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Divide and Conquer?
Decentralisation, Co-ordination and Cluster Survival

By

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Abstract:
This paper develops a simulation model of the behaviour of clusters in the face of bifurcation events in their environment. Bifurcations are understood as the regional equivalent to Schumpeterian creative destruction. The model investigates the role of decentralisation and co-ordination for the likelihood of successful adaptation by comparing adaptive performance of clusters exhibiting different degrees of decentralisation and alternative modes of co-ordination. Using Kauffman's (1993) N/K model, it is found that there is an optimum degree of decentralisation with respect to cluster adaptability while different co-ordination mechanisms face a trade-off between speed and cluster-level optimality of results. In doing so, the model sheds light on an empirical controversy regarding the role of both factors for adaptation that has emerged between the Silicon Valley – Boston 128 comparison on the one and the Italian Industrial District experience on the other hand. Moreover, the identification of the roles played by decentralisation and co-ordination for cluster adaptability in changing environments could serve as guidance for future empirical research as well as policy initiatives.

Key words: Clusters, Bifurcations. N/K model

JEL Codes: R11, R12

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All remaining errors and deficiencies are mine.

1. Why? The case for cluster dynamics

The phenomenon of non-random spatial concentrations of firms in one or few related sectors that are usually referred to as 'clusters' has become a hot topic in both economic theory and policy. Based on ideas first advanced in Alfred Marshall's 'Principles of Economics' (1890), the existence of clusters is justified by permanent advantages accruing to co-located firms. The latter stem from agglomeration economies, which state that the co-location of many firms in an area improves – due to the joint conduct of complementary and competing activities – the local input and labour markets as well as the opportunities for inter-firm observation, collaboration and learning. Put differently, agglomeration economies create an interdependence between (the success of) cluster firm activities. As a result, they lead to a greater spatial embeddedness of agents: If being local is key to obtaining access to the benefits resulting from agglomeration economies, agents will be less willing to leave the area than they would be according to mere cost or other economic considerations (Robert-Nicoud, 2004; Holmes, 1999). It is this generation of spatial inertia that has lead to the proliferation of clusters in theory and especially policy. In some instances, they are even viewed as an opposing force to globalisation, helping regions create or retain economic prosperity.[1]

What is often forgotten in the euphoria about the benefits of successful clusters to their host region is the fact that areas facing severe structural problems today (such as the old industrial centres of the Ruhr in Germany or Detroit in the US) were thriving clusters in the heyday of their industries. However, as the technological evolution progressed, agents in these clusters proved unable to adapt and were rendered obsolete. Put differently, "*what once was a leading centre of dynamism within a given line of business [can end] up as an 'old industrial region', facing great problems of renewal and finding itself out-competed by firms located elsewhere*" (Malmberg and Maskell, 2002, p. 432). This exhaustion of clusters is often brought about by bifurcation events (Maskell and Kebir, 2004), which could be viewed as instances of Schumpeterian *creative destruction* at the level of entire regions. Bifurcations include changes in technology, the nature of market demand or host-country legislation that reduce the competitiveness of the way production is carried out in the cluster to an extent[2] that implies a

[1] For case studies of clusters see Brusco, 1982, Brusco, 1986, Brusco and Righi, 1989; Dei Ottati, 1994; Goodman, *et al.*, 1989; Lazerson, 1990, Saxenian, 1991 and Staber, 1996. Uneven spatial distributions of industries at the national level are reported by Ellison and Glaeser, 1994, 1997 and 1999, Krugman, 1991 or Maggioni, 2002. A dynamic perspective on the development of a given industry's spatial distribution is adopted by Audretsch and Cooke, 2001; Bresnahan, *et al.*, 2001; Gertler, 1996; Mathias, 1983 or Rosenberg, 2002.

[2] This loss of competitiveness can occur relatively to firms in newly emerging sectors (Davelaar and Nijkamp, 1990) or with respect to non-local competitors within the industry (Klepper, 1996).

need for cluster agents to adapt to the new situation or leave the market. Bifurcations thus constitute events where current practice in the cluster has to change significantly to allow for its survival. As a result, there are many different possible development paths following them: Clusters can exhibit different levels of success in adapting or the bifurcation can constitute the starting point of a road to industrial decline. This intuition is also confirmed empirically where the response of clusters to bifurcations has differed: In some regions, a local industry survived or even prospered after events that lead to its decline in other areas.[3] In other words, there is no such thing as a deterministic life cycle for clusters leading from emergence to decline. Instead, at least in some cases, adaptation to bifurcations is possible.

Against the background of the problems found in the many old industrial areas worldwide, a central issue therefore lies with the question of whether and when agents in clusters can adapt to bifurcations in their environment and thereby avoid decline. In this context, the very advantages of the cluster (agglomeration economies) can turn into liabilities: Their existence means that changes in activity by individual actors impact on the outcome of activities by others, i.e. individual changes in strategy can produce unexpected aggregate effects. At the same time, the cluster as the repository of these externalities has no formal authority over the decisions of local agents. In a way, the adaptation of a cluster to bifurcations could therefore be understood as a special case of decentralised problem solving (by local actors) under externalities: Agents need to change their activities to recapture their stance in the competitive environment. In part, the success of cluster adaptation hinges on the quality of these individual responses. At the same time, agglomeration externalities imply that the effectiveness of agents' adjustments also depends on the (effects of) others' actions. An interesting question in the latter context regards, whether there are any aspects at the cluster level that align individual activities with better collective outcomes than others. In analogy to the theory of the firm, one might ask if there are features at the cluster level that act as a version of *dynamic capabilities* (Teece*, et al.*, 1997), favouring cluster adaptiveness by steering individual activities towards good collective outcomes.

The question of how agents in clusters characterised by agglomeration externalities can adapt to bifurcation events in their environment has so far only played a minor role in much of the

[3] For case studies of decline see Grabher, 1993, Isaksen, 2003; Meyer-Stamer, 1998, Saxenian, 1994 and Schamp, 2000. Successful renewal has been observed by Braunerhjelm*, et al.*, 2000; Bresnahan and Malerba, 1999; Cooke, 1997; Gertler, 1996 and Lee*, et al.*, 2000.

theoretical and empirical literature.[4] Whenever cluster adaptation has been investigated, no conclusive results were obtained. First, the intuition regarding the causality between different cluster-level factors and adaptiveness is usually left relatively implicit.[5] Second, much of the existing literature lies with contextual case study evidence, which does not readily lend itself to generalisation. In this empirical literature, furthermore, two opposing trends regarding the role of two cluster-level factors (decentralisation and co-ordination) for adaptation can be found. On the one hand, the comparison of the response of Silicon Valley and Boston 128 to the change arising from the introduction of the microcomputer (Saxenian, 1994), argues that the networks of independent firms in the former out-performed the large integrated enterprises of the latter. As such, it would seem that decentralised clusters with independent, small and medium sized firms have flexibility advantages in adaptation. On the other hand, research on Italian Industrial Districts (Cainelli and Zoboli, 2004; Lombardi, 2003) shows a development from such networks of independent producers towards more hierarchical structures (emergence of dominant firms or formation of business groups) as the environment changes. This phenomenon is often justified by the notion that having exclusively small firms in an area can hamper adaptability due to the need to co-ordinate and convince a critical mass of agents (Brusco, 1986). As such, the Italian case indicates, that clusters of small and medium sized enterprises might fare better in coping with change when they move towards more authoritarian decision-making structures.

This paper addresses the question of the role of the division of labour and inter firm co-ordination for the success of cluster adaptation and survival through a general theoretic model. It starts by linking existing theoretical and empirical insights to an understanding of clusters as complex systems composed of several agents conducting interdependent activities within the local value chain (section 2). Using Kauffman's (1993) N/K model, simulations of the adaptive performance of ideal-typical clusters characterised by different degrees of division of labour (large versus small firms) as well as different co-ordination mechanisms (individualism, collectivism, alliances and dominant firms) are conducted. It is found that the mode of co-ordination matters for cluster adaptiveness, especially as the degree of inter-agent

[4] "*The hallmark of successful industrial districts is change and innovation, not stability and rigidity*" (Staber, 1996, p. 308), or: "*Many of the available cluster studies in the literature have been focused on more static descriptions of their characteristics at a given point in time, although flavoured with evidence of some of the main features of their history.*" (Dalum, *et al.*, 2002, p. 2). Of course, there are exceptions from this rule (see Sturgeon, 2000 or Rowen, 2000).

[5] For instance, internationalisation of cluster firms is often mentioned as a helpful aspect in adaptation with different (mainly implicit) underlying rationales: Internationalisation can help firms observe very different practices than the locally dominant ones or it can serve as a means of reducing institutional inertia in the area (Ratti, *et al.*, 1997).

interdependence resulting from agglomeration externalities increases (as would be the case with a growing division of labour). Best performance in terms of outcome and stability of adaptive processes is obtained by 'collective' clusters composed of firms adapting for the sake of the cluster as a whole, while the 'individualistic' case (agents only adapting for their own competitiveness) performs worst. Alliance and leader firm modes of co-ordination deliver intermediate results. Their relative performance depends on the extent to which they account for actual externalities between agents. Alliance scenarios internalise a greater share of externalities than leader firm ones and thus initially out-perform them. With very strong degrees of interdependence in the cluster, the additional stability generated by having a dominant firm in the cluster however comes to offset this aspect, i.e. clusters with well connected dominant agents outperform those exhibiting alliance structures (section 3). Overall, the research indicates that there is an advantage for Silicon Valley types of clusters over more integrated ones provided interdependencies between agents are not too extreme. A move away from very collective decision-making mechanisms in favour of alliance or authority structures – as evidenced in the Italian case – leads to a reduction of adaptive performance. However, such a shift can be justified by a better results at the level of agent groups. Moreover, business or authority structures can be a good intermediate solution if the 'collective' co-ordination mechanism cannot be enforced (thanks to a prisoner's dilemma payoff structure with respect to individualistic versus collectively oriented agents). These intermediate structures can help avoid a spread of egoistic behaviour in a formerly collective cluster and thereby increase adaptive performance as compared to individualistic clusters (section 4).

