Universitat Ramon Llull

DOCTORAL THESIS

Title	**UNDERSTANDING INNOVATION AS A COLLABORATIVE, CO-EVOLUTIONARY PROCESS**
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Center	ESADE – ESCUELA SUPERIOR DE ADMINISTRACIÓN Y DIRECCIÓN DE EMPRESAS
Department	BUSINESS POLICY, HUMAN RESOURCES MANAGEMENT AND INFORMATION SYSTEMS
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Abstract

Innovation, which used to be the result of a single, sometimes heroic, entrepreneur, is progressively turning into a collaborative endeavor, better described as the result of a complex process with multiple actors.

This thesis aims to explore this collaborative aspect of innovation by digging into two strands of research. One uses Agent-Based Modeling to create theoretical models, where the other one uses qualitative analysis to devise some insights from organizations - Living Labs - that aim to involve users in innovation.

In addition to understanding innovation as an open process, a closed one seems sometimes to be equally successful. In fact, very simple and very complex mobile phones seem to follow this later approach. Under what conditions innovation benefits from being open and when better results can be obtained from retaining control of the whole process is our first research question.

This process of collaboration, characteristic of the open approach, is normally considered at a micro level, as a result of a dyadic interaction between agents. Nevertheless, there is a macro level characterized by institutions, such as Business Schools, that play an important role in uncovering Best Practices and building hypothesis that, if successful, will be adopted by the agents.

Understanding how this process works; how many cases should be collected and how comprehensive they should be; how much companies can rely on the insights of Business Schools; and when it is necessary to engage in exploration, is also necessary when characterizing innovation as a collective process.

The mechanisms of collaboration are, however, not all well-understood. Innovation is no longer in the solely hands of R&D laboratories or even organizations, users play an increasingly significant role and are being perceived as holding vast potential. Living Labs is one attempt to provide structure and governance to user involvement in innovation. Here, we will examine what is the contribution of users, how Living Labs aim to capture relevant knowledge and apply it, and when and how this proves successful.

Acknowledgements

Being able to approach academia after many years in industry and after having crossed the middle years of one's life is certainly a rare privilege.

Something that would not have been possible without the support and guidance of Ramon Casadesus-Masanell and Jonathan Wareham, who, against all odds, believed that this was not a completely foolish and senseless ambition doomed to failure. Over the years, they became friends more than advisors and without them, this thesis would never have turned into reality. Thank you very much!

I would also like to acknowledge the contribution of Artur Serra from i2Cat, without his help and support our work on Living Labs wouldn't have been possible.

Last but not least, I would like to acknowledge the support and the love of my family and friends in this endeavor, Antje, Esteve, Nuria, Diana, Marisol and many others who had the patience to support and tolerate an absent father, a missing partner, and a neurotic friend. Thank you very much to you all!

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1 Introduction

1.1 Motivation

The public understanding of innovation is full of stories of entrepreneurs that, against all odds and often humble origins, managed to transform our lives. Stories, such as Edison's Menlo Park (1876 - 1881), the HP garage in Palo Alto (1935) or Sergey Brin and Larry Page dormitory in Stanford, managed to capture public imagination, presenting innovation as the result of heroic and solitary work of exceptional people.

However, this figure of the innovator-entrepreneur is almost always immediately followed by one of the team, such as the case of the Innovation Factory of Edison, HP Labs or, more recently, the emergence of Google as an unstoppable machine of relentless innovation.

In fact, innovation is gradually being perceived as a result of increasingly large groups that were represented first as teams, and later, as networks and communities, leading to an understanding of innovation as an emergent open process based on collaboration and interchange.

Much evidence supports and explain this shift in our understanding of innovation. Among the main culprits, we can mention the emergence of the Information Society, ignited by Information Technology, where knowledge, that grows and develops when shared, experienced an intense process of democratization and globalization, becoming readily available to anybody with an Internet connection.

This democratization of knowledge, again led by Information Technology, had a parallel in the availability of tools, promoting the rise of capable teams everywhere.

Henry Chesbrough (Chesbrough, 2003) coined the expression “Open Innovation”, that better than any other portrays the understanding that corporations and governments can no longer rely on the premise that they have the best minds and ideas. Rather, Open Innovation argues that they should open their innovation process in order to be able to take advantage of an external world of knowledge and innovation.

Still, despite with this tendency towards and understanding of innovation as a complex, collaborative process with many actors, we still find the stubborn persistence of the disconnected, focused team led by innovators that defy statistics and manage to repeatedly produce products and services that take the market by storm, such as the case of Apple, Facebook, Twitter, etc.

Understanding why these two apparently contradictory tendencies coexist, and how and when companies and the society as a whole can better use which approach to innovate and capture value from this innovation, is the focus of this dissertation.

The same changes that lead to this widespread availability of knowledge and transformed the process of innovation into a collaborative one, also changed the speed, reach and the availability of the insights of the organizations devoted to understand processes of innovation, such as Business Schools, universities, research centers or the economic press, increasing their influence and their capacity of shaping future strategies of companies.

Companies increasingly rely on a mixture of contributions from organizations like Business Schools, together with the ones coming from their own exploratory process. Again, our understanding of this process is incomplete, our models still rely mostly on dyadic interactions that view innovation as exogenous, and as a result, there is a lack of representation and understanding of the importance of individual exploration versus the adoption of the insights provided by Business Schools.

We argue that now, more than ever, our comprehension of social dynamics is a process of collective construction, a collective exploration where theories and strategies of economic agents co-evolve and shape each other.

Still, there is one more paradox in this evolution of the way innovation emerges and develops. We have been describing a process of opening where the ingredients of innovation became democratized and are, in many cases, readily available to everybody. Nevertheless, our portrait of the main actors is still focused on organizations or, at most, self-organized communities or lead-users. We are certainly aware of the increasing importance and capacity of users in innovation, but our understanding of processes such as their exact roles, coordination and governance is still modest and lacks depth. We face a similar situation when confronted with relevant managerial questions such as when and when not to seek user engagement or how to capture value from their participation.

In this area, Living Labs represent an attempt to engage user innovation, providing governance to the processes and capturing insights from their involvement. Lessons learned from this and other attempts can possibly help us to understand this collaborative exploration that innovation is embracing and learn when and with whom this engagement is more appropriate and valuable.

Crowdsourcing, Living Labs and other open models of innovation, are a byproduct and a consequence of this new world characterized by global low cost communication and collaboration that Internet made possible. This is not only changing the way single innovators work, but how large and small corporations approach innovation and how governments approach policy.

This thesis aims to provide a modest contribution to the understanding of this process.

1.2 Research issues

In trying to understand innovation as a collaborative process, probably the most obvious and immediate question is to explain when and why the collaborative approach works better or; expressed in other terms, when an open approach to innovation dominates a closed one.

When considering open versus closed innovation we have to pay attention to the trade-off between adoption and value appropriation but also to the influence of both approaches in the technological trajectories of the agents involved, stimulating innovation on one side but increasing coordination costs in the other.

Therefore, the central research issue in this area will examine the benefits of discovery versus the costs of suboptimal coordination due to the divergence in objectives. This trade-off will be operationalized with the concepts of discovery and divergence, consequently allowing its further investigation.

The main contributions of this area are,

1) The development of a NK simulation model to assess the different contribution of open and closed innovation operationalizing it through the concepts of divergence and discovery.
2) Finding: The performance of the open and closed approach depends on the capacity of changing partners. If partnership is fixed then an open approach leads to better performance if complexity is low. As the partner set opens, so does the minimum level of complexity, such that open innovation leads to better performance.
3) Finding: Discovery might arise not only from exercising full strategic freedom but from restricting the available choices and learning from those made by others.

If our objective, however, is to understand innovation as a collective process, then it is necessary to explore the mechanism that drives this collective exploration. This implies in the first place depicting a model of collective discovery that covers not only dyadic interactions but also the societal institutions that collect "*Best Cases*" and evaluate the activities of companies in the market in order to reach conclusions and extract "*Best Practices*" providing useful insights to companies.

Again, explaining the variations in behavior requires situating our model in a landscape with a diversity of conditions where, the complexity of the landscape will prove to be an important element for understanding system behavior and empirical phenomena.

Interesting questions arise in this area, such as how many cases should Business Schools collect and how comprehensive they should be, when "*Best Practices*" work better than analytical results coming from a large number of observations or how many resources should companies divert to exploration or how much can they rely on the insights of Business Schools and other organizations for sustaining their performance in the market.

The main contributions of this area are,

1) The development of an Agent-Based model of pattern-based search that fits current practices in collecting "*Best Cases*" and extracting "*Best Practices*" from them.

