IC and Knowledge Formation by Hidden Structures – Long Term Costs of new Technology and Participative Design

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Abstract: Many innovative businesses formed around energy or bio-related activities, for instance, are often the result of collective action of organisations involved in many-sided markets, which can be found in and around focusing environments such as business incubators or technology centres. Within such environments, group interests beyond those of single producers and their immediate clients exist and interfere. Rather generically, important economic outcomes of innovations are sequences of cost reduction events, the pace of which is influenced by technology and networking alike. Moreover, new products or technologies are producing long term costs difficult to anticipate, which eventually, in response to private and public awareness and knowledge formation, will have to be internalized. More traditional industries like textiles rely in general on conservative business models and use new technology in rather restricted ways. Product design is fashion oriented and therefore predominantly "artistic" in nature, distribution channels are directed towards outlets facilitating physical contact of clients with the produce. New technology enters mainly via more mechanized production cycles for a given set of narrowly defined final products. The formation of Intellectual Capital (IC) in such industries is a slow. The presence of low creativity products indicates underutilization of both new product concepts and technological possibilities. Participative design procedures for new product concepts using appropriate eCommerce features point here towards a way out. Such features include well adapted recommender systems based on trust creation and opinion formation. We propose to model the effects of these long term costs of new technology and the possibly complementary effects of participative design procedures by economic agents acting within specific adaptable neighbourhoods and by formation of some trust related assets. Thereafter, the influence exerted between firms is increasing in firm similarity, in the degree of product complementarity, and it also depends on (mutual) trust relations. A sustainable innovation is more expensive than a regular one but it may lead to long term benefits and to durable competitive advantage, especially if many firms from the network collude. The associated opinion formation process which leads to sustainable innovation may be viewed as a collective cognitive process resembling that of branding and re-branding. A similar trust-based opinion formation is also regarded as part of a procedure for assessing the acceptance of many new or parallel product concepts as they derive from Participative design procedures anticipating future product uses. Stylized dynamic models, which entail an opinion formation process, can in turn be identified with different levels of sustainability commitment by innovating and imitating firms within a dynamic multi-firm setting. Such models tend to display the statistical behaviour of some aggregates known to occur in empirical innovative processes.

Keywords: IC and learning, long term environmental costs, opinion and trust formation, participative design and innovation networks, sustainability, recommender systems

1. Introduction

Innovation is an important engine of economic development but it also entails a dual nature. While it enables formidable increase in productivity and comfort, occasionally finding solutions to very hard problems, in the longer term it also creates new problems and holds the potential for more and new types of disasters. Most of these features are difficult or impossible to predict in fine detail. However, the awareness of unforeseen risks is growing in various types of consumer and producer populations around the world. A rather vague but increasingly vociferous request is to stick to "sustainable solutions" in technical, economic, and social terms, meaning to find collectively acceptable and commercially viable ways to impose a sense of "expected medium term stability" of societal development. While the basic dual nature of innovation is unsolvable in principle, there are certainly many alternative development paths, which may earn a reward in different historical and cultural contexts of development. Examples of the dual nature of innovation abound and are to be found in very disparate domains. Some more extreme cases should illustrate this. Satellite telecommunication is revolutionizing entertainment, monitoring and parts of business. Space debris as an inevitable consequence is posing serious future threats and costs. Improved or even personalized medicines cure ever more diseases but they are posing both, huge challenges and costs of care for the aged, possibly also by proliferating later-life complex illnesses. Deep sea drilling taps formidable oil and gas reserves but is also producing hard to handle spills. Alternative energy solutions to fossile fuels can lead to astronomic future decommissioning costs. And finally, proliferating high-gain advanced financial instruments can lead to hard to imagine societal costs when crises strike.

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Non of these down-side effects can be genuinely avoided, but more careful approaches, taking into account more detailed “checks and balances” of technological, economic and social forces my help develop less volatile and aggressive ways to cope with them. Such may be done by improving the assessment of future costs for various degrees of acting in sustainable ways (Schebesch et al. (2010b)). At the more conservative side of the spectrum of industries, some of which are dating back to ancient times like textiles and clothing, there may now also be potential for a revolution regarding technology and consumer behaviour. This profound change could be generated, in the case of textiles, by an intensifying interdisciplinary research into new materials and new design concepts regarding the use of fabric with essentially new physical properties. Many final industrial and retail uses have been proposed for textiles, ranging from construction to automotive interiors and many complementarities can be found. For instance, *ubiquitous computing* is often related to the use of sensors, internet functions and other computing tasks in order to meet a variety of physiological, psychological and social needs of persons, and which is often related to the use of textiles and their derived products. Until recently, such applications would have been far too expensive to use in ubiquitous ways. Now, the question is whether consumers will accept and demand smart textiles at a large enough scale.

In order to approach these issues, section 2 starts with a concept for representing the economic and societal forces shaping opinion formation, innovation and sustainability and discusses future ways of transforming the concept into concrete tools of assessment and valuation. Section 3 places the innovating firm into a central position. This will enable a multi-firm model with process and product innovation in later sections. Section 4 concentrates on empirical aspects of smart textiles as an illustration of how consumer acceptance of new product concepts may be the focus of a model using opinion and trust formation, which is presented in sections 5 and 6. Next, section 7 uses the stylized model of the firm, which combines aspects of sustainability investment with innovation processes from section 3. In a multi-firm simulation this also implies recording trust formation in close analogy to trust formation in the previous opinions formation model. Finally, section 8 contains some conclusions.

2. Opinion and IC formation in the presence of innovation

At a general conceptual level buying behaviour may be thought of as the result of an opinion formation process. One may also advance the notion that the transition from (buying a) low to (buying a) high creativity product solution is connected to intellectual capital (IC) formation grounded on the evolution of favourable opinions about the product uses within multiple user communities. Such consensus formation is based on successful *trust formation* between community members. Trust formation stands for a very important sub-process of social capital formation: Without trust both the efficiency and the degree of predictive correctness of learning using mechanisms of *indirect democracy* would be hard to explain (i.e. that of *ballots to markets* and that of *prediction markets*, Rodriguez and Watkins (2007)).

IC may attract financial capital but it is not doing so automatically. IC may be contrasted to financial capital in being much more difficult to transfer. Within a conceptual scheme IC be viewed as a (collective) capacity of formulating and resolving complex classification problems, as proposed in Schebesch (2011). Such problems can be viewed as a template to focused *what to do?* questions in complicated and often dynamic environments.

Learning relevant things can assume a form of “learning by doing”, where the result (success) of learning is a function of past action, e.g. of production (or of consumption), which can give rise to power law relationships between cost (or utility) and cumulated action (see next section). Learning can also be a function of time passed since the initial production efforts, in the sense that learning effects cannot be concentrated into arbitrarily short time spans. A similar argument holds true for *forgetting* and for *unlearning* (on consumption in networks see Wu and Huberman (2007)). The contextual relevance is enforced by learning within concrete societal environments:

- Learning how to cooperate and how to overcome excessive rivalry,
- Learning how to identify and use complementarities in order to stimulate the use of risky innovations,
- Learning how to classify and to predict with better information about the types of uncertainties involved and
- Learning how to run application specific scenario evolutions.

In more recent times, other important aspects of innovation processes such as innovation contests and social innovation are increasingly considered. Two premises lead to the growing relevance of this type of innovation procedures:

- In certain product classes and markets it becomes increasingly difficult to "forecast by expert opinion" what consumers really like.
- Organizational setup and transaction costs decrease dramatically with the spread of the internet and of different types of social forum subnets.