2. How? The model

The very nature of clusters as entities composed of firms and other local organisations whose activities are linked by agglomeration externalities implies a relatively straightforward role for the degree of decentralisation and the mode of co-ordination in their adaptation. Due to agglomeration economies, the success of individual firm activities hinges on the measures adopted by others. As a result, the likelihood of successful cluster adaptation depends on the degree of inter-agent interdependence. The latter is linked to the division of labour in the cluster: The smaller the number of activities performed by each individual firm, the greater its dependence on others will tend to be. With a growing dependence on others, the importance of co-ordination between agents increases as well. Co-ordination can then be achieved in two ways: Through 'voluntary' behavioural restraints exerted by independent agents or by differing distributions of authority between cluster firms. In both contexts, co-ordination aims at *internalising* the effects of cross-agent externalities into individual decisions. As can be expected, the effectiveness of any co-ordination mechanism will therefore depend on the extent to which it captures cross-agent interdependencies, i.e. the extent to which agents actually depending on one another are co-ordinating their activities.

A formal model analysing the roles of the division of labour and co-ordination for cluster adaptiveness has to meet a number of requirements. First, it must link activities controlled by different agents, the interdependencies caused by agglomeration externalities and the resulting collective outcomes at the cluster level with some measure of success for different cluster configurations. Second, the model would have to include the *creative destruction* brought upon the cluster by bifurcation events in its environment. Third, an investigation of the roles of division of labour and co-ordination requires that the model be able to mimic different degrees of decentralisation (increasing interdependence of agents) as well as different co-ordination mechanisms (diverging goals of agent activity). If all these aspects are included, the role of both factors for cluster survival can be investigated by comparing the adaptive performance of different cluster types.

The N/K model (Kauffman, 1993) constitutes an analytical tool able to meet the requirements. Originally developed to describe the evolution of a population of genes, the model can be extended to a variety of complex, interdependent systems[6] since it describes the latter in very general terms by two variables: The number of system elements (N) and the degree of interdependence between them (K/ C). Each of the N elements can take on a discrete number of states (A_n). A frequent case is A_n=2, i.e. the N elements have two values (usually [0; 1]). This yields a possibility space of 2^N system configurations.[7] Depending on the environmental conditions of the system, each state of an element then contributes to the *fitness* (the likelihood of survival) of the system (Kauffman, 1993, p. 33). In other words, each element state (e.g. n_1=0 and n_1=1) has a fitness value w_{na}, which is drawn randomly from a uniform distribution between 0 and 1 (e.g. w_{10}=w(n_1=0)=0.4 and w_{11}=w(n_1=1)=0.3).[8] The fitness of the entire system configuration (W(s)) is then determined as the mean value of the fitness

[6] For a discussion on the link between clusters and complex system theory see Wolter, 2005.
[7] As an example, in a system consisting of N=3 elements with A_n=2=[0;1], one configuration is {1,1,0}.
[8] The environmental conditions determine the value of a specific element's state for the fitness of the system. For instance, if the system described by N and K is the genome of a plant, one element N could be an allele enabling survival with relatively little water. This capability would contribute more to the fitness of the system 'plant' in an environment where water is relatively scarce.

contributions of the different element states.[9] This formulation allows for a mapping of all possible system configurations and their fitness in *fitness landscapes* (Wright, 1931).

The shape of these fitness landscapes then depends on two factors: The randomly drawn fitness values for element states (w_{na}) and the degree to which interdependencies between elements exist. The nature of these interdependencies in turn differs according to the kind of system analysed. In the case of *co-evolving systems* where elements are controlled by several agents, interdependence can occur at the level of the agent or between agents. The first aspect – intra-agent interdependencies – reflects the phenomenon that activities might be interrelated at the level of the firm. For example, strategy choices in research, production and marketing are interdependent in the sense that firms need to align them to produce good results. If the system to described consists of one entity controlling all system elements (e.g. a firm controlling all aspects of its strategy Rivkin, 2000 or innovations Fleming and Sorensen, 2001; Frenken, 2001), all interdependencies are of the intra-agent nature measured by the parameter K. The second aspect, inter-agent interdependence is a characteristic of systems where several agents control different system elements. They are measured by a third parameter, C. In both cases, the values of K and C indicate the average number of other elements influencing the fitness value of any system element. Put differently, if K=3, the fitness of each system element (on average) depends on the states of three other elements within the control of the same agent. If C=3, the fitness of each system element depends on three other elements that are controlled by other agents. The distribution of both types of interdependencies can however be uneven in the sense that some elements may be more 'central' in the system (exhibit higher levels of interdependence) than others.[10]

The N/K model can thus link individual activities (choices of state for the elements controlled) by different agents that control a subset of the entire system with the interdependencies attributable to agglomeration externalities (C). By deriving a system configuration from the first and taking the effects of the second into account, the success of

[9] Depending on the nature of the system, this assumption may not be realistic (Frenken and Nuvolari, 2003).

[10] A greater interdependency between system elements changes the appearance of the fitness landscape by increasing the difference in fitness values of relatively similar system configurations. If K(or C)=0, the fitness value of all elements only depends on their respective state. As a result, two system configurations differing by one element state only would have relatively similar fitness values (differing by the difference in fitness of that elements two states). If K>0, the fitness value of any element's state in the system is affected by the states of other elements and vice versa, i.e. each element has A^{K+1} different fitness contributions for different combinations of element states (Kauffman, 1993, p. 239). As a result, system configurations differing by the state of one element may differ substantially in fitness if that element has a lot of repercussions on the fitness of other element states.

different cluster configurations can be measured in terms of their respective fitness. A bifurcation, i.e. a drastic change in the environment is represented by a reshuffle of the entire fitness landscape altering the fitness contribution of all elements while leaving the structure of interdependencies intact (Levinthal, 1997; 2000).

Cluster adaptation to bifurcations involves having agents change the system configuration by modifying the states of the elements under their control. Combined with the interdependence effects resulting from K and C, this leads to different fitness values for the system. The adaptive performance of clusters can thus be measured in two ways. One involves the level of fitness obtained through agent's adaptation effort. Another regards the fluctuation in cluster (system) fitness: Since clusters compete in a wider environment, very drastic falls in fitness would affect their likelihood of survival. Put differently, the gains from a higher fitness value obtained throughout the adaptation process might be offset by the losses incurred if fitness fluctuates (falls) substantially during that time. How agents change the states of the elements under their control alongside the interdependencies captured by K/ C thus shapes the dynamics of clusters when the latter are understood as systems in the N/K(C) sense. It is in these two aspects, that the division of labour and inter-agent co-ordination mechanisms can be modelled. Previous literature on N/K systems has found that their dynamics hinge on a trinity of factors: S^3 or s*tructure, search, selection*. These parameters can be altered as to reflect different extents of decentralisation and modes of co-ordination.

The notion of *structure* refers to the shape of the system's fitness landscape, i.e. the values of N, K and C. As has been found elsewhere, more complex systems fare worse in adaptation because "*in functioning complex systems with many highly differentiated and tightly interdependent parts, it is highly unlikely that undirected change in a single part will have beneficial effects on the system*" (Nelson and Winter, 1982, p. 116). In such systems, changes in individual elements that constitute an improvement for the latter's fitness are increasingly likely to have adverse effects on the fitness of (more) other elements and are thereby more likely to decrease system fitness. It has been shown that very complex systems exhibit fitness landscapes with more (local) optima, with decreasing average fitness.[11] Very interdependent

[11] As landscape complexity increases, average system fitness approaches the expected mean value of 0.5, regardless of system dynamics (the so-called 'complexity catastrophe', Kauffman, 1993, pp. 72-73). The fitness value of individual optima can however increase compared to less complex systems thanks to the increased number of random draws for 'conditional' element fitness values.

clusters (high values of K and C) will hence fare worse in adapting to bifurcations both in terms of average fitness as well as fitness fluctuations.[12]

Hypothesis 1. *The higher system interdependence (K/ C), the lower average system fitness and the higher its standard deviation.*

The complexity of systems in the case of clusters is a result of the degree of decentralisation in them. As has been outlined before, interdependency in clusters encompasses intra- (K) and inter-agent externalities (C). The latter are a direct consequence of the degree of division of labour or decentralisation. The smaller the range of activities conducted by individual firms, i.e. the smaller the number of elements controlled by an agent, the greater the number of C externalities for any given degree of element interdependence. In a way, a stronger decentralisation would therefore be associated with higher C values. In direct comparison, it is thus argued that very decentralised clusters perform worse than more centralised ones due to the overwhelming problems associated with optimising a system characterised by very high C externalities. Put differently, if the division of labour comes to be too extreme, being in Route 128 is preferable. At intermediate stages (medium C values), however, more decentralised clusters might outperform more centralised ones since the smaller range of elements controlled by an agent (n) in decentralised clusters is faster and easier to optimise (2^n possible combinations) than the greater number associated with large, integrated firms. In that case, Silicon Valley is the better bet.[13]

Search regards the number of element altered by agents at a time. This number can vary between one (local search), several and all elements under the agent's control (long-jump search). The nature of the search process is important for the number of 'local optima' of the system, i.e. the number of configurations that are not optimal in the entire fitness landscape but constitute the best attainable alternative given the search path chosen. If search processes only allow for a limited number of elements to be modified, they can be path dependent and

[12] On the role of landscape complexity for adaptation in the case of firms see Ethiraj and Levinthal, 2004; Levinthal, 1997, 2000 or Merry, 1999.