2) Finding: In a pattern-based search setting, a smaller set of cases (to the extent that they contain relevant information) collected from the best performing agents, leads to better results than a large one.

3) Finding: Less comprehensive patterns of "I" lead to better or equal results (depending on the level of complexity) than larger ones.

4) Finding: When comparing patterns from "*Best Cases*" with analytical results computed from the set of observations collected by the agents, patterns outperform insights coming from statistical inferences when complexity is low while statistical inferences have an edge on patterns as complexity increases or the memory of the agents (or their ability to use it due to a changing or uncertain environment) decreases.

5) Finding: In a setting where agents rely on the adoption of insights coming from patterns or statistical inferences, their individual exploration is more relevant, both at individual and societal level, as complexity increases.

How this collaboration orchestrated in real life environments is introduced in section five. Concretely the aspects related to user involvement in the innovation process. This is accomplished by studying and situating the work of a new type of organizations: Living Labs, whose aim is to foster innovation by involving users as co-creators in real life experimentation environments.

The main research area in this section revolves around the role of Living Labs and when, how, and if they manage to provide an advantage over other methodologies.

The main contributions of this area are,

1) The mapping of innovation approaches with respect to their openness and to the level of user involvement in the innovation process, from methodologies led by experts where users are seen as subjects of investigation, to the ones where users are in charge of the innovation process.

2) Finding: Living Labs are more appropriate when the fit to a social and economic context is both more relevant and less trivial. Where reaching a solution that achieves such level of fit will be difficult for an startup or for a single organization. Situations where user knowledge and experimentation in real life environments can provide the kind of knowledge and validation that could help in reaching successful innovations.

Living Labs as organizations are in many cases a result of the entrepreneurial ambition of universities and research organizations that attempt to transfer and apply their knowledge to concrete settings and, by doing so, influence the reality where they are situated. This ambition is especially relevant in Europe where the gap between research and innovation seems to be bigger than in other places and significant enough to coin the expression "*The European Paradox*" (E.C., 1995). How and if this collaborative vision of innovation allows to cover this gap; what is the contribution of users in this process and how value is captured, are the major research areas of this section.

The main contributions of this area are,

1) Finding: Living Labs are able to reduce the gap between research and innovation by: a) reducing entrepreneurial personal risk, b) supporting entrepreneurship through the selection, coordination and assistance in funding of the innovation network, c) creating an innovation arena where experimentation can take place and d) fostering an initial demand allowing further development.

2) Proposition 1a**.** Living Labs observe user-lead practice in diffuse social contexts.
   Proposition 1b**.** Living Labs identify and codify tacit and practice based knowledge.
   Proposition 1c. Living Labs diffuse tacit and practice based knowledge into ad hoc innovation networks.
3) Proposition 2a. Living Labs perform exploration by assuming Knightian risk, experimentation and discovery.
   Proposition 2b. Living Labs perform exploitation via refinement, selection, implementation and execution.

4) Proposition 3a. High Level innovation is highly portable across international contexts, where mid and low level innovation is localized, geographically and spatially bound.

   Proposition 3b. Living Labs operate and mid and low level innovation strata.
5) Proposition 4. Living Labs are agnostic as to whether innovation is technologically incremental or radical.
6) Proposition 5a. Living Labs perform context-based experimentation in order to generate local modifications within existing socially negotiated meanings.

   Proposition 5b. Living Labs perform context-based experimentation in order to generate new socially negotiated meanings for products and services.

1.3 Published work

Research corresponding to section 3, "Strategic Interaction in NK Landscapes" was presented in

> E.Almirall, R.Casadesús. Strategic Interaction in NK Landscapes. *Academy of Management*. Atlanta 2006.
>
> E.Almirall, R.Casadesus-Masanell. Open vs. Integrated Innovation. *EURAM*, 2008.

and is accepted for publication in

> E.Almirall, R.Casadesus-Masanell. Strategic Interaction in NK Landscapes. *Academy of Management Review* (AMR 07-0060, forthcoming).

Research corresponding to section four, "Theories versus Patterns" is in the process of being submitted for publication.

Research corresponding to section 5, "Collaborative Innovation in Practice: The Living Labs Approach" was presented at

> E.Almirall, J.Wareham. Innovation, a question of Fit - The Living Labs Approach. *Esade-HEC Symposium on Transversal Topics,* April 2-3, 2009. Barcelona.

and is accepted for presentation at

> E.Almirall, J.Wareham. Innovation: A question of Fit - The Living Labs approach. *Mobile HCI 09*. September 15, 2009. Bonn, Germany.
>
> E.Almirall, J.Wareham. Innovation, The Living Labs Approach. *IADIS International Conference WWW/Internet 2009*. November 19-21. Rome, Italy.

Research corresponding to section 6, "Evidence of Users' and Living Labs' contributions in Closing the Gap between Research and Innovation" was published at

> E.Almirall, J.Wareham. Living Labs and Open Innovation: Roles and Applicability. *Ejov - The Journal of Organizational Virtualness* vol 10, August 2008.

presented at

> E.Almirall, J.Wareham. Contributions of Living Labs in Reducing Market Based Risk. *International Conference on Concurrent Enterpreise - IEEE, IFIP/IFAP*. June 22-24, 2009. Leiden, The Netherlands.

published as a chapter of a book in

E.Almirall, J.Wareham. The Role of Living Labs in Open Innovation. In Schumacher, J., Niitamo, V.P. (Ed.) *European Living Labs. A new approach for human centric regional innovation* (147-157). Wissenschaftlicher Verlag Berlin. Berlin, 2008. ISBN 978-3-86573-343-6

and is accepted for presentation at

E.Almirall, J.Wareham. The Entrepreneurial Role of Living Labs in Closing the Gap between Research and Innovation. *eChallenges 2009*, October 21-23, 2009. Istanbul, Turkey.

The work of this research has also translated into a number or European and National projects that the author of this thesis has co-author

2006-2010 Laboranova - IST-FP6-035262. European Project (IP) focus in building tools for fostering innovation in collaborative environments. In Laboranova Esteve Almirall has been one of the main writers of the project, leader of subproject 7, leader of several work packages and member of the Executive Board. Laboranova partners include universities such as Biba, Esade, Insead, Learning Lab (DK), Lulea Technical University (S), University of Nottingham (UK), University Paris IX Dauphine (F) and UPC (Spain) and companies such as Danfoss (DK), Fiat/Isvor (IT), SAP (D) among others. The budget of Laboranova is around 10M Euros with a EU contribution around 7M Euros.

2006 -2007 CatLab. CatLab is a project sponsored by the Generalitat of Catalonia aiming to vertebrate a Network of Living Labs in Catalonia. Participants are i2Cat, Neapolis, CitiLab, 22@, FBD, Tecnocampus and Sant Cugat City Hall. Esteve Almirall was co-coordinating the project together with Artur Serra.

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2007-2008 InfoPoints. An Spanish national project "Profit" together with Futurlink seeking to understand the role of Open Business Models in a context of Mobile Services.

2008-2009 VEP Parliament - EP-07-01-039. VEP Parliament aims to use IT and AI technology to foster political participation in Europe. Partners of the project are iCity – Hasselt, i2Cat, University of Leuven, University of Lulea and UPC. Esteve Almirall was one of the main writers of the project.

2008-2010 COLLABS – CIP224979.Community Based Living Labs to enhance SMEs Innovation in Europe. The over-all objective of the CO-LLABS Thematic Network is to achieve a European-wide adoption of ICT-based Living lab services and practices to allow SMEs to improve their innovation capabilities and processes and become part of “open innovation” environments. Esteve Almirall was one of the main writers of the project and actively participated representing ESADE.

2008-2010 Itenerarios Avanzados de Innovation – An "Avanza" Spanish National project between Esade and Barcelona Digital that seeks to understand and map best practices in Open Innovation around Europe. Esteve Almirall was one of the main writers of the project.

Also, the research in the present thesis informed and provided the insights and material for the following work in practitioners conferences and public press,

E.Almirall, J.Wareham. Closing the Gap between Research and Innovation. *Open Innovation Speaker Series*, April 20, 2009. Berkeley - U.C. .

E.Almirall. The Role of IT in Innovation. *Upgrade*, vol IX (5) 10-16, October 2008.

E.Almirall. Ecosystems, Living Labs and Open Innovation, *Den4Dek Workshop*. February 19, 2009. Zaragoza.

E.Almirall. Clusters, Innovation & ICT. *3th Symposium on Urban Clusters*, February 12, 2009. Barcelona.

E.Almirall, J.Wareham. Opening the Innovation Process: Open Innovation, User Innovation and Living Labs. *Pacific Ring Conference on Multimedia -PCM 2008*, December 9, 2008. Tainan.