While in general such approaches are clearly useful for automated marketing and forecasting procedures as described in Schebesch et al. (2010a), there is mounting evidence that they can and should be applied (with adaptations) for innovation processes too, as is outlined in Terwiesch and Xu (2008). The results of an innovation contest may be a process or a product innovation (figure 1, lower rhs process components). The innovation contest requires designing and evaluating a competition for new solutions of posted problems from a large number of participants originating from a larger societal context. In order to make these contests more efficient and more credible (i.e. to enhance serious participation), such innovation contests have to be designed to encompass two or more stages, with appropriate mechanisms for picking winners and for paying out prices for attractive or promising solutions. The outcomes of such innovation contests may contain also additional information, for instance with regard to acquaintance with and challenges caused by using sustainable processes and products, i.e. information about the trust and the degree of empathy and goodwill present in a wider population with regard to new product concepts and issues sustainability.

The relation between knowledge and innovation is addressed in Tödtling et al. (2009). While a today fashionable knowledge platform as placed into figure 1 would certainly be desirable, there seems to this day no compelling procedure concerning the efficient collection of information concerning the various shown sub-processes of innovation and how they finally relate to IC.

Figure 2 depicts the real-life feedback loops, which potentially contribute to IC formation. The figure combines two contexts, namely markets and a background of social networks with agents which may - but in general do not - belong to the markets. As innovation processes unfold, firms start a process of (mutual) trust formation, which results in trust scores, i.e. determining to what extend should firm *i* trust firm *j*. The evolution of trust scores is using information from the markets but also from the background social networks of the firms. Trust scores are important in order to guide a behavioural imitation or a technological adaptation process. High trust scores may be useful in branding and re-branding. The eventually resulting reputation is an example of *social capital*, which contributes to a more general assessment and valuation process indicated by the box *Valuation systems* of figure 2. Both, the reputation mechanism and the evolving knowledge platform (see also figure 1) do not exert an unconditional influence on market agents, and any possible effect may also be strongly delayed in time. Finally, crowdsourcing by innovation contests, which also uses agents from outside the markets, is also inherited from figure 1. Within the modelling boxes A-D we encounter o*pinion formation*, which may be used as template for behavioural or technological imitation as indicated e.g. in Martins and Pereira (2008).

In our context innovation and buying behaviour using adapted recommender systems with trust generation and also for learning of how to use complementarities seems appropriate. These can be realized within highly collaborative e-Commerce procedures (Salakhutdinov et al. (2007), Abernethy et. al. (2009)). Trust formation and recommender systems (Xiao and Benbasat (2007), Schebesch et al. (2010a)) can be cast into explicit mechanisms and computational procedures. They contribute to effective opinion formation in contexts like marketing and technology campaigns, in that they may use data about individuals but they may also be adapted to use data about the various relations between individuals, which occur within different social contexts and at different group levels.

Such recommender systems use for instance matrices containing client and product feature entries. A product is recommended to a client, if

- The client is not aware of the product or did never buy / use the product,
- There are scores from other clients concerning the very the product,
- Meaningful recommendations stem from a cluster which contains the client, and
- Only persons / organizations trustworthy to the client do participate in the recommendation.

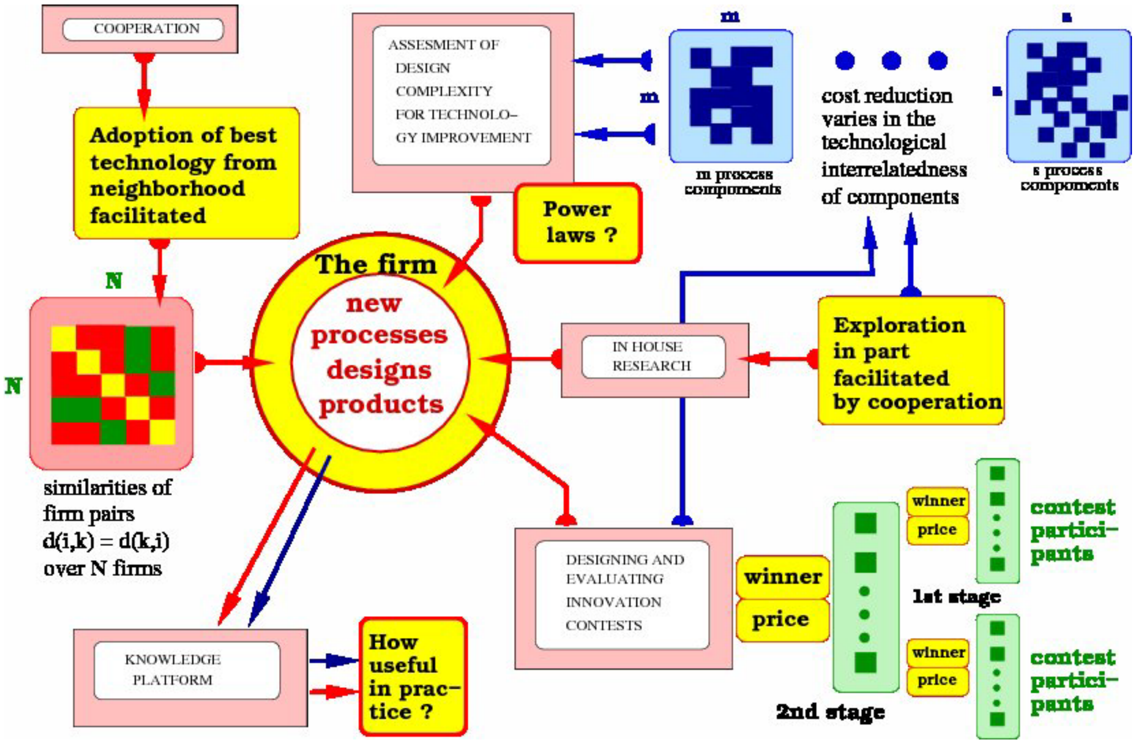

Figure 1: Innovation sub-processes: innovation contests and technological interrelatedness (adapted after Schebesch (2011))