[13] To date, the model tests only indirectly for this aspect. Simulations were run for increasingly interdependent fitness landscapes, i.e. increasing C values with identical numbers of elements per agent. In a way, less interdependent systems thereby give an idea of the dynamics of more integrated clusters while increasing fitness landscape complexity points at greater decentralisation. Already, average system fitness values (see following section) hint at an optimum intermediate degree of complexity, i.e. there are limits to the benefits conveyed by decentralisation. Future research (see concluding section) will investigate this aspect more closely when simulating adaptive performance of systems with identical co-ordination mechanisms yet different numbers of elements per agent (different extents of decentralisation).

may lead to lock in to local optima. This aspect is stronger, the lower the number of elements modified. The search strategy most susceptible to lock-in phenomena is local search modifying one element at a time. Especially in very complex landscapes (K+C approaching N), this search strategy quickly leads to lock-in since the number of local optima increases with landscape complexity.

Selection in turn means the criteria that have to be met for a modification to be considered successful, i.e. it reflects different goals underlying agent activity. In the N/K model, fitness acts as the selection criterion: Modifications of system element states are only retained, if they improve fitness.[14] However, in systems with multiple agents engaging in decentralised search activity over the subset of the system they control, the level of fitness to be improved by search strategies can differ. For instance, agents could gear their search activity at the improvement of overall system fitness, i.e. "*action would be 'local', while thinking would be 'global'* " (Dosi, *et al.*, 2003, p. 421). As a result, element modifications within the agent's scope of control would only be accepted if they improved system fitness as a whole. The role of such different selection mechanisms (incentives) in adaptation has been found to exhibit a trade-off between optimality of solutions from a system perspective (higher for more system-oriented selection) and the speed of fitness improvement (higher for more agent-oriented selection).[15] The model introduced here investigates adaptive performance for four different selection criteria, which reflect different agent goals underlying their adaptive moves

- *Individualism*: Agents seek to maximise their own fitness, i.e. that of the elements under their control,
- *Collectivism*: Agents want to maximise the fitness of the entire system,
- *Alliance*: Agents seek to maximise the joint fitness of themselves and their partner,
- *Dominant (leader) firm*: Agents aim at maximising their own and the dominant firm's fitness while the latter behaves individualistically.

[14] The notion of immediate fitness improvements through undirected search might not be as relevant for social N/K systems as compared to biological ones. For instance, one could argue that agents in social N/K systems engage in search and modification activity with a more long-term perspective, i.e. short term fitness losses would be accepted for sake of a long-term better search outcome ('deeper' search; Hovhannisian and Valente, 2004) or agents could use past experience to guide their future search ('memory dependent' search; Hovhannisian, 2004). At the same time, it is possible that agents refrain from improving certain system parts for the sake of optimising others ('satisficing'; Frenken, *et al.*, 1999) or seek pareto-optimal solutions by improving the mean fitness of all elements without decreasing that of any individual one (Frenken and Valente, 2003).

[15] This tradeoff is highlighted in the study of organisational change within the N/K framework (see Dosi, *et al.*, 2003; Dosi and Marengo, 2003; Marengo, *et al.*, 2000 or Rivkin and Siggelkow, 2003).

The origin of these different selection mechanisms could be justified by different forms of co-ordination in the cluster. In the existing literature, the mode of co-ordination is a consequence of the local institutional infrastructure, the so-called *local culture*. Here, some local cultures are assumed to be geared towards generating a very collective mindset whereas others might lead to more individualistic orientations. If power in the cluster is furthermore distributed unevenly between agents, alliance or dominant firm scenarios can materialise. Please note that the model does not describe specific institutional setups within the local culture, but only their overall result with respect to what agents in a cluster care for. There are many possible ways of ensuring that actors adapt for sake of themselves or the cluster as a whole: Collectivism might result from a general lack of egoism, strong community and family ties in the cluster as well as a significant threat of being shunned or sued by other cluster agents when behaving egoistically (Holländer, 1990).

The effect of selection (or co-ordination) for cluster adaptability will depend on three aspects: The existence of inter-agent externalities, the extent to which co-ordination accounts for them as well as the overall structure of the fitness landscape. The first point refers to the fact that selection criteria enabling some sort of co-ordination between agents will only become relevant if the latter's fitness is interdependent, i.e. if there are C externalities between actors. If such cross-agent interdependencies exist, agents co-ordinating their activities fare better than those acting egoistically, especially as the role of C externalities increases.

Hypothesis 2. *The performance of different co-ordination mechanism will differ more strongly as the role of cross-agent externalities (C) increases.*

In the presence of cross-agent externalities, the quality (performance) of any co-ordination mechanism crucially depends on the extent to which it captures the latter, i.e. whether or not the 'right' agents are co-ordinating their activities. Put differently, system performance will increase, the greater the share of C externalities captured by the co-ordination mechanism.

Hypothesis 3. *The greater the internalisation of C externalities through the co-ordination mechanism, the higher system fitness.*

Third, as fitness landscape complexity increases, the adaptation problems in highly interdependent systems (see *structure*) materialise. As a result, the internalisation of C externalities by different co-ordination mechanism might matter less for system fitness. In highly interdependent systems, partners aiming at increasing the fitness of a bigger part of the system might engage in an ongoing 'dance' where actions by one change the fitness of the other, provoking adaptation by another agent and so on. This leads to major fluctuations in cluster fitness. Co-ordination mechanisms 'ignoring' some C externalities might perform better thanks to a greater stability: Agents aiming at improving a smaller part of highly interdependent systems would lock-into a local optima more quickly as fitness landscape complexity increases. The additional stability offered by this phenomenon might come to offset the sub-optimality of system fitness resulting from an ignorance of C externalities.

3. What? Results and discussion

All simulations were run using the LSD (Laboratory of Simulation Development) platform[16] for systems (clusters) containing N=24 elements with increasing levels of fitness landscape interdependency, i.e. increasing values of the corresponding LSD parameter (EvenK). In order to avoid effects of one-off 'lucky' adaptations, 100 simulations with new fitness landscapes were conducted for each parameter. This corresponds to a cluster adapting to 100 bifurcation events. The simulations were run for a duration of 600 steps following the event. Average fitness values and standard deviations were gathered both at the system, i.e. cluster and at the (firm) group level for each simulation.

Four different types of clusters compete for the best result in adaptation (figure 1).[17] They exhibit the same division of labour with four groups. Within each group, five agents control n=6 out of 24 elements. All agents search the fitness landscape by altering the states the elements under their control with a probability of 0.5.[18] They then test the fitness and (possibly) select the new configuration according to different criteria. The evaluation of the new configuration is done according to its *expected* fitness, i.e. holding the states of the

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[16] LSD is a freely available shareware programme allowing simulations even with limited computer experience. I am heavily indebted to Marco Valente for his guidance and support in developing the model. Interested users can find the programme online: http://www.business.aau.dk/~mv/Lsd/lsd.html. The downloadable package features code, user manual and a variety of example models (including N/K ones). All results and code of the model used here are available from the author.