E.Almirall, J.Wareham. Best Practices and Methodologies of European Living Labs. *Workshop - PCM 2008*, December 8, 2008. Tainan.

E.Almirall. Best Practices and Methodologies of European Living Labs. *National Taiwan University*, Workshop, December 13, 2008. Taipei

E.Almirall. Best Practices and Methodologies of European Living Labs. *SEE Methodology Sharing Workshop*, December 12, 2008. Taipei

E.Almirall. Opening the Innovation Process: Open Innovation, User Innovation and Living Labs. *ICT Platform – Service Experience and Engineering Design Seminar*, December 11, 2008. Taipei.

E.Almirall. Coordianting Living Labs actions – The Case of CatLab. In *Open Innovation in Advanced Service-Product Development & In Collaborative Clusters*, *Esoce-Net Annual Conference*, December 2, 2008. Rome.

E.Almirall. Living Labs e Innovación Abierta. *Urban Labs 2008*. October 9, 2008. Barcelona
http://www.urbanlabs.net/index.php/Intervenciones_Keynote_Speakers

E.Almirall. Catlab- The Catalan Network of Living Labs. *Open Days EU*. October 8, 2008, Brussels.

http://ec.europa.eu/regional_policy/conferences/od2008/doc/pdf/programme_07072008.pdf

E.Almirall. Living Labs and Open Innovation. *CKIR Workshop*. August 29, 2008, Helsinki.

E.Almirall. Living Labs projects, methodologies and organization in Catalonia. *Snowpolis Worshop*, August 21, 2008, Finland. http://www.snowpolis.com/?pid=93

E.Almirall. IGC 2008. Chair of the tracks: Open Innovation.

E.Almirall. Open Innovation & User Contributed Innovation. *Especial 12x12 - Innovación, ¿una realidad global o sólo una palabra?*, Fundació Barcelona Digital – CaixaForum, December 2007, http://www.bcndigital.org/esp/n42.asp?m=4&n=2.

E.Almiral. Why Living Labs. *Co-Creative Innovation in Service-product development & solutions for creation and managing collaborative clusters*. *ESOCE-NET Industrial Forum*, Rome, December 2007.

E.Almirall. CatLab, The Catalan Network of Living Labs. *Co-Creative Innovation in Service-product development & solutions for creation and managing collaborative clusters. ESOCE-NET Industrial Forum*, Rome, December 2007.

E.Almirall. Innovació al S. XXI.COPCA. *Setmana de la Internacionalització a Catalunya*, November 2007.

E.Almirall. Els Living Labs a Europa. *CatLab la Xarxa Catalana de Living Labs, CCCB*, November 2007.

E.Almirall. Laboranova & Living Labs. *Launch of the Second Wave of Living Labs*. Brussels, October 2007.

E. Almirall. Living Labs and Open Innovantion. *Open Innovation and Renewal. CKIR workshop*, August, 2007. Helsinki.

E.Almirall. Open Innovation. *Infonomia – iF,* 53, June 2007.

E.Almirall. Laboranova and the European Network of Living Labs. *Co-Creative Research and Innovation to Connect the Lisbon Strategy to People: European Network of Living Labs Event*, Guimarães, Portugal, May 2007.

E.Almirall. Europa i2010. *Infonomia – iF* 49, Diciembre 2006.

Table 1 – Summary of Contributions and Publications

Research Area	Innovation as a collaborative process pondering the benefits of discovery versus the costs of suboptimal coordination due to the divergence in objectives
Contributions	**Publications**
The development of a NK simulation model to assess the different contribution of open and closed innovation operationalizing it through the concepts of divergence and discovery. Finding: The performance of the open and closed approach depends on the capacity of changing partners. If partnership is fixed then an open approach leads to better performance if complexity is low. As the partner set opens, so does the minimum level of complexity, such that open innovation leads to better performance. Finding: Discovery might arise not only from exercising full strategic freedom but from restricting the available choices and learning from those made by others.	**Journals & Referred Conferences** E.Almirall, R.Casadesús. “Strategic Interaction in NK Landscapes”. Academy of Management. Atlanta 2006. E.Almirall, R.Casadesus-Masanell. “Open vs. Integrated Innovation”. EURAM, 2008. E.Almirall, R.Casadesus-Masanell. “Strategic Interaction in NK Landscapes”. *Academy of Management Review* (AMR 07-0060, forthcoming).

Research Area	Understanding innovation as a collective process requires to explore the mechanism that drives this collective exploration. Depicting a model of collective discovery that covers not only dyadic interactions but also the societal institutions that collect "*Best Cases*" and evaluate the activities of companies in the market in order to reach conclusions and extract "*Best Practices*" providing useful insights to companies.
Contributions	**Publications**
The development of an Agent-Based model of pattern-based search that fits current practices in collecting "*Best Cases*" and extracting "*Best Practices*" from them. Finding: In a pattern-based search setting, a smaller set of cases (to the extent that they contain relevant information) collected from the best performing agents, leads to better results than a large one. Finding: Less comprehensive patterns of "Best Cases" lead to better or equal results (depending on the level of complexity) than larger ones. Finding: When comparing patterns from "*Best Cases*" with analytical results computed from the set of observations collected by the agents, patterns outperform "statistical inferences" when complexity is low while "statistical inferences" have an edge on patterns as complexity increases or the memory of the agents (or their ability to use it due to a changing or uncertain environment) decreases. Finding: In a setting where agents rely on the adoption of patterns or "statistical inferences", their individual exploration is more relevant, both at individual and societal level, as complexity increases.	

Research Area	Role of Living Labs and when, how, and if they manage to provide an advantage over other methodologies.
Contributions	**Publications**
The mapping of innovation approaches with respect to their openness and to the level of user involvement in the innovation process, from methodologies led by experts where users are seen as subjects of investigation, to the ones where users are in charge of the innovation process.	**Journals & Referred Conferences** E.Almirall, J.Wareham. "Innovation: A question of Fit - The Living Labs approach". Mobile HCI 09. September 15, 2009. Bonn, Germany. E.Almirall, J.Wareham. "Innovation, The Living Labs Approach". IADIS International Conference

Finding: Living Labs are more appropriate when the fit to a social and economic context is both more relevant and less trivial. Where reaching a solution that achieves such level of fit will be difficult for an startup or for a single organization. Situations where user knowledge and experimentation in real life environments can provide the kind of knowledge and validation that could help in reaching successful innovations.	WWW/Internet 2009.November 19-21. Rome, Italy. **Non Referred Conferences** E.Almirall, J.Wareham. "Innovation, a question of Fit - The Living Labs Approach", Esade-HEC Symposium on Transversal Topics, April 2-3, 2009. Barcelona.

Research Area "*The European Paradox*" (E.C., 1995) is the expression that coined the European inability to close the gap between research and innovation. This research area deals with how and if this collaborative vision of innovation allows to cover this gap; what is the contribution of users in this process and how value is captured.

Contributions	Publications
Finding: Living Labs are able to reduce the gap between research and innovation by: a) reducing entrepreneurial personal risk, b) supporting entrepreneurship through the selection, coordination and assistance in funding of the innovation network, c) creating an innovation arena where experimentation can take place and d) fostering an initial demand allowing further development. **Proposition 1a.** Living Labs observe user-lead practice in diffuse social contexts. **Proposition 1b.** Living Labs identify and codify tacit and practice based knowledge. **Proposition 1c.** Living Labs diffuse tacit and practice based knowledge into ad hoc innovation networks. **Proposition 2a.** Living Labs perform exploration by assuming Knightian risk, experimentation and discovery. **Proposition 2b.** Living Labs perform exploitation via refinement, selection, implementation and execution. **Proposition 3a.** High Level innovation is highly portable across international contexts, where mid and low level	**Journals & Referred Conferences** E.Almirall, J.Wareham. "Living Labs and Open Innovation: Roles and Applicability". *Ejov - The Journal of Organizational Virtualness* vol 10. August 2008. E.Almirall, J.Wareham. "Contributions of Living Labs in Reducing Market Based Risk". International Conference on Concurrent Enterpreise - IEEE, IFIP/IFAP, June 22-24, 2009. Leiden, The Netherlands. E.Almirall, J.Wareham. "The Entrepreneurial Role of Living Labs in Closing the Gap between Research and Innovation". eChallenges 2009, October 21-23, 2009. Istanbul, Turkey. **Book Chapters** E.Almirall, J.Wareham. European "Living Labs. A new approach for human centric regional innovation". Wissenschaftlicher Verlag Berlin. Berlin, 2008. ISBN 978-3-86573-343-6 **Research Projects** 2006-2010 Laboranova - IST-FP6-035262. European Project (IP). focus in building tools for fostering innovation in collaborative environments. In Laboranova Esteve Almirall has been one of the main writers of the project, leader of subproject 7, leader of several work

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Non Referred Conferences & Publications

E.Almirall, J.Wareham. "Closing the Gap between Research and Innovation". Open Innovation Speaker Series, April 20, 2009. Berkeley - U.C. .