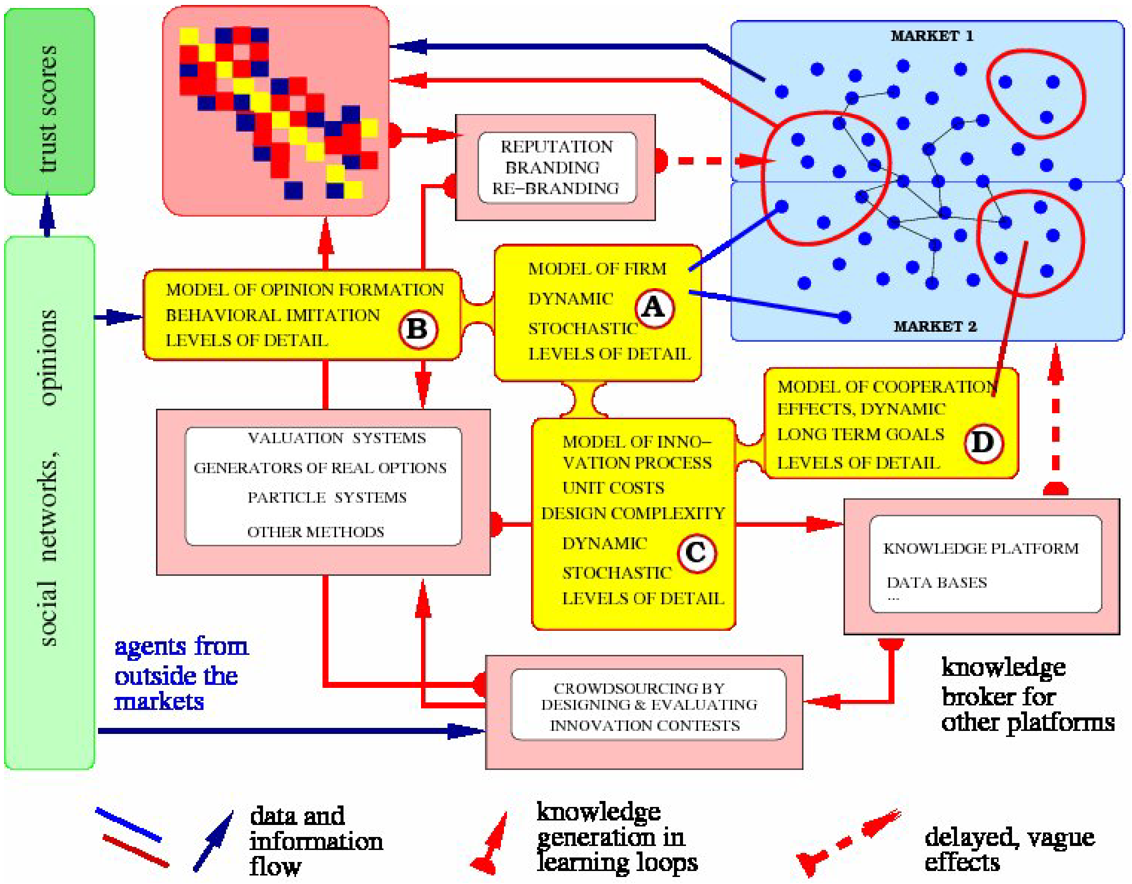

Figure 2: Feedback loops in social learning which are connected to aspects of innovation, branding, and behavioural imitation. Note the role of opinion formation, trust scores and reputation (adapted after Schebesch (2011))

The cost of designing and operating a recommender system can be substantial. Finding good client clusterings and empirically valid trust matrices can be expensive. Product score matrices may be extremely sparse, indicating that most clients do not use most products. If one intends to recommend new products and if these products did not yet produce any client scores from, one may start from *cultural habits* more or less remotely related to the very product use. Prelaunch forecasting of products *new to the market* is a recurring topic in Marketing (Urban et al. (1996), Hoeffler (2003), Natter et al. (2003)). Starting with new products thus requires the use of client similarities from other domains or markets and will have to rely more strongly on *trust* between clients. Discovering the amount of trust new technologies and product designs are capable to produce in a client population may be enabled by means of providing incentives for clients to invest into *prediction markets* (by now a widely debated topic of experimental economics, see Prediction Markets (2009)).

3. Innovations and investment into sustainability

Recent scientific and technological developments and their potential (think of nano-technology, new agro-energetic complexes, and many more) tend to need a broader consensus of interests of the implied economic and societal agents, just in order to be eventually transformed by firms into sustainable market-going products. The transformation of modern technological invention into products requires some consideration of possible consequences and risks. Direct environmental consequences of using processes are already difficult to assess, e.g. think of the large number of variants of bio-fuel processing, which are contained in public science news data bases like *Science Daily*. Consequences of using products and services may also be diverse, for instance by invoking a path dependent mechanism, which may “lock in” to customer use earlier but eventually inferior solutions, a point put forward insistently by Arthur (1989). Given multiple risks, both for the producer and the consumer of innovations, a *branded risk assessment* may be called for. This may be achieved in a credible way, for instance, by an incubator network, which allows a multi-party involvement. Brondizio et al. (2009) and Ostrom (2009) teach us – albeit in a more general context – that polycentric systems (implying multi-party involvement) hold the key to sustainable solutions of complex problems involving environmental, social and a series of commercial and economic interests.

Following Ostrom (2009) there are four types of goods, namely [1] *Common pool resources* (example: forests), [2] *Public goods* (example: knowledge), [3] *Private goods* (example: clothing) and [4] *Toll goods* (example: daycare centers), which are mainly characterized by different property or apropriability related considerations. From a perspective which is more concerned with the description of innovation by firms, we stipulate that the new technologies imply multiple and changing roles of goods: Increased *personalization* of private goods may be achieved by heavily drawing on public and private knowledge and commercialization is achieved by different business models, for instance by making use of the role of the toll goods or by means of technology induced zero-price co-offerings as has been put forward by Anderson (2009). Finally, almost all innovations draw on common pool resources, although in a more or less uncertain way, consuming them by production or by the very use of products and services.

It seems rather hopeless to attempt to build a *simple* dynamic model for the purpose of illustrating the role of the sub-processes or at least some important features thereof, as described within the boxes A,B,C, and D of figure 2 of section 2. However, in the tradition of some venerable and also some more recent work on modelling the innovation process from a theoretical viewpoint as in Reinganum (1981), Bessen and Maskin (2009), Andergassen et al. (2006) as well as from a variety of mixtures of theoretical, empirical, and computational approaches as found in e.g. Stöppler and Schebesch (1993), this section proposes to consider a computational model by starting out with a very simple “mechanism” of period-wise innovation effects on the evolving budget (or financial assets cumulated from sales, say) of a firm (the computer code of the model is available upon request).

In this stylized model the budget $Q_i(k)$ of the firm $i \in \{1,...,N\}$ from a sector of an economy is a dynamic variable, which can assume positive)assets) and negative (indicating depth) values over a time interval $k = \{0,1,2,...,K\}$, with the obvious goal of attaining $Q_i(K) > 0$ and also maximizing the final budget $Q_i(K)$ for as many firms as possible. Apart from being an obvious goal for the single firm, doing so for a portfolio of firms, i.e. to maximize $\sum_{j \in \Pi} Q_j(K)$, subject to finding a maximizing subset

$\Pi \subset \{1,2,...,N\}$, is in fact a goal of a business incubator, choosing to incubate the firms from Π. In contradistinction to a financial portfolio, here a firm would stick to exactly one incubator.

To explain the innovation related mechanism, first assume *N* = 1 and drop indices. The effective demand quantity, which, for simplicity, shall equal the sales $X(k) \geq 0,$ is measured in units of products and is given exogenously. The evolving demand will certainly influence the success of a firm, regardless of any details of the innovation process. However, innovation can make a difference over the *K* time steps, if a realistic growth processes and the accumulation of delayed cost for producing and using $X(k)$ over time by clients and society is considered. For a sufficiently narrow sector definition and a long enough time horizon *K* > 0, no demand can keep growing indefinitely. Hence assume that delayed cost occur in cumulated past production, reflecting long term cost due to environmental consequences and to social disruption of many kinds, destruction of diversity, distruction of social and intellectual capital, etc., which are collected in a cost variable $D(k) \geq 0.$ With the passage of time, independent "private" innovations occur, manifesting themselves by the reducetion of unit production cost. The price of a product unit is assumed to be equal to one, which eliberates the model from having to consider a separate price process. With this simple mechanism for sources of contributions to the budget of the model firm, for simplicity, i.e. without considering the influence of any marketing factors like price, advertising, etc., effective sales dynamics now read:

$$X(k+1) = (1 + g(A))X(k), \text{ with } X(0) > 0, \text{ and with } 0 \leq g(A) < 1.$$