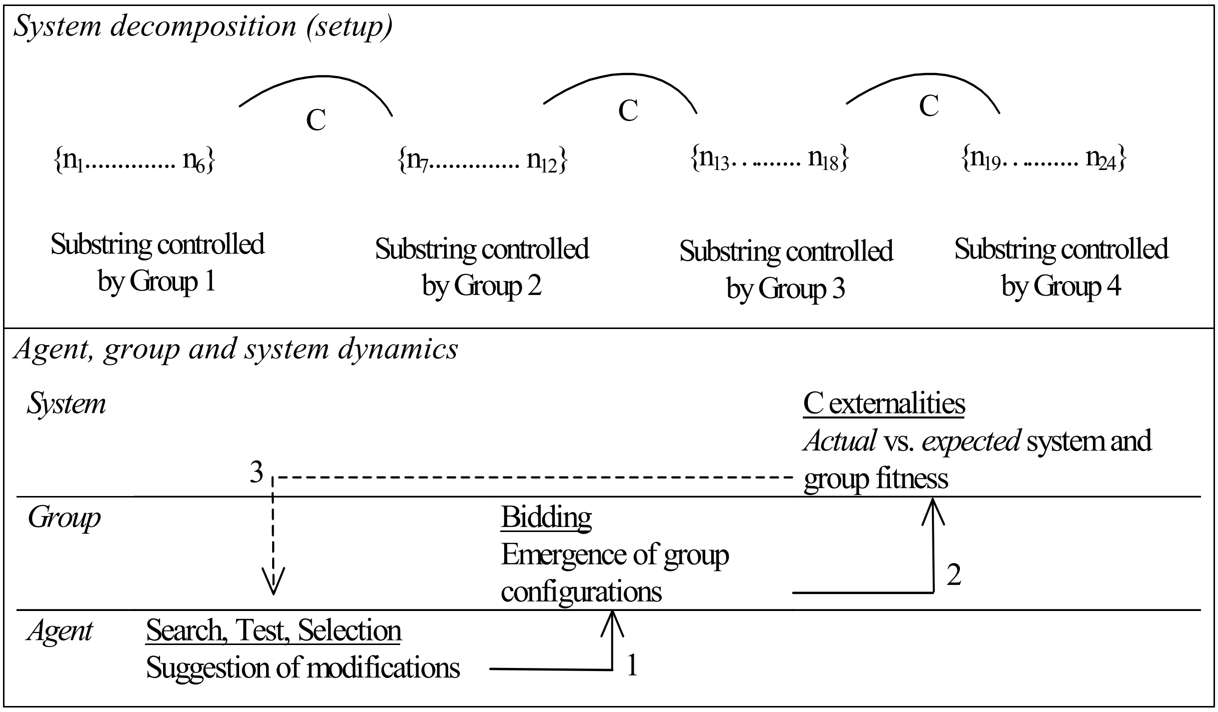
[17] In total, simulations were run four nine different clusters out of which types 3-5 represent different alliance constellations regarding the groups involved while types 6-9 reflect different positions of the leader firm (in groups 1-4). See also appendix 1. For a better overview, only the results for the best performing alliance and leader firm scenario are presented here. Full results can be obtained in appendix 2.

[18] On average, agents thereby change three out of their six elements while occasional local and long-jump search steps are possible as well. This search mechanism reduces the extent of path dependence as compared to local search alone.

elements outside an agent's control constant. In a sense, agent search and selection activity is thereby *myopic* as it selects strategies that would work well in the current context. Two aspects about clusters speak in favour of this perspective.

The first regards the notion of bounded rationality of cluster agents with respect to the exact mechanisms underlying agglomeration externalities. In other words, firms might not know that their good innovative performance partly relies on knowledge spillovers provided by competitors. Second, even if actors do know that they depend on the activities of others, it is unlikely that any individual agent can determine the exact extent of his or her individual contribution to agglomeration externalities. For instance, an individual firm cannot foresee how an increase or decrease in its labour training activity will affect the pooled labour market in the cluster. This uncertainty is due to the fact the outcome of agent activities for the nature and extent of agglomeration externalities also depends on the strategies chosen by other actors in the cluster. It would be impossible for any individual agent to be fully informed about the plans and future strategy choices of everyone else. Selecting a strategy that will work well in the current context is therefore any actor's best bet. This of course implies that individual activities may miss their goals or lead to entirely unanticipated aggregate effects.

Figure 1: The model in schematic representation

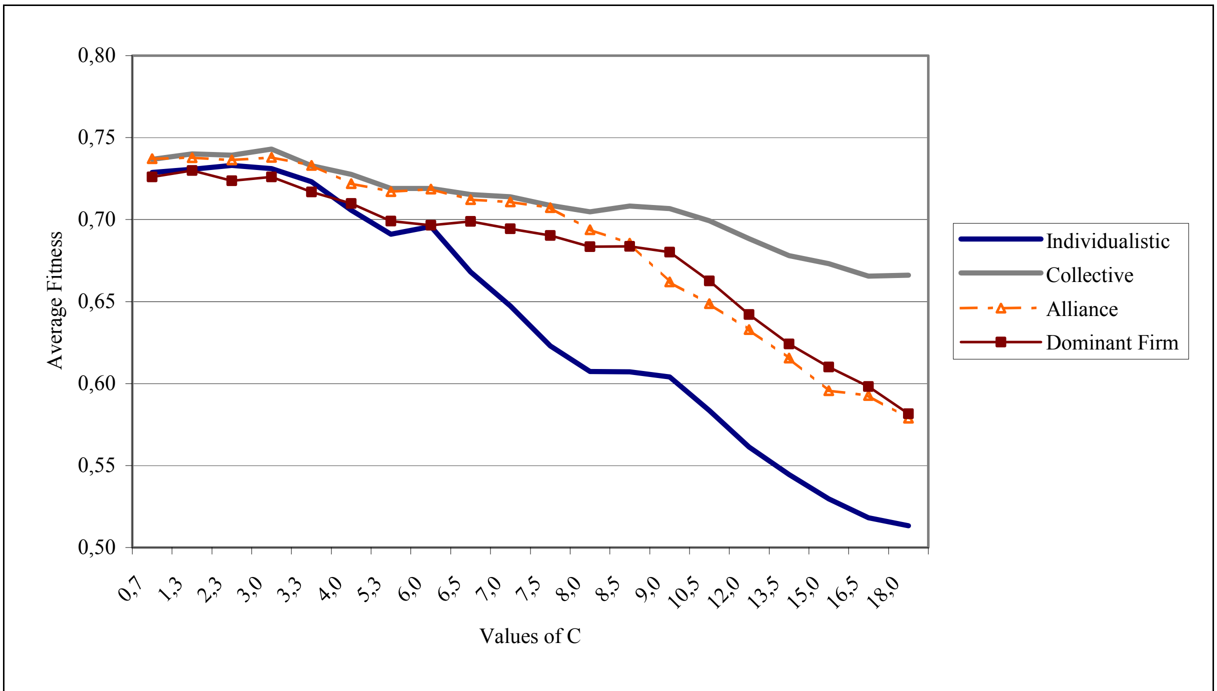


Agents then engage in a bidding process at the group level to be selected as the new configuration representing their group at the system level. For each group, the agent with the best configuration regarding *expected* fitness of the entire cluster is selected, once again ‘assuming’ that agents in other groups do not change their activities. This bidding process could be argued to represent the learning from observation that is prominent at the horizontal level of clusters, i.e. within each agent group (Maskell, 2001). A strong learning from observation would lead to a selection and imitation of best practice in each agent group. In the case of clusters where the success of firm activities is furthermore dependent on those of others, such best practice would correspond to strategies that work well in the context of other agent (group) activities. To approximate this aspect, the bidding process is based on the highest expected cluster fitness rather than individual agent or agent group fitness. While this may not necessarily lead to an immediate maximisation of agent (group) fitness when the latter is viewed in isolation, inter-agent interdependence makes adopting activities that work well within a given context of actions by others the most viable strategy for any cluster firm. The outcome of the bidding process is a new cluster configuration, which exhibits an actual fitness level that may well differ from the expected one. Agents can then engage in further search, test and selection activity in subsequent simulation steps.

The difference between the model clusters then resides with their agents *selection* process, i.e. with the fitness level that has to be improved for a modification to be considered successful (see appendix 1). Four distinct cases are modelled: Populations one and two represent clusters with an even distribution of power. In the first population, agents care only about their own fitness when selecting a strategy whereas adaptation in the second population is geared at improving cluster fitness as a whole. In the third population, agents have formed alliances between groups 1+2 and 3+4 which aim at improving joint group fitness. The last cluster type exhibits one firm (located in the first group) that has come to dominate the others, i.e. all subordinate agents seek to improve their fitness and that of the dominant firm while the latter behaves egoistically, seeking to maximise its individual fitness.