E.Almirall. "Clusters, Innovation & ICT". 3th Symposium on Urban Clusters, February 12, 2009. Barcelona.

E.Almirall, J.Wareham. "Opening the Innovation Process: Open Innovation, User Innovation and Living Labs". Pacific Ring Conference on Multimedia -PCM 2008, December 9, 2008. Tainan.

E.Almirall, J.Wareham. "Best Practices and Methodologies of European Living Labs". Workshop - PCM 2008, December 8, 2008. Tainan.

E.Almirall. "Best Practices and Methodologies of European Living Labs". National Taiwan University, Workshop, December 13, 2008. Taipei

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E.Almiral. "Why Living Labs". Co-Creative Innovation in Service-product development & solutions for creation and managing collaborative clusters. ESOCE-NET Industrial Forum, Rome, December 2007.

E.Almirall. "CatLab, The Catalan Network of Living Labs". Co-Creative Innovation in Service-product development & solutions for creation and managing collaborative clusters. ESOCE-NET Industrial Forum, Rome, December 2007.

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2 On Modeling Innovation

2.1 Why is the Agent-Based Approach Best Fitted to Modeling Innovation?

Innovation and technological change is increasingly being perceived as a major driving force in promoting economic growth and maintaining well-being in industrialized societies. The European Union 2010 Aho Report (Aho, 2006) is one of the latest evidences of this concern, and one where the need for supporting innovation is presented in a more compelling way.

This societal concern correlates with a growing interest on innovation in the academic community. Furthermore, this interest has been parallel to an increasing understanding of the phenomena and a growing accumulation of empirical findings from where a rich set of facts concerning innovation and technological change have been established.

Nevertheless, our view of innovation has changed dramatically from the time of Schumpeter (Schumpeter, 1934) to whose seminal work we owe the separation between invention and innovation - described as the actual adoption of these inventions - to our current understanding. Our view of innovation changed from describing it as a set of inventions, allowing to push forward the technological frontier to a new equilibrium, to portray innovation as a process with multiple actors and better described in terms of a complex phenomena.

A wide range of approaches has been used to gain insights about the origins and effects of innovation and to model it. Among them: static and dynamic games, evolutionary theory, dynamic equilibrium analysis or complex system theory to name only the most relevant ones. Overviews of the different strands have been produced by Nelson and Winter (Nelson and Winter, 2002), Dosi (Dosi et al., 1988), Hall (Hall, 1994), Sutton (Sutton, 1997), van Cayseele (van Cayseele, 1998) and H.Dawid (Dawid, 2006).

In our understanding, innovation has increasingly been described as a process endowed of very specific properties whose combination calls for a modeling approach that goes beyond the paradigm of a representative agent with full rationality. Moreover, elements like heterogeneity or the underlying network structure play a major role. Therefore Agent-Based models seem better suited to incorporate these properties and hence are better able to reproduce and model the stylized facts that emerge from the innovation process.

The properties that I propose for consideration are:

i. **The dynamic nature of innovation**. Since the work of Schumpeter, published in 1911 in German and translated to English in 1934, innovation has been conceived as a dynamic process (divided into invention-innovation-diffusion in Schumpeter's work) that has a time structure that must be taken into account. During the diffusion stage, not only the actors take investment decisions, but also the meanings that consumers attribute to products and new innovations and mutations of the product arise (Hargadon, 2003).

   Therefore, new understandings of the phenomena present the innovation process from a social perspective, arguing that an innovation only exists when embedded into a social practice (Tuomi, 2002), stressing even more the dynamic dimension of the process.

ii. **The understanding of innovation as a search process in a large solution space**. Understanding innovation as a search problem clearly evidences the uncertainty associated with both the difficulty to foresee both inventions and trends of economic development.

   Moreover, the vision of innovation as search, easily relates to the mechanism used in traversing the space of solutions. Incremental and radical innovation together with imitation are the most common mechanisms discussed in the literature, they all are easily represented as different types of movements in the search space. Recently the well-known metaphor or *blue oceans* (Kim, 2005) draw attention to this vision of innovation as search.

iii. **Innovation as a process that builds on heterogeneity and endogenously creates it**. Heterogeneity is both the objective and a prerequisite for innovation. Actually the objective of the innovation process is indeed differentiation; firms innovate in order to distinguish themselves from others with a better product, service or process and gain advantages from this differentiation. Therefore, heterogeneity is inherently present in the strategies pursued by the economic agents: incremental or radical innovation (Malerba and Orsenigo 1996, Rivkin 2000).

   There is also a rich literature on spillovers portraying the role of heterogeneity in facilitating the generation of new knowledge. If heterogeneity indeed plays such a big role in facilitating, triggering and promoting innovation (Page, 2007), adequately representing it should be a major concern, especially being well established, as it is, that the aggregate behavior stemming from heterogeneous agents cannot be properly reproduced by using a representative agent (Kirman, 1992).

iv. **The special nature of the good that innovation builds on: knowledge**. When modeling relations and fluxes, we normally rely on the apparatus of calculus, representing relations in the form of continuous, possibly monotonic, functions.

However, knowledge, the primary good that constitutes innovation, largely defies this approach. First, the success of a firm, in terms of innovation, depends to a large extend, not on its current investment but on its knowledge base, structure and capacity to absorb and integrate it.

And second, a knowledge base needs to be accumulated over time (Dosi, 1988). In addition, knowledge is not flat, has a lot of structure and in some cases is embodied in individuals and groups of people like in the distinction of tacit knowledge (Polanyi, 1966).

Knowledge is in addition to that often acquired and transmitted through a social process that implies learning, and in many cases knowledge flows of non-market interaction and ultimately network formation and maintenance.

v. **The recognition of innovation as a result of collective interaction**. Innovation is increasingly perceived as a social process, a process of adoption and attribution of meaning done by communities and groups of people during their normal interaction (Tuomi, 2002). This “social” aspect, always present in diffusion, has been highlighted recently as central to the innovation process.

The understanding of the role of users as creators (von Hippel, 1998), or of the role of brokerage (Hargadon, 2003) and finally the framework of Open Innovation (Chesbrough, 2003), where innovation is portrayed more as an effort and a result of interaction than solely as an internal endeavor, all contribute to portray innovation as a complex process resulting of the interaction of multiple actors and contexts rather than the romantic quest of a solitary inventor.

Empirical and theoretical work that could uncover and model interaction mechanisms in innovation is still in its infancy (Almirall and Casasdesus, 2007). However, the growing interest in interaction and early empirical evidence suggest its increasing importance, greatly promoted because of lowering of interaction costs, the widespread diffusion of even very precise knowledge, and the enormous facilitation of communication and social interaction due to the widespread use of IT.

vi. **The importance of the underlying network structure in the innovation process**. Network effects in general and how inferior technologies can achieve market dominance (David, 1985) or the effect of a substantial initial market advantage in reaching a dominant market position (Arthur, 1990) are well known and established. So it is the impact of the network in the diffusion of innovations (Rogers, 1995; Valente, 1995; Jackson, 2004; Cowan, 2004).

Recently, the growing importance of Open Source code has renewed the interest in networks and the network structure as playing an important role in innovation. Linked to that interest is the understanding of innovation as creating new meanings embedded in social practices (Tuomi, 2002). At that point networks and innovation get intimately related, innovation is not only situated in networks, but transforms them to the point that communities like Open Source rely on the use of mechanisms that effectively support recombinatorial innovation.

Therefore, we can portray the process of technological change and in general innovation as a dynamic one, embedded in constantly evolving networks, build on and resulting on the heterogeneity of the agents involved, that could be described as a search process in a complex landscape, where agents interact and deal with a very particular type of good that can be shared without minoration and can only be acquired through a learning process.

Given these characteristics, the use of Agent-Based Models sounds appealing, as a method that could not only accurately represent the process of innovation itself but also reproduce empirically established stylized facts of it (Dosi et al. 1995,97; Sutton 1997; Silverberg and Verspagen 2005). Among these facts we can mention:

- The skewed firm size distribution observed, known as Zipf Law (Zipf, 1949).
- The persistent heterogeneity of firms in terms of technology and profits, with no visible convergence.
- The fact that the arrival of innovations, even if stochastic, is clustered in a given point of time more than in a uniform distribution.
- Positive correlation between entries and exits of firms not related to profitability.

Agent-Based Models can reproduce these patterns, and some of them as emergent properties of aggregate behavior based on micro-foundations incorporating known features of the innovation process.