In order to produce exactly two consecutives sales regimes, we set $g(A) = g_{const} > 0$ for all *k* such that $X(k) \leq A,$ and $g(A) = 0$ otherwise. Hence the evolution of the monotonous sales curve $X(k)$ will switch exactly once from geometrical growth to zero growth. Next, we state the evolution of the cost variable $D(k) \geq 0,$ which reflects the delayed cost of producing and using the product, in that this is an increasing function of the cumulated sales:

$$D(k) = \left(\sum_{s \leq k} X(s) \right)^{\alpha}, \text{ with } \alpha > 0, \text{ and } X(0) = 0.$$

Owing to the constant sales in phase 2 of the sales evolution, delayed costs can eventually overtake sales revenues. Owing to the assumption of unity prices, quantities and values coincide. The firm can counteract the accumulation of delayed costs by **investing a share of the sales revenue** into developing sustainability measures. Hence, there is a "policy" of diverting a share of the sales into such long term purposes. This is most simply expressed by a variable $0 \leq h(k) \leq 1,$ which may be fixed or adaptable over time (see also the simulations from section 7). We then have the following dynamic budget equation for the firm:

$$Q(k+1) = Q(k) + X(k)(1 - c(k)) - D(k)\exp(-\beta I(k)) - I(k), \text{ with } Q(0) \text{ given.}$$

The variable $I(k) = h(k)X(k)$ stands for the *sustainability investment* of the firm in period *k*. The term $(1 - c(k)) > 0$ means unit price minus unit costs (or unit profits) in the boundary case of zero delayed costs and zero investments (i.e. *D*(*k*) = *I*(*k*) = 0, for all *k*). The effects of delayed costs can be reduced by sustainability investment. In order to give to this effect a plausible evolution over time, a suitable $\beta > 0$ (usually small) has to be selected by the modeller. More elaborate, possibly path dependent expressions could be used here instead, but their justification would need some compelling empirical, e.g. sector-specific explanation.

The remaining item to be defined in our model is that of evolving unit costs $0 < c(k) < 1.$ Their range necessarily results from the simple assumption of a constant unit price of 1. For the time evolution of unit costs we assume that *sequential innovations* lower them at irregular time intervals. We do not keep track of extra investments for these innovations, partly owing to the fact that, in order for the firm to survive, they will occur anyway, regardless of the level of sustainability commitment. Hence, they may be thought of as being suitably incorporated into the past unit costs. The innovation process is assumed to be completely random:

$c(k+1) = \delta(k)c(k),$ with $c(0) > 0$ given and with $0 \le \delta(k) \le 1$,

with $\delta(k)$ being the result of a random draw in each *k*. A *time point with innovation* occurs occasionally. If *k** is such a time point, then $\delta(k^*) = \Delta(k^*) < 1$. For all other time points, $\delta(k) = 1$. If a random draw $\Delta(k)$ from the uniform density over the interval [0,1) exceeds a threshold of 0.8, say, then an innovation occurs. The magnitude of the cost decrease in *k** is hence bounded by (0.8, 1) times *c*(*k**). As we will see in section 7, this simple assumptions about the innovation process may suffice in order generate plausible statistical features, especially in conjunction with interactions between many firms.

Technological progress by means of cost reduction of processes can eventually induce product innovation. Hence, evaluating the design complexity of technologies and its influence on cost reductions over time, and especially so over past cumulated production as in McNerney et al. (2009), will be most important in order to assess the pace and regularity of innovation events as a function of its underlying "engineering design". A new technology is represented by the introduction of a new interconnection matrix between process components. Sustainable technology solutions may be characterized by certain types of “recognizable” interconnection matrices. As sketched in figure 1 of section 2 by the $m \times m$ and by the $s \times s$ process component interconnection matrices, one may model the stochastically varying costs $c_{ij}(k)$ occurring over consecutive time steps $k = 0,1,...$ (associated with the element-wise entries of the matrices from the same figure 1, say) by computing for each component $i = 1,...,m$ (for the first matrix, say) the total costs $C_i(k) = \sum_{j \in U(i)} c_{ij}(k),$ with $U(i)$ being the set of all components which component *i* depends on. An innovation adoption *occurs* whenever $C_i(k) < C_i(k-1).$ The density function from which to draw new cost coefficients embodies the "difficulty of reducing costs" $\lambda > 0$ as in McNerney et al. (2009), for instance $f(c) \propto c^{\lambda-1}$, with this proportionality relation stemming from an assumed cumulative distribution $\int_0^c f(s)ds \propto c^{\lambda}$. The unit cost resulting from such an innovation-adoption process computed for a technology matrix with inter-related components and evaluated over sequences of such matrices is often similar to a so called *power law*

$c(y) \propto y^{-\alpha}$, with *y* being the **cumulated past production** with the technology,

and with (in general non-integer) *efficiency* or *power* $\alpha > 0$. Power laws describe approximate relations between data points by linear functions in double logarithmic plots (here, if *c*(*y*) is plotted against *y*) and are very popular in the social network modelling community for signalling the presence of certain non-linear dynamics, which tend to have long-memory effects or tendencies towards clustering, etc., as is described in the reviews of Newman et al. (2006) and Wang et al. (2009) respectively. Before considering the dynamics of many firm innovation processes with investment in sustainability as introduced at the beginning of this section we next turn to the equally important case of consumer opinion formation when new products or new product uses are proposed.

4. New products in old industries: The case of smart textiles

From an exploratory the point of view which emphasizes artistic potential and technological fantasy, smart textiles seem to offer a broad spectrum of new opportunities ranging from new product creation to finding new uses of existing and complementary products being thus a good example for reviving venerable industrial sectors. Judging by new design opportunities put forward at specialized workshops (i.e. Baurley (2006)) and by the long list of potential applications of smart textiles which in part coincide with the use of smart materials (i.e. Ohmatex (2007)), and in part with new combinations of functionalities (Advanced Materials (2007)) of cloth related products, one still awaits a commercial take-off. Although there are signs of awareness of the opportunities (technical textiles have a clear market position, i.e. Byrne, C. (2007)) actual market-driven development of smart textiles is less dramatic than one would expect based on information primarily related to technological possibilities.

Figure 3 lists some possible consumer trends (left hand side) in smart textiles and derived products, which are strongly depending on eventual acceptance. The latter is in turn strongly depending on personal networking. For instance, the degree to which (body invasive) sensor implants will be accepted by a large customer base in the future certainly depends on a crowding or imitation effect: consumer needs of the future will be strongly related to emerging social trends.