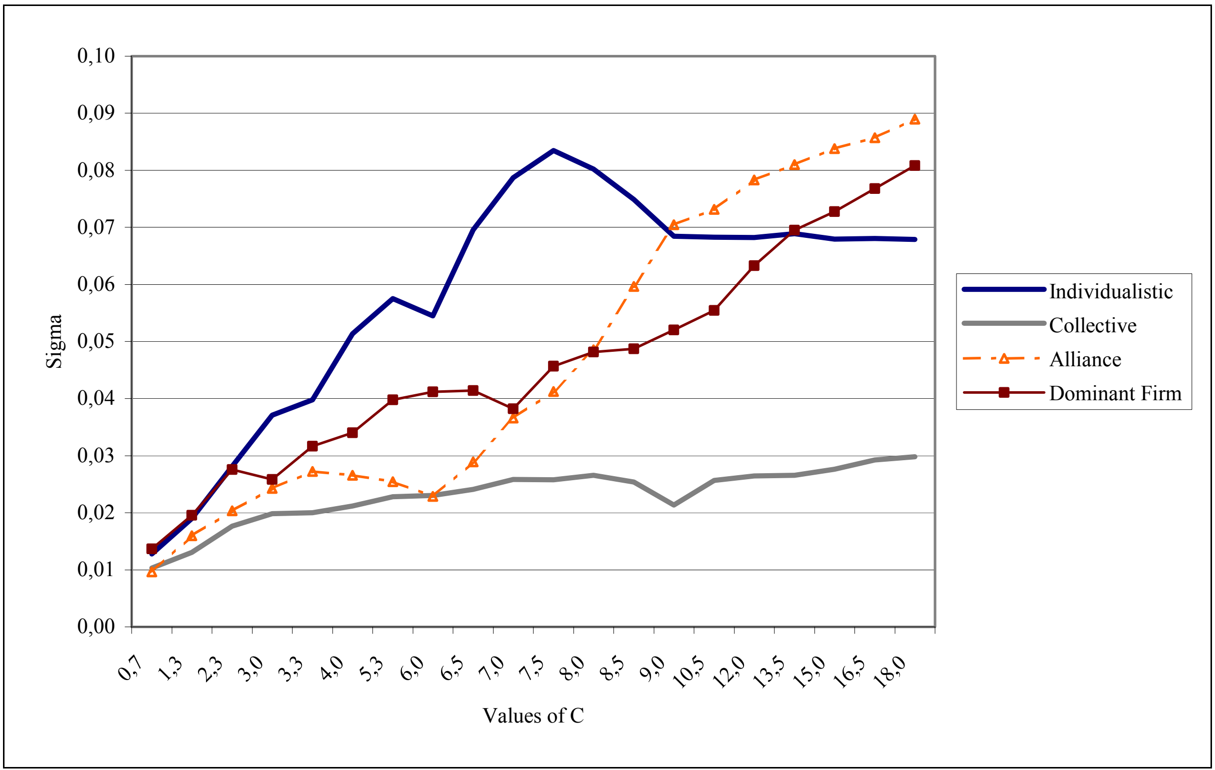
Simulation results were averaged over the 100 runs conducted for each parameter value. Comparing performance (mean fitness) and stability of adaptation (standard deviation) yielded a set of interesting results. First, evidence supporting hypothesis 1 is found: *With increasing fitness landscape complexity, the average system fitness obtained through adaptation declines and the fluctuation in system fitness increases.* This is hardly surprising considering that a greater number of interdependencies between agent activities makes it harder to optimise (parts) of the system since changing one element has repercussions on the fitness values of many others. However, the losses of system fitness differ between the co-ordination mechanisms modelled, leading to a ‘scissor-like’ image of average system fitness (see also figure 2). For small values of C, all decision-making mechanisms perform relatively similar but beyond a critical value, a gap begins to open up with the *collective* population performing best by losing only 9.59% of its fitness value between the simplest and the most complex fitness landscape. The *individualistic* scenario performs worst and loses almost one third (29.55%) of its fitness. Both *alliance* and *leader firm* scenarios position themselves between these two extremes, losing about 20% of fitness as the complexity of the fitness landscape becomes maximal. This observation is in line with hypothesis 2: *Co-ordination begins to matter as the role of cross-agent externalities increases.*

Figure 2: Fitness landscape complexity (increasing values of C) and average system fitness



Throughout all simulations, the collective cluster performed best both in terms of maximising average fitness as well as minimising system-wide fitness fluctuations (figures 2 and 3). The individualistic cluster in turn began faring worst once the importance of inter-agent externalities increased beyond C=4.04. An interesting phenomenon regards the relative performance of alliance versus dominant firm clusters: As the values of C increase, the leader firm scenario begins to perform better than the alliance one, both in terms of average fitness as well as standard deviation of system fitness.

Figure 3: Fitness landscape complexity (increasing values of C) and stability of adaptation processes



This shift in relative performance poses a puzzle since alliance clusters internalise a greater share of C externalities into agent decisions. According to hypothesis 3, they should thus out-perform dominant firm ones. However, the opposite occurs in clusters with very central dominant firms (dominant firm in the 1st to 3rd group) once C>9. This is attributable to two special constellations in the fitness landscapes. First, increases in C imply an increasing centrality of the dominant firm in group one, which begins to receive and generate a greater share of C externalities (see also appendix 3), i.e. other groups in the cluster become more and more linked to the dominant actor by C externalities. Second, the behaviour of the leader firm stabilises with the complexity of its fitness landscape subset. As was elaborated in the previous section, search on more complex landscapes leads to a faster lock-in with local optima. As a consequence, the leader firm becomes less active in changing its configuration and thus causes less disturbance in cluster adaptation.

Both effects work to offset the initial disadvantages of leader firm clusters as compared to alliance ones. What then causes their shift in relative performance is an additional effect that can be circumscribed as *alignment of goals* in dominant firm clusters. All subordinate agent search on an n=6 landscape and evaluate their modifications based on the aggregate of their own and the dominant firm's fitness. As a consequence, they evaluate their changes on their n=6 subset and another subset consisting of the elements (n_1-n_6) controlled by the dominant firm. This second subset is identical for all subordinates, i.e. their evaluations are subject to a partial alignment of goals. In comparison, alliance clusters base their strategy evaluation on separate subsets of the fitness landscape (n_1-n_{12} for groups one and two, n_{13}-n_{24} for groups three and four), i.e. they lack an alignment of goals between alliances. This implies that the probability of finding stable configurations of the C related elements is lower for alliance clusters where agents try to optimise different yet connected subsets of the fitness landscape than for dominant firm clusters where subordinate agents try to optimise the same subset of the fitness landscape and ignore the externalities between them.

Having seen that the collective case is the best obtainable scenario from the cluster's perspective leads directly to the question of why Italian Industrial Districts are moving away from that decision-making structure. Three possible rationales exist for this phenomenon. First of all, industry structures need not be geared at optimality. Put differently, firms might have come to dominate the cluster or to form more closely knit business groups for a variety of reasons within a period of stability. If a bifurcation then hits the cluster, the latter is 'stuck' with its decision-making structure and the consequences this entails for adaptive performance. In a way, such a perspective would turn causalities around: Decision-making structures form through other influences and then have an impact on the adaptability of the cluster in the face of drastic environmental changes.

However, even within the highly idealised N/K world, some notions could be advanced in favour of group and authority constellations as compared to the collective case. Previous studies employing the N/K model to the case of organisational adaptation have noted that systems targeting their search and modification at the optimisation of the entire system are bound to take longer than systems involved with decentralised search geared at optimising system parts. This is attributable to the larger problem space of entire systems as compared to their smaller parts.[19] The model presented here to date does not check for the speed of fitness improvement. This aspect could be accounted for by reducing the number of simulation steps and comparing the ensuring results: A lower speed in finding 'good' adaptation outcomes the collective system would imply that average fitness decreases and fluctuations increase with shorter simulations.

[19] It takes longer to find an optimum in a problem space of N=24 with two possible states for each element (equalling to 2^{24} possibilities already in the absence of interaction effects) than in one of N=6 (2^6) or N=12 (2^{12}).

Table 1: Mode of co-ordination and average group fitness

	Individualistic				Collective			
C	Group 1	Group 2	Group 3	Group 4	Group 1	Group 2	Group 3	Group 4
0.67	0.74021	0.72711	0.72341	0.72405	0.75065	0.73130	0.73066	0.73480
1.30	0.73321	0.73146	0.72241	0.73605	0.74574	0.73890	0.72549	0.74982
2.33	0.75869	0.73424	0.71778	0.72164	0.75424	0.73891	0.73037	0.73332
3.00	0.72625	0.70140	0.72601	0.77043	0.74098	0.72820	0.73268	0.77036
3.33	0.74243	0.71363	0.69287	0.74319	0.74657	0.72040	0.73156	0.73269
4.33	0.70960	0.69163	0.71242	0.70906	0.73351	0.72922	0.70919	0.73804
5.33	0.69894	0.68292	0.69303	0.68972	0.72490	0.71338	0.71393	0.72402
6.00	0.69998	0.69914	0.69194	0.69213	0.72029	0.71858	0.71866	0.71856
6.50	0.66022	0.65744	0.67323	0.68141	0.70661	0.71302	0.72017	0.72162
7.00	0.62246	0.62575	0.65667	0.68476	0.70552	0.70590	0.72192	0.72221
7.50	0.59270	0.59284	0.63012	0.67618	0.68916	0.69571	0.70496	0.74488
8.00	0.57094	0.57144	0.60452	0.68277	0.69103	0.69169	0.70492	0.73155
8.50	0.56044	0.55942	0.58263	0.72636	0.67396	0.68799	0.71015	0.76077
9.00	0.54747	0.54743	0.54709	0.77426	0.69037	0.68189	0.68045	0.77428
10.50	0.53904	0.53950	0.53913	0.71673	0.68574	0.68600	0.67746	0.74776
12.00	0.52996	0.53037	0.53060	0.65417	0.66943	0.68094	0.67271	0.73022
13.50	0.52528	0.52425	0.52458	0.60428	0.66407	0.67500	0.67105	0.70176
15.00	0.51791	0.51807	0.51898	0.56390	0.67794	0.67685	0.66932	0.66838
16.50	0.51502	0.51510	0.51583	0.52647	0.67042	0.65476	0.66795	0.66912
18.00	0.51343	0.51367	0.51355	0.51269	0.66550	0.67176	0.66407	0.66333