Moreover, Agent-Based models can also be used to evaluate the effect that a change in mechanism or in policy measures could have on the system. This is now particularly interesting because IT technologies can and are increasingly being used in creating virtual communities and virtual markets (*e.g.* eBay, social networking sites, etc.) providing new grounds for innovation networks.

2.1.1 Agent-Based Models in Evolutionary Economics

Evolutionary economics looks at economic systems as a continuing process where the economic decision is determined by a selection process rather than optimization.

Schumpeter with his notion of creative destruction and his vision of the economy as a continuously changing system is perceived as a pioneer in the field. However, modern evolutionary economics gained momentum around 30 years ago.

The largest strand of research is focused on models of natural evolution based on game theory and centered on dynamic equilibrium selection. Their research is about the type of interaction that emerges from repeated direct interaction between agents.

Another strand of research interprets technological change as an evolutionary process and tries to gain insights on the co-evolution of technology and industry structure. This strand is inspired on the work of Nelson and Winter (Nelson and Winter, 1982) and accepts agent-based simulations as a valid tool.

This family of models of technological change present innovation as a three-step process. In the first stage there is a generation of variety by individual innovators. In the second, a selection is performed on the basis of one measure of success. Finally on the third stage there is a reduction of heterogeneity due to adaptation. The process halts when the population becomes homogeneous.

Also, a distinctive characteristic of these models is the way that the decision making process in the firm is modeled. Instead of perfect rationality, firms are supposed to act on the basis of procedural rationality that assumes that firms develop routines to deal with frequent situations and act accordingly. Procedural rationality lead to behavioral continuity, of which there is empirical evidence (Nelson and Winter, 1982).

Agent-Based Modeling fits well modeling procedural rationality, where decisions are taken based on sets of a hierarchy of rules, because of the lack of mathematical methods allowing and adequate characterization of it.

Undoubtedly, a very influential book in the field of evolutionary economics has been "**An evolutionary Theory of Economic Change**" (Nelson and Winter, 1982), not only because of their findings but also because of the way simulation studies were motivated and conducted and how they influenced subsequent work.

In part IV, an evolutionary model of economic growth is presented where a firm has a capital stock and two input factors: labor and physical capital. Both input factors can be improved by local search and imitation. In this model there is a fixed supply of labor and wages determined by the total demand of labor and gross capital invested, which is determined by gross profit.

Nelson and Winter claim that models should be based on plausible micro-foundations and therefore, this model was calibrated using data reported by Solow (Solow, 1957).

In part V, they presented a model of competition and industry evolution where a heterogeneous mix of imitators exists. The mix is determined by the investment of firms in either imitation or innovation, resulting in the adoption of the highest productivity level or the development of new techniques. The level of investment was modeled based on market share, profit, price-cost margin and depreciation-rate.

In the first run of simulations, Nelson and Winter vary the degree of concentration resulting in larger productivity for more concentrated industries but with no relationship between concentration and expenditures in R&D. Also, innovators were less profitable than imitators.

In a second run, they varied several industry characteristics, like the aggressiveness of investment policies or the difficulty of imitation, finding that aggressiveness of investment was the most crucial factor for industry concentration.

In 1984 they extended the model, making strategies adaptative on the basis of past successes and allowing additional industries to enter the market if the return of capital is high.

In that case they focused on a description of the two regimes, entrepreneurial and routinized, found in the later work of Schumpeter. The entrepreneurial regime was characterized by a larger number of innovation attempts but lower probability of success for a single innovation, while the randomized regime exhibits a smoother dynamics for the best technology but a higher degree of concentration and higher R&D expenses. In general, differences between both regimes matched Schumpeter descriptions.

Nelson and Winter simulations presented in many ways a simplified view because of assumptions largely unrealistic. For example, companies never changing their decision rules or the lack of interrelation between the firms. Also, their representation of technological change was similar to a black box, where an inflow of funds mechanicistically produced a productivity increase.

They presented a firm with role-based autonomous agents, where the interplay between the dynamics of industry concentration and productivity distribution generated non-trivial implications. Also, it is important to note the emphasis on model calibration and on relying on empirically supported micro-foundations that led to the reproduction of stylized facts as reported by Solow (Solow, 1957) and as described by Schumpeter (Schumpeter, 1934).

2.1.2 Agent-Based Models of Innovation

On the following lines we will review some of the most used agent-based models of innovation on the basis of the six categories proposed as the more relevant differentiators of the innovation phenomena, and in terms of adequacy for the use of Agent-Based Modeling as the primary technique for representation.

Our objective will be to show how the different models were selected, and show indeed relevant properties and lead to insights that would not be possible, or at least more difficult or unnatural, with other techniques. That way we aim to portray how the use of Agent-Based Modeling in innovation is helping to advance the field, pushing forward the state of the art and discovering new challenges and opportunities.

Of all six properties, there is one that is intrinsically inherent to any simulation, and therefore we will encounter it in every model: the dynamic nature of the process. All simulations presented are the representation of a dynamic process in evolution, therefore this characteristic will not be treated separately.

Last, we must consider that this taxonomy like many others, is done *a posteriori*. Therefore, even if we present models that in our opinion highlight better a certain property or aspect, many others are present and some models could easily fit into more than one category.

2.1.2.1 Innovation Viewed as Search

How firms address the problem of finding the best strategy or the best technology and what are the consequences at a global level of the different micro-behaviors, is a problem not addressed in the analytical neoclassical literature. On the contrary, R&D expenditures are transformed either deterministically or stochastically into cost reductions, improvements on quality or product differentiation.

However, the view that technological invention can be conceptualized as a search process has been quite common (March, 1991; Kauffman, Lobo and MacReady, 1998; Lobo and MacReady, 1999).

Kauffman, Lobo and MacReady presented a search simulation based on NK landscapes (Kauffman, 1993). NK landscapes were first intended as models for representing biological evolution and were later applied to the representation of technological and strategic search spaces.

A NK landscape is governed by two variables: N that determines the size of the landscape and K that models the number of variables that interact in assigning a value to each point of the landscape. When K=0, each of the N variables stand for itself and only one peak exists, but as K increases, so do the number of peaks or local optima, making it impossible for agents seeking a global optima to reach it without crossing valleys that separate local optima. Therefore, K allows tuning the complexity of the landscape. Thus, NK spaces are simple and elegant ways to produce tunable landscapes in terms of both number of variables and complexity resulting from their interaction, this tunable property makes them specially appropriate for modeling technological or strategic search spaces.

In their model, Kauffman, Lobo and MacReady (Kauffman, Lobo and MacReady, 1998) created production recipes in order to represent a diversity of strategies for traversing the landscape. Also, a search cost was introduced as a constraint to the search process. Results showed that if the initial position is poor, then it is optimal to search far away. However as firms succeed in their search process and improve their position, returns from search diminish and it becomes optimal to confine search to a local region of the landscape.

Following this line, Rivkin and Siggelkow (Rivkin and Siggelkow, 2003) explored NK models where the interaction between the elemental components that modeled the landscape was patterned instead of random. Previous work on traditional NK models with random interactions between elements illustrated the benefits of broader search as the interaction intensified. Rivkin and Sigglekow showed that a shift in the pattern of interactions could have an important effect in the landscape because the number of local optima increase by more than an order of magnitude, therefore agents could benefit from a broader exploration in those cases.

The problem of search is also closely related to the consequences of confronting a large space of solutions: uncertainty. Uncertainty in how strategies compare, uncertainty about the speed of technological change and industry growth and uncertainty on the payoff distribution of each strategy or on market and the reaction of firms to it.

Birchenhall presents the evolution of business models as a search problem. In his work there is a co-evolution of both potential new designs and models to evaluate them, using genetic algorithms (Birchenhall, 1995). Fitness of the strings that represent the evaluation models is determined by the evaluation errors of these models in the past. His findings show that the use of models for evaluation increase the performance of the firm compared to the direct implementation of every new design.

Cooper presents a simulation where design problems are represented by binary strings of a certain length that describe the key parameters of the design (Cooper, 2000).

Cooper tries that way to represent "*ill-structured*" problems that are hard to solve and compares the search process done in isolation with social learning. The search process done by individual firms is modeled using a simulated annealing algorithm, while social learning firms collect bits from a given number of other firms in order to form new designs.

Cooper describes that social learning speeds up the process, and partial imitation is faster than complete imitation of the top performer in completing the search process. Additionally, partial imitation avoids industry lock in suboptimal designs.

Natter considers the co-evolution of several models in the firm in a market with monopolistic competition (Natter et al., 2001). They use artificial neural networks in order to decide which type of production process to implement in a context where a marketing agent and a production agent predicts the attractiveness of the product in the market and adapt product features and cost respectively.

