the consideration of the dynamics in an agent’s social network. Dependent on the relationship between $i$ and $j$, we distinguish between an in-group (members of a social network seen as friends) and an out-group (members with adversary relations, enemies as in Fent et al. (2007)).

In addition to in-group relations within a social network, we include a dynamics of the agents’ social network. This is based on a feedback mechanism between an agent’s behaviour and her personal network: past interactions with partners from the agent’s in-group affect her individual behaviour which in turn influences the structure of the in-group, iteratively. Hence, as the novel element, our model combines both opinion dynamics and network dynamics at the level of individual agents.

Both aspects relate to the fact that interaction between agents is not cost-free. First, we argued that costs increase with differences in agent behaviour since many actions are beneficial as long as both agents behave in the same way. As a consequence, interactions are conditional on sufficient behavioural similarity. Moreover, interacting agents approach each other’s behaviour to lower interaction cost. Second, costly interactions make keeping past partners very beneficial. As a result, agents will want to keep their past partners (their in-group) and will modify their behaviour accordingly. The behaviour of the group will therefore determine the possible range of agent behaviour. Conversely, agent behaviour feeds back on her in-group and therefore allows for changes in group structure as a function of interaction and behavioural dynamics. Section 4 provides more detail on the formal treatment of these mechanisms.

4 Modelling the emergence of consensual behaviour

We argued before that costly interactions result in two effects, (i) consensus formation, i.e. optimising behaviour within a group to avoid friction, and (ii) network formation, i.e. optimising
the agents’ social network structure by deleting links with agents whose behaviour largely deviates from one’s own, thus making interaction more costly (or creating links with agents whose behaviour is more similar). The two interlinked dynamics are specified as follows.

**Consensus formation.** In order to reflect the first consequence of costly interactions, we need a model that makes interaction conditional on agent behaviour. Following Deffuant et al. (2000), agent $i$’s behaviour $x_i$ is represented as a real number between 0 and 1. Thus, we are able to measure the distance between two agents’ behaviour and to model a gradual approach if these agents interact. This is different to the cultural dissemination framework of Axelrod (1997) where cultures constitute a finite, discrete and in general non-metric set. There, interaction between two agents can only lead to complete assimilation of behaviour for one of them, whereas agents approach each other’s behaviour in our model. We further define the behaviour profile $x = (x_1, ..., x_n)$.

In our model, in accordance with Deffuant et al. (2000), two agents $i$ and $j$ are randomly chosen at each timestep. They can only interact if the difference in their behaviour does not exceed a threshold value $\varepsilon$ which can be regarded as a measure of openness. Regarding agent interaction, we can also interpret $\varepsilon$ as the difference in behaviour where the costs and benefits break even: With greater behavioural differences, interaction costs would increase while the benefits are assumed to be constant. Such an interaction would lead to a net cost to the agents involved and will therefore not occur. As the benefits and costs are identical for all agents, the necessary condition for an interaction of $i$ and $j$ becomes:

$$|x_i(t) - x_j(t)| < \varepsilon.$$  

If two agents interact, they try to maximise the benefits of this exchange. As benefits are constant and costs decrease with behavioural differences, the behaviour of interacting agents becomes more similar as both approach each other by identical amounts:

$$x_i(t+1) = x_i(t) + \mu(x_j(t) - x_i(t))$$
$$x_j(t+1) = x_j(t) + \mu(x_i(t) - x_j(t)).$$  

The speed of approach in behaviour depends on the parameter $\mu$. It reflects the well-established phenomenon that interacting parties become more similar (e.g. Axelrod 1997; Macy and Skvoretz 1999; McPherson et al. 2001; Strang and Soule 1998).

The dynamics specified by Eqs. (1), (2) are referred to as the **baseline model** in the following, as they result in the known behaviour already discussed by Deffuant et al. (2000). We now extend this model by introducing the second aspect: Costly interactions imply benefits to keeping past partners. This is modelled by aggregating each agent’s past interaction partners. Each agent $i$ thus has a set $I_i$ of other agents constituting her in-group, i.e. the agent’s acquainted partners. As the agent would like to interact with these partners later, she tries to keep her behaviour

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8 As in Moscovici and Doise (1992) where opinions too far from the majority don’t enter group discussion.
sufficiently similar to them. As agent behaviour changes with her interactions, we argue that the
in-group exerts an influence on the agent’s future interactions. This is achieved by combining
an agent’s behaviour $x_i$ and the mean behaviour of her in-group $\bar{x}_{I_i}(t)$ to determine the effective behaviour

$$x_{\text{eff}}^i(t) = (1 - \alpha_i(t))x_i(t) + \alpha_i(t)\bar{x}_{I_i}(t)$$

at time $t$. The use of the mean behaviour is chosen to mirror that the agent is equally interested
in interacting with any of her past partners.