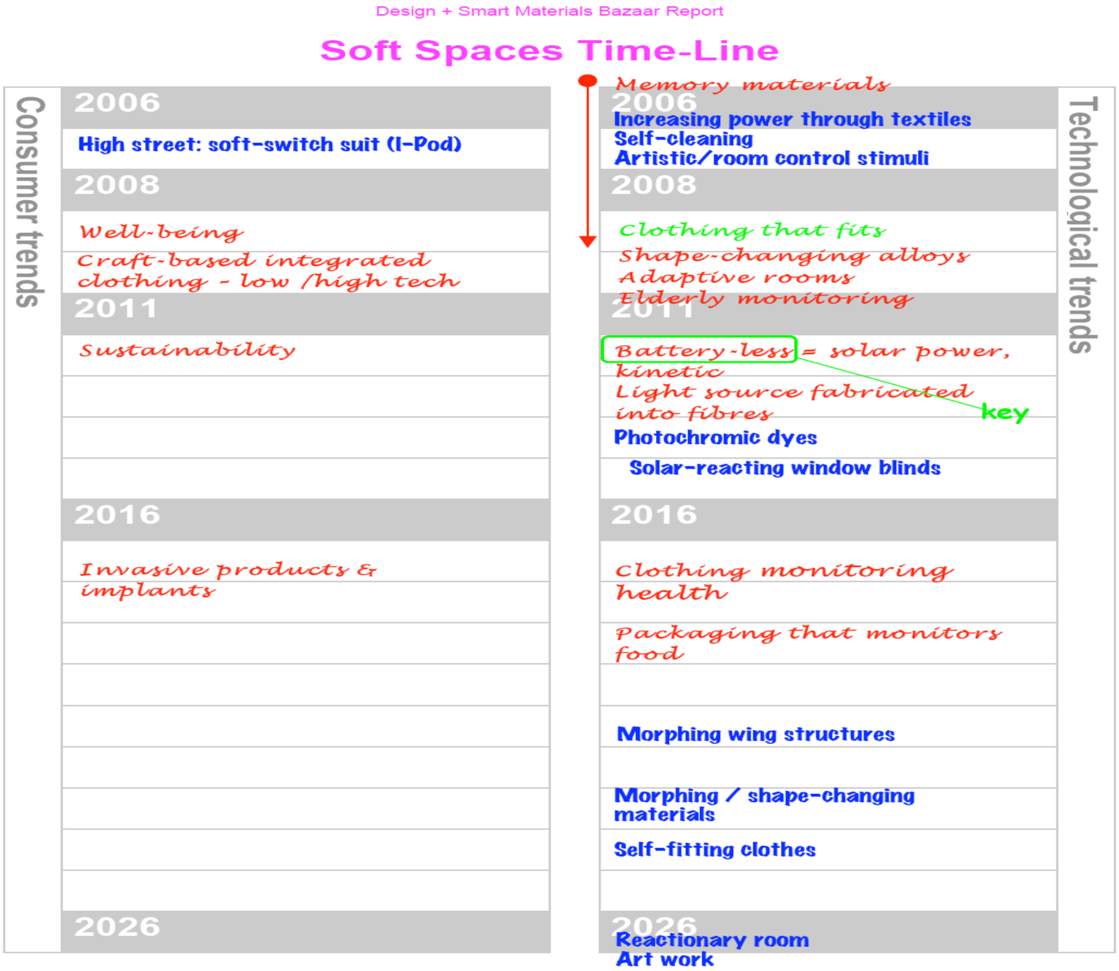

Figure 3: Example of exploratory soft forecast of consumer and technology trends reflecting an optimistic view expressed at a 2006 London workshop on smart materials (adapted after Baurley 2006, p32)

Possible technological trends (figure 3, rhs) include different types of smart materials, and emerging applications in clothing, containing rather dramatic examples like *self cleaning* and *self fitting clothes*. These design examples are not meant to be exhaustive but are merely intended to portray the diversity and the rich potential for finding complementarities of many kinds as is the use of new internet services and the use of new power sources in the concept examples of figure 4.

Despite of these manifold concepts and opportunities of artistically and technologically induced designs for clothing and for other applications based on the use of smart textiles there remains a question mark of whether these will eventually translate into effective business opportunities and markets.

At a societal level one would expect important beneficial industrial transformations to be induced by the intellectual capital (IC) resulting from building up such markets. At the conceptual level, one would then be interested in explaining a transition from a low profile behaviour of buying traditional textiles to buying smart textiles may take place and how this could be possibly be achieved by IC formation within a learning cycle which affects producers and consumers alike. Effective utility of smart textiles may be established by means of participative design processes for new product variants and by using appropriate eCommerce features. Mechanisms for achieving this are described in the next two sections.

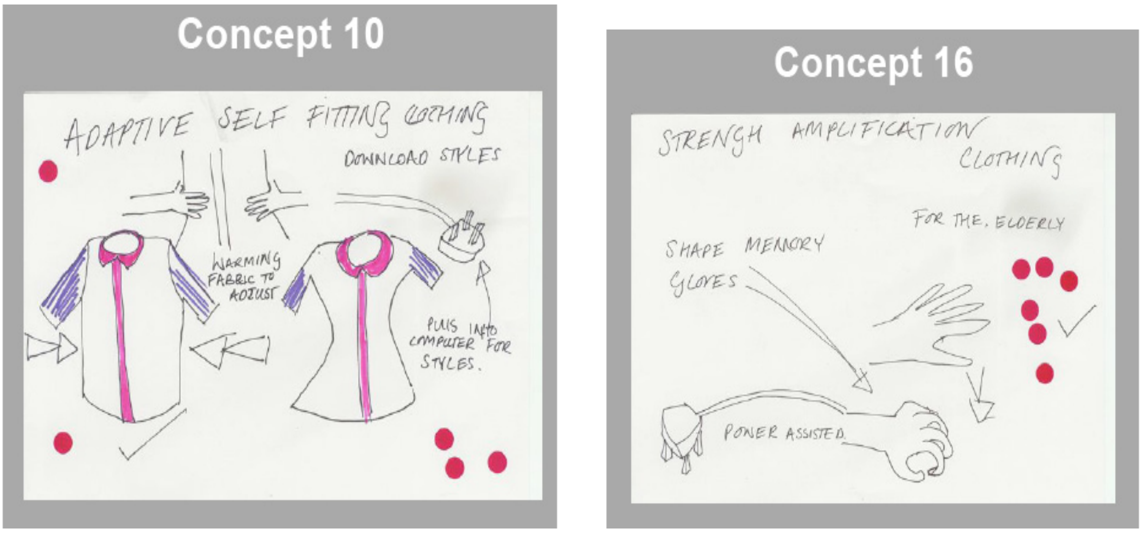

Figure 4: Two examples of concepts presented at the workshop referred to in figure 1 concerning the use of smart textiles and related concepts, left inset: "adaptive, self fitting clothing according to downloaded style instructions". Right inset: "strength or power amplification in gloves"

5. Opinion formation and new product concept selection

Buying behaviour and ensuring the visibility of new consumer products like those based on smart textiles, which are not covering self-explanatory basic needs of people, can be in part traced back to opinion formation process within social networks. Opinion formation evolves alongside *trust formation*. Trust between clients is an important ingredient for building recommender systems based on past client scores (Schebesch et al. (2010a)) effectively contributes to tilting buying behaviour.

For simplicity assume that the only observable may be network structure and whether the group of people behind the network has reached a solution (a "consensus"). Then we can use a rather simple dynamic opinion formation model, which can also be considered as a paradigm for modelling the formation of conventions and of standards, by using a procedure of message exchange between agents in social (client community, etc.) environments. Dynamic opinion formation can also be related to the modelling of negotiation processes, see Baronchelli et al. (2007). In the present context opinion formation is proposed to model the emergence of sub-networks in client populations or *extended virtual enterprises* including producers, which are composed of persons evolving similar opinions e.g. about buying or producing.

Models for dynamic opinion formation may use *bounded confidence*, basically to restrict interaction within groups of *culturally similar partners* - a concept used to describe the emergence of communication in networks. The full mathematical consequences of such models are not known as of today (Blondel et al. (2008)), but there are insights by means of numerical experiments:

- Basically, out of many initial options, *consensus* emerges.
- However, for certain parameter ranges, the dynamics typically exhibit *opinion polarization*, i.e. convergence towards two or many opinions.
- Another typical feature are *phase transitions*: for some critical parameters abrupt changes occur in behavioural type, for instance the sudden transition from consensus to polarization.