Simulations show the superiority of team-based structures and highlight the need to align incentive schemas with the organizational structure.

Windrum and Birchenhall (Windrum and Birchenhall, 1998) reproduce in their simulations stylized patterns of decreasing product innovation through the life cycle and the co-existence of several designs. This later aspect is interpreted as niche markets, being the dominant product a special case of them. For their simulations they propose a schema of shifting landscapes where consumer preferences co-evolve with product designs. The product designs are modeled using Genetic Algorithms and a fixed set of consumer types exist. Frequency of consumptioin depends on how well consumers have been served in the past.

Fagiolo and Dosi presented a model of discovery where the agents were situated in a two dimensional lattice (Fagiolo and Dosi, 2003). The output of each agent is based on a productivity parameter that was technology dependent and the number of agents using that technology. Agents were at any time in one of the three following stages: 1) **mining**: producing using the current technology, 2) **imitating**: moving through the lattice on the basis of signals of other agents, 3) **exploring**: moving randomly through the lattice searching for more productive technologies.

The model was able to produce the typical S-shape adoption curves and clusters of agents at different co-existing technologies of comparable productivity, although clusters moved slowly towards more productive technologies. Also the model GDP time-series reproduced some well-established characteristics of real world GDP data like persistent fluctuations and did not exhibit scale effects.

Chang and Harrington presented a model of discovery and diffusion of knowledge where a number of agents had to solve a number of tasks represented by a vector of binary strings, each task had an optimal method to solve it which must be discovered by the agents (Chang and Harrington, 2006).

Initially the agents draw random methods but after they had the opportunity to either innovate, choosing a random method, or imitate copying a method from another agent. Choice between imitation and innovation was taken probabilistically on the basis of past successes. The model produced an emergent behavior of dividing the agents into groups with similar goals.

Rivkin introduces a new element in the search process: the level of complexity of the landscape where the agents perform the search (Rivkin, 2000). Using the NK model, devised by S. Kauffman (Kauffman, 1993) he represents different levels of complexity and observe how it affects the results of a population of agents using two mechanisms: incremental improvement and imitation.

Under incremental improvement, Rivkin shows how agents get increasingly trapped in local maxima as the complexity of the landscape increases.

With imitation, complexity also affects negatively the performance of the agents. Small errors in imitation process could have large implications if the landscape is complex enough, because agents could easily fall in deep valleys situated around local optima.

The model presented by Rivkin provides a theoretical framework to explain some facts quite common in strategy, like why winning strategies remain unmatched even though they are public, or why bundles of organizational practices diffuse slowly even if they are known as better performers.

Rivkin's contribution is likewise important because he endows the search space of properties like the interrelation of variables, which represent known stylized facts. Unlike Kauffman who elaborated models where the landscape co-evolves, in the model proposed by Rivkin, the landscape is always static and invention is not mapped.

2.1.2.2 The Importance of Diversity in Modeling Innovation

Heterogeneity is modeled in the neoclassical framework by the heterogeneities of agent characteristics or by the diversity of initial endowments.

In Agent-Based Computational Economics the strategies are normally presented as rule-based and uncertainty is taken into account. Therefore, it is natural to deal with heterogeneity of the strategies, and almost any Agent-Based Computational Economics (ACE) model deals with it.

A very recent interesting work on the role of heterogeneity explored in the book "*The Difference*" (Page, 2007).

Chiaramonte and Dosi (Chiaramonte and Dosi, 1993) presented an evolutionary model in which they compared results between models, where technological competences and other decision parameters were homogeneous with others where they were heterogeneous. Two sectors: capital goods and consumption goods were present in the simulation where two mechanisms: incremental and radical innovation, were modeled. The diffusion of technologies was modeled explicitly and market interaction in a reduced form using relative indicators of the competiveness of the firm as a proxy.

Their findings suggested that populations with homogenous technological competences and decision rules achieve less technological progress and lower long-term aggregated income. Also persistent heterogeneities emerged both in market share and labor productivity.

Ballot and Taymaz (Ballot and Taymaz, 1999) presented an interesting result showing that ex-ante diversity in the strategy is not sufficient to achieve high productivity levels, it is necessary that firms could adapt. Their model is based on the interplay between agents that can choose between four different strategy decision rules. They also show that heterogeneity in strategy is self-sustained and its absence reduces total output and the level of technology attained. These are important findings because in neoclassical models ex-ante diversity is considered sufficient.

Building on the Nelson and Winter model, Llerena and Oltra (Llerena and Oltra, 2002) presented a framework where a set of firms build their own stock of knowledge while a different set invest mostly in absorptive capacity.

The central idea of the model is drawn from empirical research, reflecting the fact that innovation probability in a firm is not related to current investment in innovation but to the stock of accumulated knowledge. In order to implement this insight into the model, the productivity of the firms that innovate internally depends solely on their own, while the productivity of firms that invest in absorptive capacity, portrayed as imitators in the model, is drawn from the average industry productivity weighed by their market share.

The model shows that populations where the two types of industries co-exist are more successful than homogeneous populations, but it also reproduces a stylized common situation, resulting in populations with a few and large cumulative firms (internal innovators) and a large number of non-cumulative firms (firms that invested mostly in absorptive capacity). Even if the authors did not frame their model in the current research on Open Innovation, it fits well in addressing central steams of research in Open Innovation literature.

At a firm level, Dawid and Reimann (Dawid and Reimann, 2005) addressed the question of when it is better for a firm to focus on innovation or on imitation. They did that using a dynamic model and finding that deviating from current practices pays off while generating heterogeneity at the same time.

2.1.2.3 Knowledge as a Non-Rival good that must be learnt

Knowledge is the basic building block of innovation, though the fact that knowledge is a special type of good that can be reproduced at no cost but must be learnt, makes it difficult to model it using the classical mathematical apparatus.

Moreover, success in creating innovation does not depend solely on current investment, but on the size, type and structure of accumulated knowledge. Since Cohen and Levinthal proposed the concept of absorptive capacity as a way of understanding how firms can capture knowledge through interaction with their surrounding network. This new understanding captured by firms augments the previous one. Firms not only have to decide between exploitation and exploration but make trade-offs between different types of knowledge capacities, between building their own knowledge base and building capacity to absorb knowledge from their networks (Cohen and Levinthal, 1989). Furthermore as Cohen and Levinthal showed there is empirical evidence of the relationships between the extent of spillovers flowing into a firm and its own R&D efforts.

Like any other economic decision, the choice between building absorptive capacity and internal knowledge draws from the set of limited resources at a firm's disposal. Therefore we are faced with the type of resource allocation decision under uncertainty which is common in economy.

All these aspects play an important role in innovation, and their mapping in models could possibly provide insights on how the process of innovation works that could not be studied using more traditional methods.

In addition, the relevance of spillovers (Griliches, 1992; Geroski, 1996) in the innovation process, adds a new aspect making an even stronger the argument in favor of agent-based modeling.

Ballot and Taymaz (Ballot and Taymaz, 1997) were among the first to approach the trade-off between exploitation and exploration through agent-based modeling. Their work was based on data about the Swedish economy elaborated by Eliason (Eliason, 1991). In their models firms gained knowledge through training, but two types of knowledge were considered: skills that could increase productivity and general knowledge that helped in increasing the probability for radical innovations. They found a positive relationship between early investments in general knowledge and profit rate and a general negative relationship between building specific skills and the profit rate.

Cantner and Pyka (Cantner and Pyka, 1998) addressed the same problem of allocation. In their model they consider the alternative of allocating expenditures investing on internal R&D or on building absorptive capacity. The model considers both process and product innovations and incorporates effects due to spillovers.

The level of investment on R&D was fixed and simulations differed on the amount devoted to build absorptive capacity. Their findings show that if spillovers were present, a minimal investment in absorptive capacity will lead to better results, however, if the potential for spillovers was large, firms that accumulated absorptive capacity performed better. This effect was nevertheless jeopardized if appropiability conditions were high or cross-effects between markets were low.

Gilbert et al (Gilbert et al., 2000, 2001) attempted to provide a model that could capture some properties of knowledge that differentiate it from other types of goods. To that extent they represented knowledge with "*kenes*", a collection of triples where each portrays a giving technological capability. A "*kene*" is composed of 1) a technological capability, 2) a specific ability and 3) a cardinal value.

Armed with this representation, Gilbert et al. (Gilbert et al, 2000, 2001) created a platform to simulate innovation networks in various industries. There, agents selecting triplets at random, and the abilities of the agent and its level of expertise determine financial rewards. Learning by doing is also incorporated in the models, by increasing the levels of expertise involved in the current research direction and decreasing the levels of unused abilities. Agents can also modify their "*kenes*" through internal R&D efforts where both incremental and radical changes are possible.