In Eq. (3), $\alpha_i \in [0, 1]$ corresponds to the influence of agent i’s in-group on her effective behaviour.
We use this parameter to mirror the strength of group influence. Based on the aforementioned
notion that agents like to keep their past partners, the influence of the group would increase
with its size. In this model, we define $\alpha_i$ endogenously by

$$\alpha_i(t) = \frac{|I_i(t)|}{|I_i(t)| + 1}.$$ (4)

Hence, we assume that each agent puts equal weight on her own and each in-group member’s
behaviour. If $i$ has never interacted with another agent, her in-group is empty ($|I_i| = 0$) implying
$\alpha_i = 0$. Hence, the effective behaviour of agent $i$ is then identical to her behaviour ($x_{\text{eff}}^i = x_i$).
Further, $\alpha_i$ approaches 1 with growing in-group size $|I_i|$. If the in-group is large, $i$’s effective
behaviour will therefore tend towards the average in-group behaviour.

In our model, two agents wanting to interact now have to compare the distance between their
effective behaviour (influenced by their respective in-groups) instead of that of their own behavioir. As a result, the necessary condition for interaction between agents becomes

$$|x_{\text{eff}}^i(t) - x_{\text{eff}}^j(t)| < \varepsilon.$$ (5)

If two agents with empty in-groups interact, this is identical to Eq. (1) as $x_{\text{eff}}^i = x_i$ and $x_{\text{eff}}^j = x_j$
for $I_i = I_j = \emptyset$.

**Network formation.** In addition to maintaining their in-group, agents also seek to expand it
with suitable new partners. To specify this, we assume that in-groups are initially empty for all
agents. Later, they evolve according to the agents’ interactions as follows: In each simulation
step, two agents $i$ and $j$ are randomly selected. If Eq. (5) holds for them, they interact and
are added to each other’s in-group (if they are not already contained). Over time, agents $i$ and
$j$ may interact with different agents. Therefore, their effective behaviour can be altered either
directly due to a change of $x_i$ and $x_j$ resulting from interaction with other agents, or indirectly

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9This treatment of group influence by averaging has a long tradition. Formal models of group decision-making
(French, 1956; Harary, 1959; Hesselmann and Krause, 2002; Lehrer, 1956; Lehrer and Wagner, 1981; Wagner,
1978) account for group influence by weighted averages. Social impact theory (Latané, 1981; Latané and Nowak,
1991) also constructs group influence by averaging. Similar to social impact theory, our model features a decreasing
marginal group influence with respect to adding more agents to the in-group.
by interactions of agents in their in-group affecting the average behaviour of the respective in-group. Thus, we may encounter a situation where agents $i$ and $j$ interacted at time $t$ and were added to each other’s in-group while later at $t' > t$, their effective behaviour may be modified such that $|x_i^{\text{eff}}(t') - x_j^{\text{eff}}(t')| \geq \varepsilon$. In this case, agents $i$ and $j$ could no longer interact when selected and would be removed from each other’s in-group.

Thus, if $i$ and $j$ are selected at time $t$, we have

$$I_i(t+1) = \begin{cases} I_i(t) \cup \{j\} & \text{if } |x_i^{\text{eff}}(t) - x_j^{\text{eff}}(t)| < \varepsilon \\ I_i(t) \setminus \{j\} & \text{if } |x_i^{\text{eff}}(t) - x_j^{\text{eff}}(t)| \geq \varepsilon \end{cases}$$

$$I_j(t+1) = \begin{cases} I_j(t) \cup \{i\} & \text{if } |x_i^{\text{eff}}(t) - x_j^{\text{eff}}(t)| < \varepsilon \\ I_j(t) \setminus \{i\} & \text{if } |x_i^{\text{eff}}(t) - x_j^{\text{eff}}(t)| \geq \varepsilon \end{cases}$$

Note that the in-group relation is symmetric but may not be transitive, i.e. agent $i$ being contained in agent $j$’s in-group and agent $j$ being contained in agent $k$’s in-groups does not require $k$ being in $j$’s in-group.