	Alliance (1+2, 3+4)				Leader firm (in group 1)			
C	Group 1	Group 2	Group 3	Group 4	*Group 1*	Group 2	Group 3	Group 4
0.67	0.74523	0.73523	0.73717	0.73127	*0.75557*	0.70339	0.72173	0.72380
1.30	0.74850	0.73223	0.71915	0.75068	*0.75467*	0.70688	0.72051	0.73730
2.33	0.75214	0.75074	0.70799	0.73484	*0.75244*	0.70850	0.71517	0.71828
3.00	0.71935	0.72026	0.74210	0.77035	*0.76824*	0.64808	0.70664	0.74475
3.33	0.74438	0.72758	0.71503	0.74525	*0.76341*	0.62881	0.74073	0.77076
4.33	0.72914	0.70469	0.72196	0.73191	*0.76819*	0.62604	0.73328	0.71198
5.33	0.72171	0.70427	0.72340	0.71858	*0.77092*	0.61780	0.71093	0.69709
6.00	0.71585	0.73105	0.71433	0.71308	*0.77308*	0.62873	0.69138	0.69286
6.50	0.70652	0.71297	0.70194	0.72726	*0.78513*	0.62785	0.67846	0.70398
7.00	0.70529	0.70245	0.70612	0.72924	*0.76673*	0.63273	0.65661	0.72184
7.50	0.69218	0.69300	0.71219	0.73212	*0.75930*	0.62928	0.63677	0.73612
8.00	0.66969	0.67354	0.70363	0.72809	*0.75124*	0.61840	0.62738	0.73681
8.50	0.64706	0.64790	0.68606	0.76181	*0.74617*	0.61687	0.61493	0.75696
9.00	0.62163	0.61432	0.63809	0.77426	*0.72174*	0.61286	0.61234	0.77386
10.50	0.61758	0.61934	0.62941	0.72888	*0.71422*	0.60917	0.60780	0.71955
12.00	0.60833	0.61544	0.62134	0.68629	*0.69955*	0.59995	0.59749	0.67106
13.50	0.60401	0.60286	0.60614	0.64899	*0.67929*	0.59022	0.59091	0.63615
15.00	0.58969	0.58810	0.58884	0.61568	*0.67191*	0.57849	0.58297	0.60703
16.50	0.59260	0.59398	0.59048	0.59360	*0.66405*	0.57510	0.58003	0.57332
18.00	0.58022	0.57709	0.58061	0.57754	*0.63426*	0.56735	0.56055	0.56452

Another interesting and more game-theoretic explanation of the phenomenon emerges from an investigation of the average fitness per group for each co-ordination mechanism. In this context, a shift in co-ordination mode could be explained if the collective case worked well for the cluster as a whole but not necessarily for individual firm groups: Agents in the latter would then have an incentive move away from the collective mode to one that increases their individual fitness. The results presented in table 1 however indicate that this intuition is insufficient to explain all shifts in inter-agent co-ordination. Being the leader firm increases fitness for all parameters as is apparent from the comparison of performance for group one in the collective and leader case (see italics in table 1). For some parameter values (see underlined values), certain groups also exhibit a higher fitness in the case of alliances between groups 1+2 and 3+4. However, no parameter constellation exists in which the alliance scenario performs better than the collective case for *both* partner groups. Instead, the collective case also maximises agent group fitness in most instances.

Alliance or leader firm scenarios can however be viewed as a good intermediate solution in another context. If for some reason the observation and punishment mechanisms in the cluster's local culture were insufficient to 'guarantee' a collective orientation by all cluster agents, the collective regime might be destabilised once deviants register (short-term) fitness gains in comparison to co-operating agents. It would be argued that in periods of stability, any deviation from collectivism could be discovered by its adverse effects on other agents and the cluster as a whole. The very nature of change however implies that this evaluation mechanism loses some of its accuracy. As the competitive environment changes to reduce the fitness of the cluster, individual agents could defect i.e. change their orientation and activity from collective to individualistic. To avoid punishment by other local agents, they would then ascribe the effects of their defection on other cluster agents to the change in the environment.

To test for this intuition, the simulation model was extended to include the effects of egoistic agent and group behaviour in otherwise collectively oriented clusters. Simulations were run with an increasing number of egoistic agent populations (ranging from one to three) in the cluster. When comparing average group fitness in these mixed clusters with that found for the individualistic and collective case, a strong *prisoner's dilemma* emerges. In terms of average fitness, any agent group has an incentive to act egoistically as being the only egoistic group in an otherwise collective cluster maximises fitness. At the same time, any cluster group suffers worst in terms of fitness if it is exposed to egoistic behaviour by its *neighbour* (defined as the group it was most linked to by C externalities). This fitness value is below that obtainable for the individualistic case.[20] In terms of group fitness, the following ranking therefore emerges: *Egoistic>Collective>Individualistic> Egoistic neighbour*. As a result, in the presence of any C externalities between groups, egoistic behaviour will spread in the cluster once one group starts behaving egoistically as it 'infects' its respective neighbour. One of the possible

[20] Of course, results in terms of fitness were even worse when the group was the last collectivist in the cluster.

outcomes of such a development would be a shift in cluster decision-making from the collective to the individualistic case. As the latter performs worst regarding overall system and group fitness levels, agents in the cluster might be motivated to form alliances or authority relationships, where the co-ordination mechanism is easier to maintain. This helps avoid the even deeper fall in fitness provided by a shift towards the individualistic regime and may well be more desirable from the cluster's perspective than is usually acknowledged.

4. So What? Summary and conclusion

This paper set out to investigate the role of decentralisation and co-ordination for cluster adaptiveness and survival. Modelling clusters as systems of interdependent agents and using Kauffman's N/K model to simulate their performance (fitness) in adaptation to bifurcations, several interesting results emerged. First, findings indicate that there is an optimum degree of decentralisation: Initially, system performance begins to increase with fitness landscape complexity but beyond a critical level, it starts falling rapidly. This phenomenon is caused by a trade-off between the positive effects of element interdependence on system fitness and the negative results stemming from the difficulty of optimising very interdependent systems. As a result, one would argue that a decentralised Silicon Valley type of cluster would only outperform Boston's Route 128 if decentralisation did not become too extensive.

Second, the role of co-ordination mechanisms for cluster adaptiveness was included by modelling agents with different 'goals' and comparing the results obtained throughout their adaptation both at the agent group and the system level. It was found that the impact of the co-ordination mechanism on adaptive performance increased with the role of cross-agent externalities. Regarding their relative performance, co-ordination mechanisms differed according to the degree to which they accounted for inter-agent interdependencies. The collective (full co-ordination) and individualistic (no co-ordination) cases acted as benchmark scenarios with the former performing best in terms of results and stability of the adaptation process. Intermediate forms of co-ordination involving only some cluster agents (alliance or dominant firm clusters) positioned themselves between these two extremes. Their relative performance could be explained by the extent to which they accounted for the actual cross-agent externalities existing in any given cluster. However, the relationship between 'internalisation' of C externalities and the performance of a co-ordination mechanism broke down in very interdependent clusters. Here, the dominant firm scenario began to fare better than the alliance one: While the latter allowed for better adaptation results by including a greater share of cross-agent externalities, the stability offered by a leader scenario ignoring some externalities came to outweigh its disadvantages regarding overall system performance.

While performing worse than the collective case, alliance and dominant firm scenarios can still be more attractive than the former from a couple of perspectives, thereby providing one possible explanation for the shift in Italian Industrial Districts towards both modes of co-ordination. On the one hand, the collective case performs best in adaptation from the entire cluster's perspective, but does not necessarily do so for all cluster agents. Some might fare better (in certain parameter constellations) by forming groups or by attempting to become the dominant player. On the other hand, the collective case might be an unstable one. If local institutions are insufficiently strong to guarantee a corresponding mindset of all cluster actors, the collective case can easily deteriorate into the individualistic one – thanks to a prisoner's dilemma payoff structure in agent group fitness. In order to avoid this, cluster agents might move towards alliances or dominant firms as more stable solutions guaranteeing a better adaptation to bifurcations than if every agent acts only in his or her own interest.

The model developed here addresses the existing literature in a number of ways. On the one hand, it attempts to provide a more conclusive analysis on the factors that have been argued to help adaptation in case studies by showing when decentralised clusters out-perform more centralised ones. As such, the model aims at resolving an empirical paradox by showing one possible rationale for the contrast of the Silicon Valley–Boston 128 comparison with the Italian Industrial District experience. On the other hand, the results generated by the model could serve as means of guidance for future empirical studies by highlighting causalities between decentralisation, co-ordination and cluster survival that would invite further investigation. Second, the model extends the application of Kauffman's N/K approach to a new class of social systems, which entails an important modification: Contrary to existing N/K applications, elements *outside* an agent's control can enter his evaluation and selection mechanism. Third, the research introduces a more dynamic perspective of change and adaptation into the cluster literature where this issue has so far only played a minor role.

While the model presented here generates a number of interesting results, it is not without limitations. Most of these regard its current setup and will be discussed as avenues of future research. However, two general points of note emerge. On the one hand, the model focuses on *cluster-level* factors steering individual activities towards good collective outcomes. Important aspects shaping *agent* dynamics are therefore not accounted for. Put differently, the model can show, which degree of decentralisation or which mode of co-ordination will work well for a system if its agents behave in a certain way. Issues shaping individual behaviour (e.g. organisational inertia or heterogeneity with respect to agent capabilities) are outside the analysis. Second, the intricate interdependencies between agents imply that model results are to be viewed as trends and averages rather than deterministic predictions. For instance, even if a cluster with a collective mode of co-ordination performs best in adapting (on average), other modes might get lucky in individual adaptive processes and out-perform the former. Put differently, within the 100 simulations run for each parameter, the relative performance of clusters in adaptation occasionally does not correspond to the results reported here.