Moreover, interaction was also modeled explicitly, giving to the agents the capacity of starting a network with other agents with whom they shared an innovation hypothesis (in that case rewards were divided) or partnering with other agents, in that later case triplets were added and the expertise level computed as the maximum of both agents.

Representing knowledge explicitly with kenes provides the opportunity to study it more closely, not only in terms of its distribution, finding out concentrations in specific areas, but also looking closely at the transmission mechanisms and further diffusion, modeling that way knowledge resulting from interaction and making it possible to see, for example, how *spillovers* that occur between partners with complementary knowledge bases, diffuse through networks.

2.1.2.4 Interaction: The Mechanics of Innovation

Although in our actual understanding innovation is better portrayed as a non-linear phenomenon where many actors play different but decisive roles in constant interaction, interaction in innovation is many times modeled in a rather restrictive form.

In the last two decades we witnessed the discovery of the role of many new and sometimes unexpected actors such as users (von Hippel, 1988), universities or governments in the innovation process, and with them the role that interaction and cross-fertilization between both new and traditional actors plays in the innovation process. Special attention has been awarded to the role of academic research and the one of the public sector in promoting projects that later on could trigger spillovers and diffuse through the network.

However, most of the agent-based models of innovation have largely ignored these new actors restricting their view to companies and the interaction between companies.

We confront a similar case with dealing with the micro processes supporting innovation: interaction is mostly depicted through the mechanisms of incremental innovation, radical innovation and partial or complete imitation.

Probably Schumpeter (Schumpeter 1934) was the first to argue that economic development arise primarily from recombination. Related to that, are the concepts of knowledge spillovers and technological externalities. Knowledge spillovers are closely associated with diffusion and can be portrayed as tool sharing. We can encounter them when a person shares a perspective, heuristic, knowledge in general, with someone else. On the other side, technological externalities occur when one technology can be applied in a context different from the one that it was designed for.

The work of Hargadon on brokerage provided empirical evidence and insights on the workings of this mechanism (Hargadon, 2003). Recombination and brokerage found its way in agent-based models through partial imitation or the use of genetic algorithms. Still, many aspects of it, like the process of rapid incorporation of the most salient or successful features of a product, technology or strategy to many others or its intimate relation with diffusion are yet to be explored.

A model attributed to Kenneth Arrow, Paul Romer and others conceives spillovers as a phenomenon that occurs not only inside industries but also intra-industries. On the contrary, the work of Jane Jacobs (Jacobs, 1984; Feldman and Audrestsch, 1999) supports the claim that knowledge spillovers have a geographical bias.

In addition, technological externalities, the use of existing components in new application domains, have been explored by Levinthal (Levinthal, 1997) and Kogut (Kogut and Zander, 1992).

In addition, the concept of knowledge externalities, or put in more general terms, the recombination of existing knowledge as a base for the creation of new knowledge, has been approached by Martin Weitzman with the “meme theory” (Weitzman, 1998). Weitzman considers ideas to be similar to generic material that like it can be combined and recombined to produce, in that case, economic growth.

As we discussed before, the concept of recombination has a long history in the field, where has been presented in different ways, partially because in real life there is no shortage of examples: radios in cars created the car radio and more recently, phones and iPods are creating the iPhone.

Micro-founded models that aim to reproduce stylized facts are predisposed to explicitly model interaction. The work of Chiaromonte and Dosi (Chiaromonte and Dosi, 1993; Dosi et al., 1994) is an example of this. There the economy is divided in two sectors: capital and consumption goods and both incremental and radical innovations are modeled, also is the diffusion of technologies.

Even if the model focus more on aspects like heterogeneity or reproducing stylized facts, it portrays a good example of how from micro-behaviors and models of interaction can emerge properties that are in accordance to empirical findings like inter-firm asymmetries in productivities and profits or persistent heterogeneities in market share and labor productivity.

Cooper (Cooper, 2000) provides another example of interaction not yet discussed, that views innovation diffusion as social learning. In his model designs are represented by strings of bits and one way to solve them is to collect bits from other successful firms forming a new design. Cooper shows that this social learning not only speeds up the innovation process but also prevents industry lock in suboptimal designs (Rivkin, 2000).

Models endowed with a richer representation of knowledge are also prone to devote more attention to interaction and put more detail on it. This is the case of the platform proposed by Gilbert el al. (Gilbert et al., 2000, 2001) that represents knowledge by the use of "*kenes*". Agents not only engage in incremental or radical innovation changes but form networks and cooperate with partners sharing innovation hypothesis and providing explicit models of diffusion and brokerage.

Interaction in innovation, however, has always been depicted as a mechanism between firms in full control of all the components of their designs or strategies. However the reality of innovation is many times far away from this vision. Both the notion of the network society (Castells, 1996) or the concept of Open Innovation (Chesbrough, 2003) portray companies that have partial control of their technical processes or strategies, as parts of it are under control of partners. This conceptualization brings a new understanding to innovation and how it can be modeled. A first approach in that line is the work of Almirall and Casadesus (Almirall and Casadesus, 2007), this is however a territory yet to be explored.

2.1.2.5 Innovation and Networks

Behind many of the assumptions of modern micro economics lays the notion of a competitive market: A market with an infinite number of buyers and sellers and where none of them is powerful enough to decisively influence price.

However, empirical everyday evidence easily contradicts this notion. Economic agents are bounded in their cognitive and social abilities, being able only to establish relationships with a close knit of related agents. This becomes even more evident when we attempt to model empirically-based micro-behaviors.

The old tension between markets and hierarchies usually addressed in Organizational Theory settings has been updated in the last decades where we assisted to a progressive blurring of the boundaries of the firm. The concept of the network economy (Castells, 1996) portrays this new type of environment where treating companies as single entities does not conform with reality anymore. The widespread use of outsourcing and the understanding of innovation no longer as an intra-firm but as an open phenomenon (Chesbrough, 2003) supports even more the notion of innovation as emerging from the interaction of agents in networks.

There is now a sizeable amount of empirical work that provides support for this approach. Special mention deserves the seminal effort of Saxenian on Silicon Valley (Saxenian, 1991) that was followed by other on the biotech industry (Orsenigo et al., 2001; Powel et al., 1992), on the automobile industry (Dyer, 1996) and on the fashion industry (Uzzi, 1997) to mention a few. In all these cases the peculiar characteristics of the industry became clear once agents were situated in a particular network.

In addition, since the 80’s network and network externalities have raised the interest of economists. Even if the initial and prototypical example has been the telephone, nowadays Internet and the type of virtual linkages that it allows, concentrate almost all the attention. Moreover, the Internet makes possible new types of organizations and collective invention to flourish, just to mention one, Open Source draw much of the attention for its singular characteristics and accomplishments.

Networks have been closely related to diffusion and much of the work in networks and economy has been on diffusion of technologies. The field was pioneered by the sociologist Griliches (Griliches, 1957) with his studies on diffusion of the hybrid corn in USA and by James Coleman (Coleman et al., 1966) studying the spread of tetracycline among Illinois doctors. The main result of Coleman was that the drug spread faster among those that were "*well integrated*" in a community. Everett Rogers in his book

Diffusion of Innovations summarized in an excellent monograph all this work on sociology (Rogers, 1995).

From a theoretical point of view, early contributions have concentrated in epidemic models. Later on sociologically founded micro-behaviors were incorporated arising to

a) relational network models which posit that direct contacts influence the spread of innovations (opinion leadership, group membership, …) and,

b) threshold models, initiated by Granovetter (Granovetter, 1978) by postulating that individuals were not homogeneous in their degree of adoption or c) critical mass models (Oliver and Maxwell, 1988) which claim that widespread diffusion only occurs when enough individuals have adopted. Valente contributed with an excellent review of the work on network models of innovation (Valente, 1995).

Ising models were the first ones used in simulation. In an Ising model, agents are located in fixed points of a regular space, typically on a line or on a two-dimensional lattice. Even though the general model was developed in 1925 (Ising, 1925) it has been widely used in a variety of simulations, among them the study of technological diffusion (Allen, 1982). The advantage of Ising models lies on its tractability and simplicity. Nonetheless complex patterns of interaction can emerge from this type of models.

Random graphs are another type of structure that has been used for modeling technology diffusion (Steyer and Zimmerman, 1998). In these graphs, agents are connected to each other with some probability, resulting in structures that are not locally dense and have, on average, low path lengths. However the empirical studies that we mentioned before showed that innovation benefits and is facilitated by the agglomeration of human capital and that diffusion benefits from short path lengths.