As indicated before, the behaviour of interacting agents becomes more similar. This means that interaction at time $t$ alters the agents’ behaviour according to Eq. (2). For $t+1$, this also feeds back on the effective behaviour of $i$ and $j$, Eq. (3), as well as on the effective behaviour of agents whose in-group contains $i$ or $j$. The effect of modifying $i$’s behaviour for her effective behaviour will decrease with larger $I_i$. Over time, the agent can interact with others in and outside her in-group if Eq. (5) is satisfied. This influences her behaviour as well as the evolution of her in-group over time. Agents previously outside $i$’s in-group are added to the set $I_i$ once $i$ successfully interacts with them. The addition of new agents to $I_i$ influences her effective behaviour and thereby her potential for future interaction. Thus this model provides a feedback mechanism between the agents’ behaviour and their in-group’s structure.

In the context of local cultures, we are mainly interested in whether the dynamics lead to consensus or in quantifying the degree of heterogeneity in agent behaviour. We therefore investigate how the results for the baseline model are affected by the two extensions proposed here, namely the evolving agent network and its feedback on agent behaviour. As known, equilibrium outcomes depend on the key parameter $\varepsilon$ which distinguishes between open-mindedness and narrow-mindedness of agents. Similar to the baseline model, high values of $\varepsilon$ favour consensus or a small number of unrelated population subgroups (=components).

Note that in equilibrium, the dynamics always partition the agent population into a certain number of network components, where all agents within a component share the same behaviour. Obviously, the difference

10 Many models in sociology build upon a reciprocal link of behaviour and interaction. See Carley (1991); Coleman (1961, 1980); Friedkin and Johnsen (1990); Marsden and Friedkin (1993); Nowak et al. (1990). Empirically, the mechanism has been observed by Ennett and Baumann (1994) and many others.

11 For both models, this does not hold in general as the probability of consensus and the average maximum component size as a function of $\varepsilon$ are not monotonically increasing (see Ben-Naim et al. (2003) for the baseline model).
between the behaviour in any two components is at least the threshold $\varepsilon$ as interaction between agents from different components would still be possible otherwise. Further, each agent’s in-group coincides with her respective network component: Agents within a component are fully connected but have no links to outside agents.

5 Findings

As explained before, agents need to agree on a desirable business behaviour to allow for a local culture and cluster benefits to emerge. This consensus results from past interactions and the successful behaviour therein. The strength of any local culture thus relates to the spread of a specific behaviour in the population. Therefore one quantity measured in our simulations is the frequency of consensus among all agents, i.e. how often all agents exhibit the same behaviour in equilibrium. As the behaviour profile does not converge within a finite number of timesteps, we call a behaviour profile $x$ consensus profile if the maximum distance between two agents’ respective behaviours is at most $\varepsilon$. In this case, all agents’ behaviour will finally converge to the mean behaviour in the population. Similarly, we can define a sufficient condition for non-convergence. First, there must be two components whose distance is at least $\varepsilon$, i.e. if there exist agents $i$ and $j$ with $|x_i - x_j| \geq \varepsilon$ and there is no other agent whose behaviour is between $x_i$ and $x_j$. Second, we require that there are no links between these $\varepsilon$-separated components. In this case, the respective limit behaviours for $i$ and $j$ even for large $t$ cannot coincide. However, we should also take into account to what extent there is a shared behaviour among the agents in case of no consensus. We measure this by the size of the largest component of agents with identical behaviour. For example, a situation where 95 agents share the same behaviour is much closer to consensus than one where the population of agents splits into three equally sized components with different behaviour.

We analyse the local cultures model with respect to these quantities by means of computer simulations and compare the results to the baseline model that has no feedback between behaviour and network. The key parameter varied is $\varepsilon$, high values of which characterize the openmindedness of the agents.

The main result relates to the question whether the feedback mechanism between the agents’ behaviour and their network structure (group influence) is beneficial in the sense that a common behaviour is fostered. Our simulations (see Figure 1 and Figure 2) show that for more narrow-minded agents, i.e. small thresholds $\varepsilon$, the group influence results in both a higher average frequency of consensus and a larger maximum component size as compared to the baseline model. Hence, the mechanism introduced in our model increases the likelihood of consensus formation.