The basic dynamics of opinion formation are well described by Krause's consensus formation model (Krause (2000), Blondel et al. (2008)), which simply states: First assume that $n > 0$ agents $i = 1,...,n$ are connected via a topology which is inducing a neighborhood. These agents are evolving their respective opinion $X(i,t) > 0$ over discrete time $t = 0,1,...,T$ by updating for every agent $i = 1,...,n$ the following (purely deterministic) difference equation:

$$X(i,t+1) = \sum_{\{k(i)\}} \frac{X(k,t)}{|\{k(i)\}|}, \qquad \text{with random } X(i,0) > 0,$$

where the index $k(i)$ is running over the neigborhood of every agent i and where "$|.|$" denotes the number of respective neighbors. The index set $\{k(i)\}$ is computed by finding all the

$$\{k : \| X(k,t) - X(i,t) \| < w\}, \quad \text{for a given} \quad w > 0.$$

Here $\|.\|$ stands for a *distance function*, which simply measures the absolute difference between opinions or opinion values of agents k and i. By convention, the *n* starting opinions are sorted, i.e. with $X(n,0) > X(n-1,0) > \ldots > X(1,0) > 0$. Owing to the agent-dependent dynamic index set $\{k(i)\}$ the dynamic process $\{X(.,t)\}$ is adaptable to every interconnection topology *evolving over time* in the agent's relational network. Adaptation is steered by setting *w*>0 for the size of the neighbourhood. Simulations show that the overall dynamical properties of opinion formation are more complicated then perhaps guessed from their simple equations.

In simulations performed by Blondel et al. (2008), large numbers of agents with different opinions generically evolve into a small number of different opinions and do not depend on the initial opinion distribution. In figure 5 opinion formation simultaneously evolves the interconnection network between agents. Dense networks (having large neighbourhoods) tend to produce less final opinions and their final connectivity matrices - as the one shown in figure 5 (C) - tend to differ less from initial matrices - as shown in figure 5 (A). In practice, client or innovation networks are expected to be formed by sparsely coupled individuals (like those of figure 5) or even to be formed by individuals which are members in many different networks (see Ahn et al. (2009)).

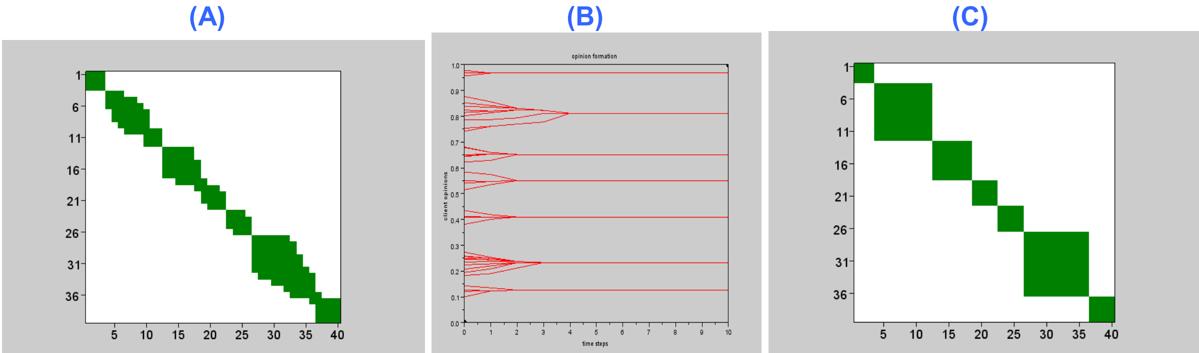

Figure 5: Simulated opinion formation with 40 individuals representing 40 different starting opinions for a small neighborhood using w=0.047, i.e. within a sparse social network: (A) network matrix for *t*=1, (B) emergence of seven final opinions at *t*=10, and (C) network matrix for *t*=10. Individuals located within a cube share the opinion in *t*=10.

6. Trust-based cascaded opinion formation

Using the general features of opinion formations outlined in section 5 a very robust producer-consumer opinion formation process is presented, which polarizes opinions from a potentially large list of starting options. As with future applications of smart textiles from section 4, such product options do not interrelate at early time steps of opinion formation. As time evolves, we assume that trust increases between agents, albeit with different rates in different contexts. For simplicity, dynamic effects of forgetting and unlearning are neglected. As in section 5 we start out with an opinion formation process $X(i,t) > 0$ over discrete time $t = 0,1,\ldots,T,$ which we term *opinion formation of consumers*. Next, we adjoin a second process $Y(i,t) > 0,$ called *opinion formation of producers,* which functions according to the same dynamic equations as process X. For simplicity we assume a unidirectional dependence $X(Y),$ which reflects a trust increase with those consumers which form opinions in the vicinity of those evolved by the producers. The difference to the basic process described in section 5 is how we determine the dynamic neigborhood of every agent. The index set $\{k(i)\}$ of every consumer $i = 1,2,..., N_X$ is now computed using a *trust-based* radius $W(i,t) > 0$ (instead of constant radius $w > 0$), which partially depends on the match with the opinions evolved by the producers $j = 1,2,..., N_Y$ and which evolves over time according to

$$W(i,t+1) = W(i,t) + W_X + W_{XY} \sum_{j=1}^{N_Y} u\left(\| X(i,t) - Y(j,t) \| < W_{XY}\right), \text{ with } 1 >> W(i,0) > 0,$$

with $u(.)$ the unit function, which returns 1 if the argument is true and 0 otherwise, and with the parameters selected to be $W_X = 0.5$ and $W_{XY} = 0.075$. The index set $\{h(j)\}$ of every producer j is updated by a trust-based radius $V(j,t) > 0$, which simply increases with time, namely

$$V(j,t+1) = V(j,t) + V_Y, \text{ with } 1 >> V(j,0) > 0, \text{ and with parameter } V_Y = 1.5.$$

If $N_X > N_Y$ as assumed in the sequel, the starting opinions of the producers $\{Y(j,0)\}$ are a true subset of the starting opinions of the consumers $\{X(i,0)\}$, reflecting more focused information of the producers. Figure 6 depicts an example of a cascaded opinion formation process, where the outcome of the consumer opinions (right plot) depends on the outcome of the faster opinion formation process of the producers. Nine opinions converge to an opinion representing a product solution with lower creativity and six to a high creativity solution (left plot). On the consumer side (rhs plot), all opinions tend towards nearby located high creativity solutions.

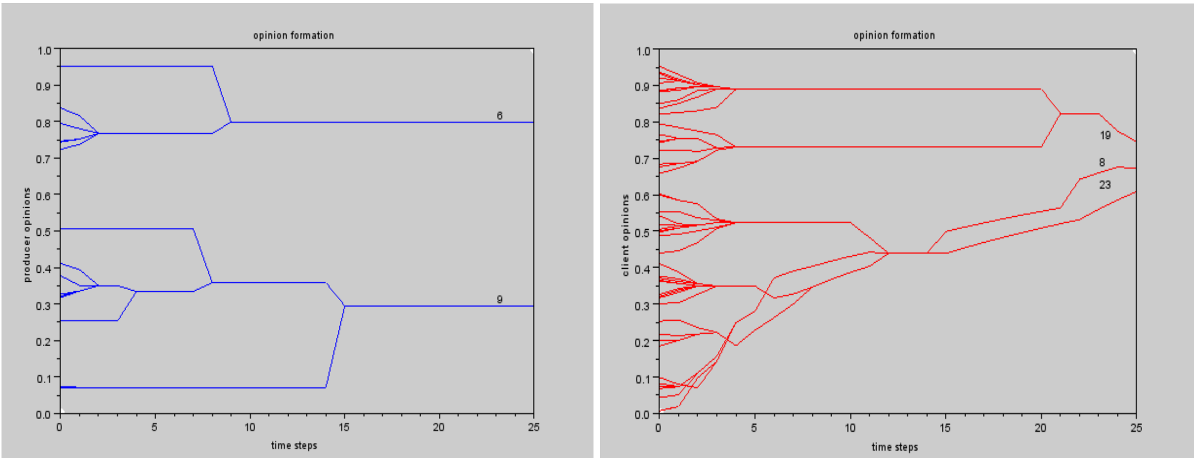

Figure 6: An opinion formation process with a starting number of opinions of producers $N_Y = 15$ (some are place in close vicinity to others) and a starting number $N_X = 50$ of consumer opinions, consumer opinions are converging towards "creative" solutions represented by higher ranking opinions on the scale. Less creative solutions (9 on the producers side) are abandoned