The results presented so far invite a number of interesting avenues for future research. One regards an analysis of the sensitivity of the existing simulation results with respect to the number of agents. In how far do simulation results change, if the number of agents in each group increases (e.g. from 5 to 10) or decreases (e.g. from 5 to 2)? It is expected that changing the number of agents will mainly affect the stability of adaptation processes. If there are less agents in each group trying new configurations of their elements, experimentation will shift from the agent/ group to the system level. Configurations that would not win the bidding process in larger agent populations could come to be the best configuration obtainable with less agents per group. As a result, the fluctuation of system fitness will increase. Another issue regards the role of the number of agents in the dominant firm scenario. Does the stability of the dominant firm scenario disappear, if a dominant group of five agents replaces the dominant firm in current simulations? It is argued that this is not the case: The stability of the dominant firm scenario in very interdependent clusters was attributable to the effects of C and K interdependencies outlined in the previous section. Both would remain unchanged in the presence of a dominant group of agents. Instead, in line with the aforementioned intuition on the role of agent numbers, the existence of several dominant agents can be expected to decrease the fluctuations in this group's configuration, thereby exerting a further stabilising effect on the overall system. Both aspects were found to hold in subsequent simulations: While relative performance of co-ordination mechanisms remained unchanged, absolute performance increased with the number of agents. Similarly, results were robust with respect to changes in the extent of outside disturbances. Altering only part of the fitness landscape in a perturbation event did not affect the findings on the role of co-ordination and division of labour for adaptation (results not reported here).

Beyond these more immediate tests, two additional avenues for future research emerge. The most important of these concerns the search mechanism used by cluster agents. As has been advocated in much of the literature applying the N/K model to the social sciences, random mutation is not a realistic search process for agents capable of conscious and deliberate activity. An interesting case therefore regards how the model's results change if more elaborate search mechanisms are used increasing the breadth and depth of search, i.e. the number of elements modified on the one, and the long-term perspective of search on the other hand. A second aspect to be investigated more regards the role of decentralisation for cluster survival. It could be accounted for by having populations with different divisions of labour and identical co-ordination mechanisms adapt within the model. This would yield more detail on the extent to which decentralisation benefits cluster adaptiveness and under which co-ordination mechanism it does so most.

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Appendix 1: The populations

Table 2: Populations and their co-ordination mechanism

Pop.	Label	Co-ordination mechanism
1	Individualistic	Agents select strategies that improve their own fitness, i.e. agents in the first group take the fitness of elements n_1-n_6 into account when evaluating their strategy, those in group two care for n_7-n_{12}, etc.
2	Collective	Agents select strategies that improve cluster fitness as a whole, i.e. all agents take the fitness of elements n_1-n_{24} into account when evaluating their strategies.
3	Group A (1+2, 3+4)	Agents form groups and select strategies that improve group fitness, i.e. agents in the first and second group take the fitness of elements n_1-n_{12} into account, agents in groups 3 and 4 consider n_{13}-n_{24}.
4	Group B (1+3, 2+4)	Agents form groups and select strategies that improve group fitness, i.e. agents in the first and third group consider the fitness of elements n_1-n_6 and n_{13}-n_{18}, agents in groups 2 and 4 consider n_7-n_{12}/ n_{19}-n_{24}.
5	Group C (1+4, 2+3)	Agents form groups and select strategies that improve group fitness, i.e. agents in the first and fourth group consider the fitness of elements n_1-n_6 and n_{19}-n_{24}, agents in groups 2 and 3 consider n_7-n_{18}.
6	Dominant 1[21]	The cluster has a dominant agent located in the first group and all other agents try to improve that agent's fitness alongside their own, i.e. agents in groups 2-4 care for the elements n_1-n_6 alongside those under their control. The dominant firm only cares for its own fitness, i.e. elements n_1-n_6.
7	Dominant 2	The cluster has a dominant agent located in the second group and all other agents try to improve that agent's fitness alongside their own, i.e. agents in groups 1,3 and 4 care for the effects of their strategies on the fitness of elements n_7-n_{12} alongside those under their control. The dominant firm only cares for its own fitness, i.e. elements n_7-n_{12}.
8	Dominant 3	The cluster has a dominant agent located in the third group and all other agents try to improve that agent's fitness alongside their own, i.e. agents in groups 1, 2 and 4 care for the effects of their strategies on the fitness of elements n_{13}-n_{18} alongside those under their control. The dominant firm only cares for its own fitness, i.e. elements n_{13}-n_{18}.
9	Dominant 4	The cluster has a dominant agent located in the fourth group and all other agents try to improve that agent's fitness alongside their own, i.e. agents in groups 1-3 care for the effects of their strategies on the fitness of elements n_{19}-n_{24} alongside those under their control. The dominant firm only cares for its own fitness, i.e. elements n_{19}-n_{24}.

[21] In the dominant or authority scenario, the group containing the dominant firm consists out of one instead of five agents.

Appendix 2: Simulation results

Table 3: Fitness landscape complexity and average system fitness over 100 simulations

FL Complexity[22] *Pm.*	*K*	*C*	Individualistic (1)	Collective (2)	Group 1+2; 3+4 (3)	Group 1+3; 2+4 (4)	Group 1+4; 2+3 (5)	Dominant firm 1 (6)	Dominant firm 2 (7)	Dominant firm 3 (8)	Dominant firm 4 (9)
4	*2.33*	*0.67*	0.72869	0.73685	0.73722	0.72889	0.72962	0.72612	0.72839	0.72730	0.72701
5	*2.50*	*1.30*	0.73078	0.73999	0.73764	0.73189	0.73293	0.72984	0.72399	0.72612	0.72759
7	*3.17*	*2.33*	0.73309	0.73921	0.73643	0.72981	0.73213	0.72360	0.72554	0.72263	0.72886
9	*4.25*	*3.00*	0.72303	0.73281	0.73306	0.72314	0.73332	0.71693	0.72542	0.72918	0.71864
8	*3.67*	*3.33*	0.73102	0.74306	0.73802	0.73354	0.74217	0.72593	0.74200	0.72832	0.73136
10	*3.67*	*4.33*	0.70568	0.72749	0.72192	0.71543	0.72368	0.70987	0.71875	0.70999	0.71490
11	*3.92*	*5.33*	0.69115	0.71906	0.71699	0.70178	0.70773	0.69918	0.71020	0.69515	0.70489
12	*5.00*	*6.00*	0.69580	0.71902	0.71858	0.69605	0.69791	0.69651	0.69839	0.70353	0.70052
13	*4.58*	*6.50*	0.66807	0.71536	0.71217	0.68873	0.68786	0.69885	0.69876	0.69695	0.68511
14	*4.33*	*7.00*	0.64741	0.71389	0.71078	0.67646	0.68223	0.69448	0.69482	0.69104	0.67041
15	*4.25*	*7.50*	0.62296	0.70868	0.70737	0.67459	0.66676	0.69037	0.69061	0.68720	0.65036
16	*4.33*	*8.00*	0.60742	0.70480	0.69374	0.66373	0.66699	0.68346	0.69021	0.68219	0.62834
17	*4.58*	*8.50*	0.60721	0.70822	0.68571	0.66855	0.66405	0.68373	0.68310	0.68077	0.61782
18	*5.00*	*9.00*	0.60406	0.70675	0.66207	0.66709	0.65926	0.68020	0.67967	0.67778	0.60126
19	*4.58*	*10.50*	0.58360	0.69924	0.64880	0.65085	0.64337	0.66269	0.66135	0.66658	0.60036
20	*4.33*	*12.00*	0.56127	0.68832	0.63285	0.62572	0.63241	0.64201	0.64470	0.65105	0.58501
21	*4.25*	*13.50*	0.54460	0.67797	0.61550	0.61158	0.61924	0.62414	0.62933	0.62761	0.59007
22	*4.33*	*15.00*	0.52972	0.67312	0.59558	0.60021	0.59629	0.61010	0.61324	0.60829	0.57918
23	*4.58*	*16.50*	0.51811	0.66556	0.59267	0.58885	0.58046	0.59812	0.59370	0.59099	0.57100
24	*5.00*	*18.00*	0.51334	0.66616	0.57886	0.58349	0.57491	0.58167	0.57664	0.58532	0.58537

[22] ‘*Pm*’ corresponds to the value of LSD parameter EvenK.

Table 4: Fitness landscape complexity and average standard deviation of system fitness over 100 simulations