This result, interestingly and counterintuitively, changes for larger thresholds and therefore more open-minded agents. Here, the feedback mechanism weakens the emergence of a local culture in
Figure 1: Average frequency of consensus dependent on $\varepsilon$ for 5000 runs and different values of $n$ and $\mu$. The agents’ initial behaviour is random according to a uniform distribution, the initial network is empty. For narrow-minded agents (small $\varepsilon$), the group influence fosters consensus while for open-minded agents (high $\varepsilon$), the probability of identical behaviour is lower than in the baseline model without group influence.
Figure 2: Average maximum relative component size dependent on $\varepsilon$ for 5000 runs and different values of $n$ and $\mu$. The agents’ initial behaviour is random according to a uniform distribution, the initial network is empty. For narrow-minded agents (small $\varepsilon$), our model increases the average maximum component size compared to the baseline model without group influence. For open-minded agents (high $\varepsilon$), there is almost no difference between the two models with respect to the average maximum component size.
Figure 3: Standard deviation of the maximum relative group size dependent on $\varepsilon$ for 5000 runs and different values of $n$ and $\mu$. The agents' initial behaviour is random according to a uniform distribution, the initial network is empty.
general. Agents subject to group influence reach less consensus on average than in the baseline model. We note, however, that the mechanism’s effect differs between the two measures: While the frequency of consensus is significantly decreased (Figure 1), the effect on the maximum component size is much smaller (Figure 2). To explain the influence of agents open-mindedness, we argue that the feedback mechanism in the local cultures model implies two opposed effects compared to the baseline model. On the one hand, agents with “extreme” initial behaviour (i.e. an initial behaviour close to zero or one) are less likely to interact with other agents and are therefore more likely to stay in that border area. The longer these agents remain in isolation (i.e. without interacting), the denser the network of other agents becomes, implying more averaging of behaviour in determining the effective behaviour of these networked agents. As more averaging leads to values closer to the mean, there are fewer and fewer agents within the interaction range of any isolated agent (as compared to the baseline model), and full consensus becomes more unlikely.

On the other hand, the feedback mechanism fosters consensus by increasing the coalescence of subpopulations with different behaviour, i.e. components within the network. To illustrate this, consider the simulation depicted in Figure 4. In Figure 4(a) there are two nearly separated components in our model, the upper, smaller one with a higher average behaviour, the lower, larger one with a lower average behaviour. The two links that connect these components would not persist in the baseline model as the respective nodes’ difference in terms of their own behaviour is above the threshold. However, as this is not the case for their effective behaviour, the involved agents can still interact in our model. Hence, the two agents from the upper component still influence agents in the lower component by increasing their effective behaviour (compared to their other neighbours whose behaviour is lower). For the same reason, the two upper agents’ effective behaviour is decreased by its neighbours from the lower component. Thus, they could establish further connections to the lower component. Nevertheless, interaction with agents from the upper component would increase their behaviour and hence increase the distance to their neighbours from the lower component. Therefore, whether the two components stay connected and finally evolve to a complete graph or become separated depends on which nodes are chosen in the near future, i.e. is a path dependent process. Any interaction between the different components increases the probability of their coalescence, any interaction within the same component decreases that probability. In our example, one agent can establish further connections to the lower component (Figure 4(b)) and in return enables its neighbors from different components to interact (Figure 4(c)). Very quickly, more and more agents from the different components interact, become more similar and finally make the components coalesce (Figure 4(d)). This effect

12 A video of this simulation can be found at http://web.sg.ethz.ch/publications/local_cultures/web-cultures.html. For a dynamic network layout, we use the arf algorithm [Geipel 2007].
13 This increase would have two reasons: first the increase of their own behaviour, second the decrease of their lower component’s neighbours’ influence on their effective behaviour as the share of lower component agents of the neighbourhood also decreases.
Figure 4: Network evolution for a simulation with 50 agents and $\varepsilon = 0.3$ at different timesteps. The agents’ initial behaviour is random according to a uniform distribution, the initial network is empty. A node’s colour indicates the respective agent’s behaviour (white=0, black=1). A green dashed link denotes that the respective agents’ difference in effective behaviour is below the threshold while their respective own behaviours differ more than $\varepsilon$. Thus, such a link persists in the local cultures model but would be deleted in the baseline model. A red dotted link indicates that the respective agents’ difference in effective behaviour is above the threshold, i.e. the link would be deleted if the respective agents were chosen at that timestep.
of coalescing components is also apparent in a higher variance of the maximum component size for narrow-minded agents as compared to the baseline model (cf. Figure 3).

Which of these effects decides over the strength of a local culture depends on the threshold $\varepsilon$: For narrow-minded agents, the baseline model is generally more likely to obtain several components instead of consensus. Thus, in the local cultures model, the increased probability of the coalescence of components increases both the frequency of consensus and the maximum component size. For open-minded agents, this effect vanishes because of the greater ex-ante likelihood of consensus in the baseline model. In this situation, the effect of isolation of agents with extreme behaviour comes into play: While both models favour consensus in general, it is more likely for the local cultures model to find agents at the spectrum’s borders being separated from the other agents because of the faster dynamics towards the center. Therefore, the frequency of consensus is lower in this model. On the other hand there are only few agents separated from the majority, so the maximum component size is only slightly decreased by the feedback mechanism in the local cultures model. Hence, if we only consider this quantity to measure a local culture’s magnitude, the feedback mechanism significantly strengthens a local culture for narrow-minded agents and only slightly weakens it for open-minded agents.