Figure 7 depicts a process with the same consumer starting opinions and the same parameters for both processes, but with more starting opinions on the producer side. Two converging producer opinions occur with slightly less original opinions (11 out of 30, or 36%) now representing the more creative solution. The consumers retain two distant extreme opinions (originating from 11 and 13 starting opinions, respectively), while a slight majority of different initial opinions tend towards opinions representing medium creativity. In a distant future the opinions will eventually fuse into some intermediate opinion value, somewhat below of that of the final opinion of the process from figure 6.

Generically, the qualitative properties of this cascaded opinion formation process are very stable with regard to changes in the parameters and also with regard to smaller changes of initial opinion distribution of both processes. Next a process similar to trust-based opinion formation is applied to the interactions between innovating firms with sustainability investment.

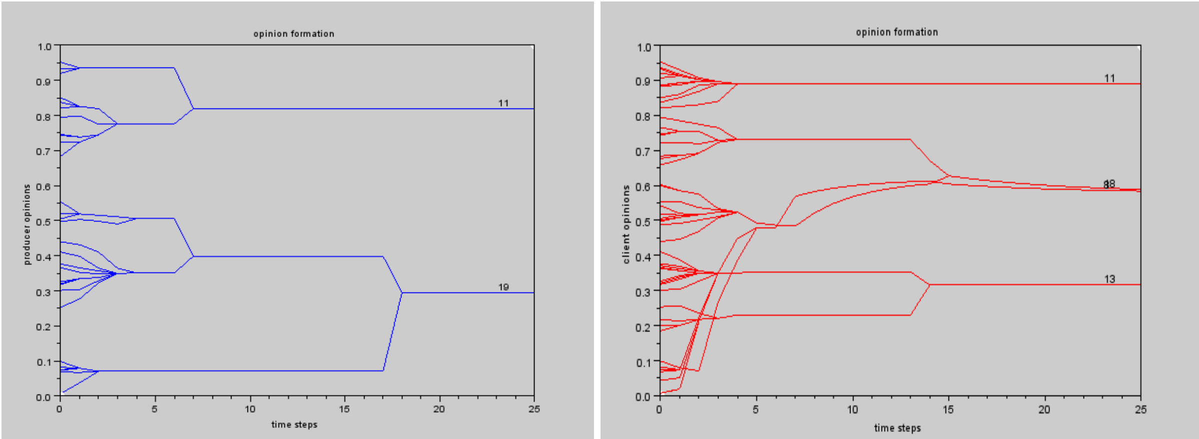

Figure 7: An opinion formation process with the same parameters as that of figure 6 except an increased number of starting opinions of producers $N_Y = 30$.

7. Neighbourhood interactions between innovating firms

Suppose that in a sector there exist $N = 50$ (say) innovating firms as described in section 3. The first questions arises as to whether there is an order according to which to sort - or at least a criterion by which to group these firms at time step $k = 0$. For some more interesting grouping (relating to technology and the role of firms in a network, etc.) the simple model of section 3 does not process enough information. In order to enable some diversity in the model dynamics, we sort firms by their initial sustainability commitment shares, $h_i(0)$, which we assume to increase linearly in $i = 1,2,...,N$, assuming values in the interval $[0, H]$, with $H < 1$. Other state variables also defined in section 3 are initialized to the same value for all firms, e.g. all starting budgets are equal: $Q_1(0) = ... = Q_N(0)$.

As in the case of dynamic opinion formation from section 5 and 6 interacting firms are modelled by using neighbourhoods $U_i(k)$, which indicate for every firm $i \in \{1,...,N\}$ the set of those firms, which are sufficiently similar in order to allow for easy technology imitation. We compute such neighbourhoods at every time step *k* and for every firm *i* by

$$U_i(k) = \{\forall j : j \neq i, | h_i(k) - h_j(k) | < D\}, \text{ for every } i = 1,2,...,N, \text{ and every } k = 1,2,...,K-1,$$

and by using upper bound $D < H$ for the distances of the firms within a respective neighbourhood. While the shares $0 \le h_i(k) \le H$ may be seen as a proxy for *sustainability commitment*, the neighbourhood size implied by $D < H$ may be seen as a proxy for the *degree of clusterization* in the sense of facilitating access to knowledge within larger communities of firms. The dynamics of the interaction between the innovating firms as described in section 3 is assumed to be governed by the following:

- If there is no innovation event (see section 3) at time step *k* in firm *i*, then this firm is searching for another firm *j** within neighbourhood $U_i(k)$ from which to imitate. Such a firm *j** may or may not be found in period *k*.
- However, if such a firm is found, that is, if $j^* = \arg\min\{c_j(k) < c_i(k) : j \in U_i(k)\}$ then set $c_i(k) = c_{j^*}(k)$ and also $h_i(k) = h_{j^*}(k)$. Hence, technology of firm *j** is imitated now by firm *i* and the behavioural imitation is to switch to the sustainability commitment of the apparently more successful firm *j**.
- In some of the model simulations, a most simple adaptable sustainability commitment, i.e. $h_i(k+1) = \lambda h_i(k) + (1-\lambda) h_{j^*}(k)$, with values $\lambda = 0.9$, and 0.5 is being used.

- In addition, a $N \times N$ trust matrix T is updated. At k=0 we initialize $T_{ij} = 0,$ for all i,j, and $T_{ij^*} = T_{ij^*} + 1,$ that is, firm j^* being the source of imitation receives a "unit of trust" from firm i. Note that, in general, the emerging T will not be symmetrical.

Proceeding to the simulation of the innovating firms two neighbourhood sizes with D=0.055 and D=0.15 are used. All firms are initialized identically, except for sustainability investment share $h_i(0) \geq 0,$ which ranges from $h_1(0) = 0$ to $h_N(0) = H = 0.45.$ While the time points of innovation events expressed by successive unit cost reduction are generated by independent random draws (see section 3), the effective use of an innovation depends on whether its unit costs are eventually inferior to unit costs of technologies already adopted by imitation. Hence, following an imitation event, all successively decreasing own unit costs, which are larger than the unit costs just adopted, are also replaced. Figures 8 and 9 contain the results for the two neighbourhood sizes D.