FL Complexity			Individualistic	Collective	Group 1+2;	Group 1+3;	Group 1+4;	Dominant	Dominant	Dominant	Dominant
Pm.	*K*	*C*	(1)	(2)	3+4 (3)	2+4 (4)	2+3 (5)	firm 1 (6)	firm 2 (7)	firm 3 (8)	firm 4 (9)
4	*2.33*	*0.67*	0.01281	0.01029	0.00961	0.01328	0.01302	0.01366	0.01386	0.01269	0.01306
5	*2.50*	*1.30*	0.01900	0.01309	0.01600	0.01953	0.01718	0.01955	0.01643	0.01617	0.01835
7	*3.17*	*2.33*	0.02814	0.01766	0.02036	0.02855	0.02327	0.02755	0.02168	0.01793	0.02378
9	*4.25*	*3.00*	0.03981	0.02002	0.02723	0.04128	0.02675	0.03169	0.02381	0.02656	0.03212
8	*3.67*	*3.33*	0.03712	0.01984	0.02429	0.03841	0.02437	0.02582	0.01902	0.02547	0.03849
10	*3.67*	*4.33*	0.05133	0.02120	0.02656	0.04428	0.03414	0.03402	0.02735	0.03197	0.03819
11	*3.92*	*5.33*	0.05751	0.02281	0.02546	0.05051	0.04817	0.03980	0.03678	0.03843	0.03902
12	*5.00*	*6.00*	0.05448	0.02306	0.02284	0.05302	0.05346	0.04118	0.04381	0.04185	0.04159
13	*4.58*	*6.50*	0.06959	0.02410	0.02894	0.06394	0.06146	0.04145	0.04197	0.04667	0.05237
14	*4.33*	*7.00*	0.07870	0.02582	0.03663	0.06904	0.06823	0.03825	0.04128	0.05167	0.06129
15	*4.25*	*7.50*	0.08347	0.02581	0.04126	0.07095	0.07368	0.04567	0.04477	0.05437	0.06737
16	*4.33*	*8.00*	0.08023	0.02656	0.04855	0.07428	0.07150	0.04815	0.04439	0.05620	0.07085
17	*4.58*	*8.50*	0.07488	0.02540	0.05961	0.07088	0.07325	0.04869	0.04967	0.05343	0.07008
18	*5.00*	*9.00*	0.06845	0.02134	0.07044	0.06723	0.06907	0.05204	0.04892	0.05035	0.06842
19	*4.58*	*10.50*	0.06830	0.02568	0.07315	0.07144	0.07514	0.05546	0.05805	0.05513	0.07252
20	*4.33*	*12.00*	0.06822	0.02644	0.07831	0.08128	0.07673	0.06330	0.06303	0.06155	0.07729
21	*4.25*	*13.50*	0.06888	0.02654	0.08101	0.08125	0.08192	0.06949	0.06623	0.06856	0.07793
22	*4.33*	*15.00*	0.06795	0.02762	0.08378	0.08692	0.08533	0.07276	0.07407	0.07512	0.08051
23	*4.58*	*16.50*	0.06803	0.02926	0.08570	0.08553	0.08683	0.07679	0.07692	0.07771	0.08278
24	*5.00*	*18.00*	0.06790	0.02982	0.08893	0.08611	0.08825	0.08082	0.08055	0.07644	0.07966

Appendix 3: Selected values of EvenK and the nature of fitness landscapes

Table 5: Fitness landscape for EvenK=5

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13	N14	N15	N16	N17	N18	N19	N20	N21	N22	N23	N24
w_1	-	x	x	x	x																			
w_2	x	-	x	x	x																			
w_3	x	x	-	x	x																			
w_4	x	x	x	-	x																			
w_5	x	x	x	x	-																			
w_6						-	***x***	***x***	***x***	***x***														
w_7						***x***	-	x	x	x														
w_8						***x***	x	-	x	x														
w_9						***x***	x	x	-	x														
w_{10}						***x***	x	x	x	-														
w_{11}											-	x	***x***	***x***	***x***									
w_{12}											x	-	***x***	***x***	***x***									
w_{13}											***x***	***x***	-	x	x									
w_{14}											***x***	***x***	x	-	x									
w_{15}											***x***	***x***	x	x	-									
w_{16}																-	x	x	***x***	***x***				
w_{17}																x	-	x	***x***	***x***				
w_{18}																x	x	-	***x***	***x***				
w_{19}																***x***	***x***	***x***	-	x				
w_{20}																***x***	***x***	***x***	x	-				
w_{21}																					-	x	x	x
w_{22}																					x	-	x	x
w_{23}																					x	x	-	x
w_{24}																					x	x	x	-
	Group 1						Group 2						Group 3						Group 4					

K= 2.50 (60/24)[23] C= 1.33 (32/24)

Table 6: Fitness landscape for EvenK=8

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13	N14	N15	N16	N17	N18	N19	N20	N21	N22	N23	N24
w_1	-	x	x	x	x	x	***x***	***x***																
w_2	x	-	x	x	x	x	***x***	***x***																
w_3	x	x	-	x	x	x	***x***	***x***																
w_4	x	x	x	-	x	x	***x***	***x***																
w_5	x	x	x	x	-	x	***x***	***x***																
w_6	x	x	x	x	x	-	***x***	***x***																
w_7	***x***	***x***	***x***	***x***	***x***	***x***	-	x																
w_8	***x***	***x***	***x***	***x***	***x***	***x***	x	-																
w_9									-	x	x	x	***x***	***x***	***x***	***x***								
w_{10}									x	-	x	x	***x***	***x***	***x***	***x***								
w_{11}									x	x	-	x	***x***	***x***	***x***	***x***								
w_{12}									x	x	x	-	***x***	***x***	***x***	***x***								
w_{13}									***x***	***x***	***x***	***x***	-	x	x	x								
w_{14}									***x***	***x***	***x***	***x***	x	-	x	x								
w_{15}									***x***	***x***	***x***	***x***	x	x	-	x								
w_{16}									***x***	***x***	***x***	***x***	x	x	x	-								
w_{17}																	-	x	***x***	***x***	***x***	***x***	***x***	***x***
w_{18}																	x	-	***x***	***x***	***x***	***x***	***x***	***x***
w_{19}																	***x***	***x***	-	x	x	x	x	x
w_{20}																	***x***	***x***	x	-	x	x	x	x
w_{21}																	***x***	***x***	x	x	-	x	x	x
w_{22}																	***x***	***x***	x	x	x	-	x	x
w_{23}																	***x***	***x***	x	x	x	x	-	x
w_{24}																	***x***	***x***	x	x	x	x	x	-
	Group 1						Group 2						Group 3						Group 4					

K= 3.67 (88/24) C= 3.33 (80/24)

[23] The value of the K (average number of within-agent elements influencing an element) was derived by dividing the number of intra-agent externalities (56-all black x) with the total number of elements (24). This yields K=2.33. Similarly, the average number of inter-agent interdependencies was derived from the total number of C externalities (16, ***bold x***) divided by the number of elements (24), i.e. C=0.67. The K and C values for all other EvenK were determined accordingly.

Table 7: Fitness landscape for EvenK=14

	N 1	N 2	N 3	N 4	N 5	N 6	N 7	N 8	N 9	N 10	N 11	N 12	N 13	N 14	N 15	N 16	N 17	N 18	N 19	N 20	N 21	N 22	N 23	N 24
w_1	-	x	x	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*										
w_2	x	-	x	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*										
w_3	x	x	-	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*										
w_4	x	x	x	-	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*										
w_5	x	x	x	x	-	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*										
w_6	x	x	x	x	x	-	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*										
w_7	*x*	*x*	*x*	*x*	*x*	*x*	-	x	x	x	x	x	*x*	*x*										
w_8	*x*	*x*	*x*	*x*	*x*	*x*	x	-	x	x	x	x	*x*	*x*										
w_9	*x*	*x*	*x*	*x*	*x*	*x*	x	x	-	x	x	x	*x*	*x*										
w_{10}	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	-	x	x	*x*	*x*										
w_{11}	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	x	-	x	*x*	*x*										
w_{12}	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	x	x	-	*x*	*x*										
w_{13}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	-	x										
w_{14}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	x	-										
w_{15}															-	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*
w_{16}															x	-	x	x	*x*	*x*	*x*	*x*	*x*	*x*
w_{17}															x	x	-	x	*x*	*x*	*x*	*x*	*x*	*x*
w_{18}															x	x	x	-	*x*	*x*	*x*	*x*	*x*	*x*
w_{19}															*x*	*x*	*x*	*x*	-	x	x	x	x	x
w_{20}															*x*	*x*	*x*	*x*	x	-	x	x	x	x
w_{21}															*x*	*x*	*x*	*x*	x	x	-	x	x	x
w_{22}															*x*	*x*	*x*	*x*	x	x	x	-	x	x
w_{23}															*x*	*x*	*x*	*x*	x	x	x	x	-	x
w_{24}															*x*	*x*	*x*	*x*	x	x	x	x	x	-
	Group 1						Group 2						Group 3						Group 4					

K= 4.33 (104/24) C= 7.00 (168/24)

Table 8: Fitness landscape for EvenK=20

	N 1	N 2	N 3	N 4	N 5	N 6	N 7	N 8	N 9	N 10	N 11	N 12	N 13	N 14	N 15	N 16	N 17	N 18	N 19	N 20	N 21	N 22	N 23	N 24
w_1	-	x	x	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_2	x	-	x	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_3	x	x	-	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_4	x	x	x	-	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_5	x	x	x	x	-	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_6	x	x	x	x	x	-	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_7	*x*	*x*	*x*	*x*	*x*	*x*	-	x	x	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_8	*x*	*x*	*x*	*x*	*x*	*x*	x	-	x	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_9	*x*	*x*	*x*	*x*	*x*	*x*	x	x	-	x	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_{10}	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	-	x	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_{11}	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	x	-	x	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_{12}	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	x	x	-	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*				
w_{13}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	-	x	x	x	x	x	*x*	*x*				
w_{14}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	x	-	x	x	x	x	*x*	*x*				
w_{15}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	x	x	-	x	x	x	*x*	*x*				
w_{16}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	-	x	x	*x*	*x*				
w_{17}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	x	-	x	*x*	*x*				
w_{18}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	x	x	x	x	x	-	*x*	*x*				
w_{19}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	-	x				
w_{20}	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	x	-				
w_{21}																					-	x	x	x
w_{22}																					x	-	x	x
w_{23}																					x	x	-	x
w_{24}																					x	x	x	-
	Group 1						Group 2						Group 3						Group 4					

K= 4.33 (104/24) C= 12.00 (288/24)