What is the effect of variations to the population size $n$ and the convergence speed $\mu$ on our findings? To explain this we consider how both parameters affect the consensus frequency in our model and the baseline model. In both cases, an increase in the population size usually leads to a decreased consensus probability as it becomes more likely that a single agent with extreme initial behaviour is separated from the rest of the population. For open-minded agents, this effect is amplified by the faster dynamics towards the center in the local cultures model. Thus, we observe that the reduction in frequency of consensus is greater than in the baseline model (cf. Figure 1). With respect to the average maximum component size, an increase in the population size increases the advantage of the local cultures model compared to the baseline model for narrow-minded agents (cf. Figure 2). In this case, the increased number of agents leads to a higher probability for bridging links between two almost separated components. Hence, these components more often coalesce and thereby increase the difference between the maximum component size in our model and that in the baseline model as $n$ grows. This is also indicated by the increased distance of the two models’ respective variance peak (cf. Figure 3). If we decrease the convergence speed $\mu$, we observe an increase in the consensus frequency for both models for all thresholds $\varepsilon$ as the agents’ behaviour moves slower towards the center. With respect to the maximum component size, this only holds for the baseline model. Figure 5 shows that this quantity decreases for narrow-minded agents, i.e. if $\varepsilon$ is small. The reason is that the coalescence of components becomes less likely for smaller values of $\mu$ as interaction with a bridge link between two almost separated components becomes less effective in this case.
6 Discussion

The present paper set out to study the emergence of local cultures. To do so, it focused on the first stage of the process where agents need to obtain consensus on acceptable business practice. Within a bounded-confidence model of opinion dynamics, we added a feedback mechanism between a agent’s behaviour and the evolving agent network. The effect of this mechanism depends on the value of the interaction threshold $\varepsilon$. In comparison with the baseline model (Deffuant et al., 2000), our feedback increased the likelihood of consensus for narrow-minded agents (small $\varepsilon$) as the group effect may foster a coalescence of otherwise separated components. For open-minded agents (large $\varepsilon$), the likelihood of consensus decreased because the group effect worked to speed up convergence as compared to the baseline case. In some instances, this convergence was too fast for all agents to reach consensus. However, this constellation still had a substantial proportion of component agents finding consensus (the maximum component size was almost as large as in the baseline case). The fact that all component agents want to maintain their networks thus leads to behavioural constraints that may impede full consensus for very open-minded agents but increases it for narrow-minded ones. As local cultures can also emerge within a sub-population, the aforementioned results suggest that the desire to maintain interaction networks has a positive effect on the emergence of (full or partial) consensus, which would then form the basis of a local culture.

A next step in advancing the model would consist in a benchmark against data. Unfortunately, the key model parameters (especially open-mindedness of agents) are very difficult to operationalise and thereby measure. As a result, any data investigation would probably have to rely
on qualitative, case-study evidence investigating how component agents choose to interact with each other and whether a concern for one’s past partners does exist. Such findings would give an inclination of whether the mechanisms proxied in the model are actually at work. Beyond a data benchmark the link between open-mindedness and group effects on consensus could be investigated experimentally. Participants could be surveyed on open-mindedness and would be allocated to two groups accordingly. The experiment could then study in how far the consensus dynamics differ between both groups.

A second avenue for expanding the present paper consists in model extensions. Two aspects spring to mind. First, one could investigate the effect of heterogeneity among agents regarding their open-mindedness (ε). Recent contributions (Lorenz, 2008) suggest that heterogeneity plays a substantial role for the likelihood of consensus in the baseline model. Second, one could introduce non-empty initial networks (in-groups) to proxy that entrepreneurs in components often have an initial set of acquaintances from living in the area or studying in the same university. Given the contrasting effect of groups on consensus, it would be interesting to investigate in how far non-empty initial in-groups affect it. In a more general theoretic context, it would pay to apply this model to the emergence of norms and conventions in general. Given the more expansive body of research in this field, opportunities for benchmarking the model’s results against other existing studies will probably arise. It would be particularly interesting to see whether our counterintuitive result on group-effects and consensus is applicable to other constellations.

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