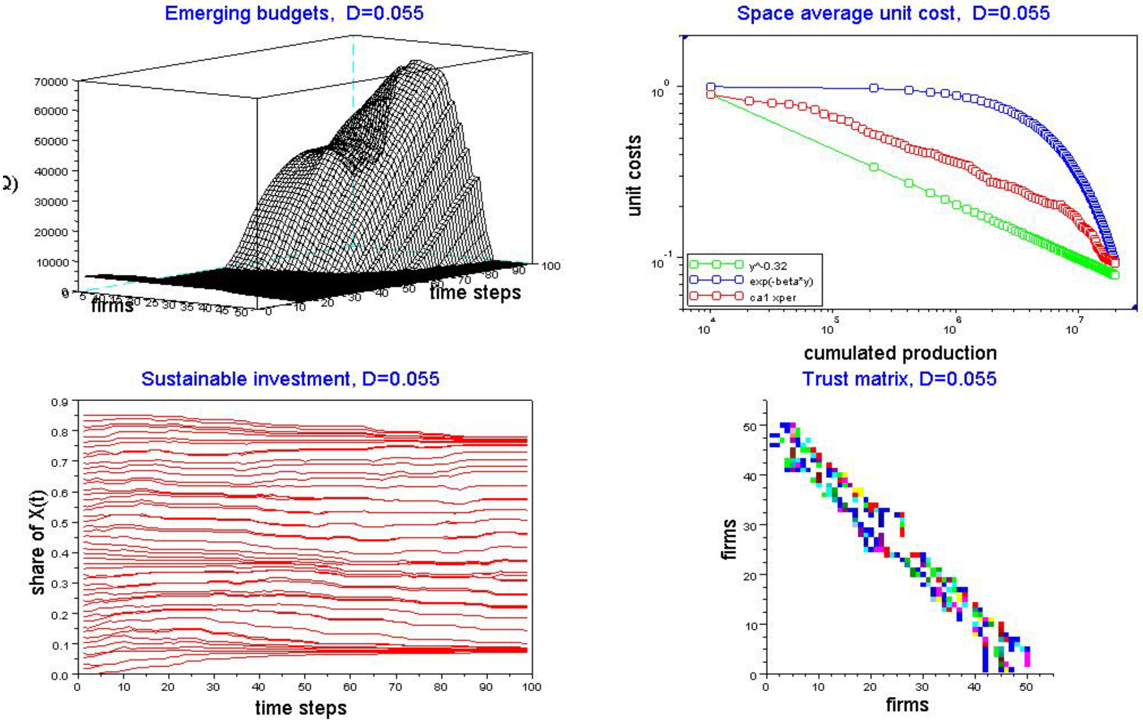

Figure 8: Run with adaptive sustainability commitment using $\lambda = 0.9$ and smaller neighbourhoods

Figure 8 display the budget evolution over firms and time (upper lhs), the innovation curve averaged over all firms (red, upper rhs) which in part evolves parallel to the theoretical power law (green), the adaptation of sustainability investment shares over time (lower lhs) and the trust matrix at final time step k=100 (lower rhs), where different colours stand for different trust levels which have been formed between firms equalling the number of times a firm being a source of imitation to other firms.

Replacing the smaller with the somewhat bigger neighbourhoods (i.e. looking at the difference between the runs displayed in figure 8 and figure 9) leads to observing that sustainability investment shares focus much stronger, which in turn leads to a more uniform budget evolution over firms but also to a more involved trust block formation, which tends to form two bands and many distinct sub-blocks. The innovation curve still remains close to the theoretical power law curve but exhibits regimes (horizontal sections) where nothing seems to be learned with increasing cumulated production.

8. Conclusion and outlook

Starting from general considerations about innovation, knowledge, learning and social feedback mechanisms, the paper develops a concept for integrating innovating firms and sustainability investment into a stylized dynamic model which is similar to opinion formation processes used in order to model polarization of consumer and producer decisions concerning the adoption of new products. In both cases neighbourhoods induced by similarities of innovating firms and opinions about new product proposals respectively are driving the dynamics of the models. In the case of innovating firms, a trust score matrix is recording actual imitation events which lead to behavioural and technological niches. Some interesting emerging model behaviour is found when neighbourhood size is increased. In the case of new product choice, a cascaded opinion formation process model combines opinion formation of customers and producers. Here too, a form of trust formation is used in order to adapt the neighbourhoods for opinion formation over time.

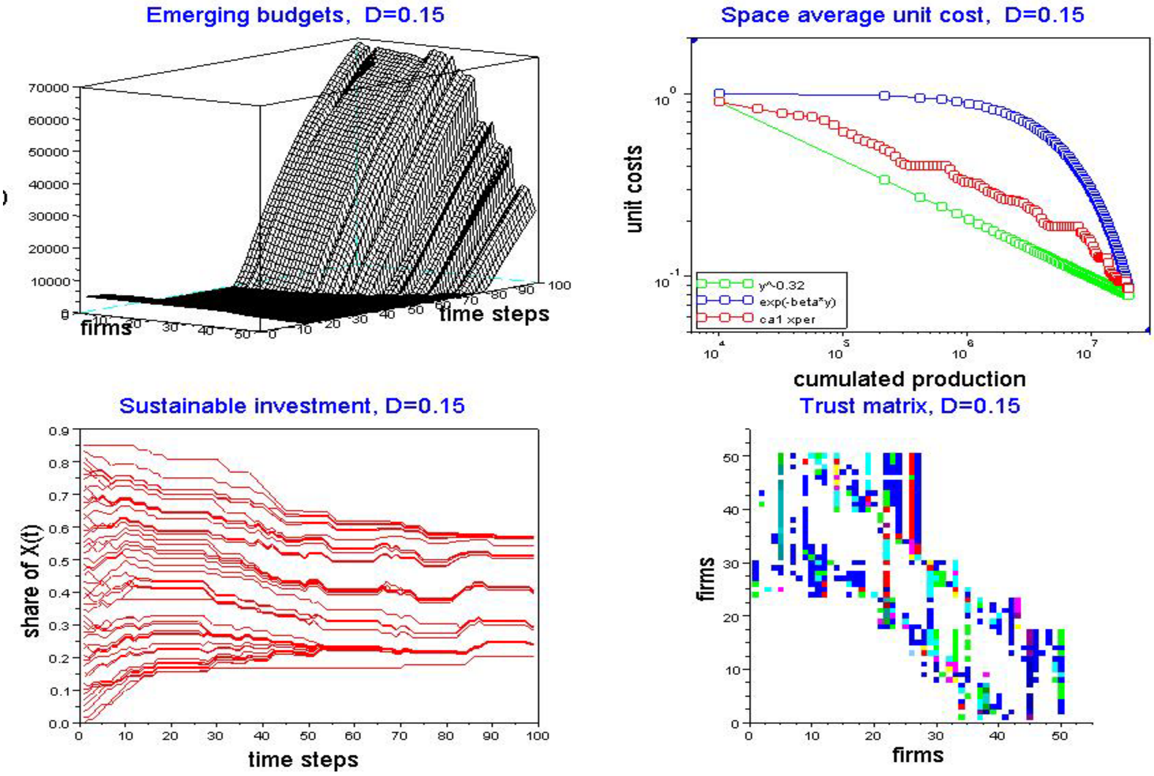

Figure 9: Run with same parameters as in figure 8 but with bigger neighbourhood radius of *D*=0.15

In future work, such cascaded opinion formation will be related to recommender-like systems, which are able to identify hub-consumers from large client data bases or client networks in order to boost opinion convergence and eventually sales. In this context, IC formation may be expressed by the very fact that producers and consumers collectively learn to prefer products which embody high levels of creativity. The various communities of producers and consumers are increasingly interrelated. At a general level we therefore argue in favour of using some mechanism for trust generation and also for learning of how to treat sustainability issues and also of how to identify complementarities in products and technologies possibly all by means of appropriate e-Cooperation platforms.

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