Representing these properties in a network model implies that agents must exhibit a high local density or high "*cliquishness*" while maintaining short path lengths. These two properties are well represented in a one parameter network model developed by Watts and Strogatz and in general, graphs that exhibit both characteristics simultaneously (high locality and short path length) have been named small worlds. Consequently the match between these two main characteristics of the model and the findings of empirical research, small worlds have become popular in modeling technology diffusion and innovation.

Cowan and Jonard presented two models of Innovation diffusion based on small worlds. In “Network Strucuture and the Diffusion of Knowledge” (Cowan and Jonard, 2004) they presented technology transfer in a barter exchange following descriptions made by von Hippel (von Hippel, 1998) of managers engaging in informal knowledge transfer after work. In this model, agents engage in knowledge trades with other agents in the neighborhood as long as it is mutually beneficial. In doing so the endowments of the agents change.

Their model shows that in bartering encounters the small world network is best in terms of maximizing the knowledge assets of the agents. However, the optimal type of network is very dependent of the level of absorptive capacity. In the extreme, when agents are able to completely absorb others agents' knowledge, not small worlds but random networks, is the structure that performs best.

Cowan and Jonard also developed another model where knowledge is broadcasted rather than transmitted by direct interaction. The objective in that case was to test different types of structures. Results showed, like in the previous case, a strong dependency on absorptive capacity. When absorptive capacity was low, regular structures performed better, contrary to when it was high where random structures obtained the best results. In addition, this model introduced a form of innovation, illustrating that when innovation is low average path length dominates the system that performs better in the case of random networks. However, when the innovation level is high or moderate, networks perform better.

From another point of view, Goyal and Joshi (Goyal and Joshi, 2002) and Goyal and Moraga (Goyal and Moraga, 2001) presented models where agents were forming partnerships depending on the cost of link formation and the level of competition in the market. When cost of link formation was low, the complete network was both uniquely stable and uniquely efficient under quantity competition.

On the other hand, when all firms make positive profits but lower costs firms make higher profits the complete network is uniquely stable. However, when only the lowest cost producers make positive profits then we find a small sub-network that contrasts with the remaining firms who are isolated.

In all these models link formation has been purely modeled on the basis of cost. However, it is widely known that the importance of trust in forming partnerships and its creation and development can be described as a learning process. One of the models that follows this approach is Kirman and Vriend (Kirman and Vriend, 2001) where network structure is established on the basis of buyer and seller loyalty, resulting on a configuration where most buyers use only one seller.

Research on networks is becoming increasingly popular and growing rapidly. Codified knowledge can be broadcasted, but tacit knowledge must be acquired through interpersonal contacts, and in any case knowledge is acquired through a learning process. These particular characteristics make the use of network models for understanding the dynamics of innovation and diffusion, promising. However a major challenge lies in the empirical analysis of existing network structures, because of the difficulty in finding relevant information and the large amount of data required.

2.2 NK Landscapes

NK landscapes were devised by Stuart Kauffman as a model for species fitness, mapping the states of a genome onto a scalar fitness (Kauffman and Levin 1987; Kauffman, 1989; Kauffman ,1993). The NK model provides a fitness landscape whose ruggedness can be "*tuned*" by a single parameter: K; this is one of the beauties of the model and part of the reason why it has been widely used.

The NK model is a model of a genome with N genes. Each gene has A alleles, mostly A=2, representing a binary genetic code. Each of the N genes constituting the genome can interact with other K genes. These epistatic interactions are in fact the ones responsible for the ruggedness of the landscape.

In its simplest model, when A=2, each gene i of N depends of other K genes that interact with it epistatically. Thus for each possible combination 2^{K+1} a random number is drawn from a uniform distribution between 0.0 and 1.0, this will be the contribution of gene i depending on the other K genes with whom it interacts.

The next step in the model is to define the dependencies between the genes composing the genome N. Three different ways have been mostly used in the literature: random assignment (Kauffman, 1993), sequential (where the successive K genes are assigned to i) (Levinthal, 1997) and nearest-neighbor (where its flanking K/2 neighbors to either side are chosen) (Kauffman, 1993).

Once selected both the dependences between genes and the contribution of each gene, depending on the combination of K+1 genes. Both are maintained through the whole landscape construction.

Finally the fitness of each possible genotype is the average contribution of its genes:

$$W = \frac{1}{N}\sum_{i=1}^{N} w_i$$

where w_i stands for the contribution of each gene, depending on k other genes besides itself, and W represents the fitness of the whole genome.

The NK model has been used to represent different scenarios. We are going to follow Rivkin’s (Rivkin, 2000) and Levinthal’s (Levinthal, 1997) approach and use it to represent the strategy of a firm and its reward in the market given its strategy.

Hence in our case, a strategy s will be represented by a vector $\{s_1, s_2, \dots s_n\}$ where each component can be activated or not, producing a total of 2^N possible configurations.

The value of each strategy component s_i will depend of other K components. So for each 2^K possible combinations a value will be drawn from a uniform probability distribution [0..1] and the contribution of each component s_i will be assigned taking in consideration the other K components.

The overall value associated to a strategy s (a point in the NK landscape) is the average over the N value contributions.

$$P(s) = \frac{\sum_{i=1}^{N} C_i(s_i; s_{i1},..., s_{iK})}{N}$$

When K=0 each component depends only of itself, so for every point in the landscape differing in only one component, the maximum difference in fitness will be 1/N, resulting therefore in a smooth landscape. Contrary to that, when K is big, each component depends of K others, so given two points in the landscape that differ in only one component their maximum difference in terms of fitness will be k+1 / N consequently resulting in a roughed landscape.

So the number of local maxima – a point with fitness greater than all its neighbors, a.k.a. all other points that only differ from it in one component – will depend on the value of K. For K=0 only one local (and global) maxima will exist (the one whose each component of N has greater value).

On the other side, for K=N-1 the number of local optima is very large. The probability P_s that a given strategy is a local optima is just the probability whose fitness is greater than its N neighbors, so:

$$P_s = \frac{1}{N+1}$$

and the total number of existing strategies in a landscape of parameter N is 2^N, so the expected number of local optima for one component neighbors is

$$S_1 = \frac{2^N}{N+1}$$

that give us a fairly large number. For example for a strategy of 16 components, we will have only one local maxima for K=0 and 3,855 for K=15.

Table 2 – Number of local peaks

Panel A: Number of Distinct local Peaks

	N = 4	*N = 8*	*N =12*	*N =16*
K = 0	**1** (0)	**1** (0)	**1** (0)	**1** (0)
K = 1	**1.78** (0.74)	**2.76** (1.72)	**4.26** (2.91)	**8.86** (7.85)
K = 2	**2.36** (0.72)	**4.96** (1.71)	**11.04** (4.35)	**24.68** (12.27)
K = 3	**3.4** (1.23)	**8.3** (1.87)	**23.28** (5.86)	**66.56** (20.24)
K = 4		**12.08** (2.21)	**39.70** (7.40)	**132.34** (21.61)
K = 5		**17.08** (2.52)	**59.70** (7.58)	**223.56** (21.16)
K = 6		**22.28** (2.86)	**90.30** (8.30)	**360.48** (27.16)
K = 7		**28.80** (3.07)	**121.10** (8.45)	**546.60** (38.32)
K = 8			**158.94** (9.56)	**765.68** (44.58)
K = 9			**205.20** (8.48)	**1034.14** (41.58)
K= 10			**255.00** (12.03)	**1357.04** (37.03)
K =11			**314.68** (10.76)	**1736.54** (35.80)
K =12				**2173.72** (44.94)
K =13				**2670.70** (41.92)
K = 14				**3221.34** (38.93)
K = 15				**3857.34** (37.29)

Panel B: Proportion of local Peaks vs. points

	N = 4 *16 points*	*N = 8* *256 points*	*N =12* *4,096 points*	*N =16* *65,536 points*
K = 0	**6.250%**	**0.391%**	**0.024%**	**0.001%**
K = 1	**11.125%**	**1.078%**	**0.104%**	**0.013%**
K = 2	**11.750%**	**1.937%**	**0.269%**	**0.038%**
K = 3	**21.250%**	**3.273%**	**0.568%**	**0.102%**
K = 4		**4.719%**	**0.969%**	**0.202%**
K = 5		**6.672%**	**1.457%**	**0.341%**
K = 6		**8.703%**	**2.205%**	**0.550%**
K = 7		**11.250%**	**2.956%**	**0.834%**
K = 8			**3.880%**	**1.168%**
K = 9			**5.010%**	**1.578%**
K= 10			**6.226%**	**2.071%**
K =11			**7.683%**	**2.650%**
K =12				**3.317%**

K =13	4.075%
K = 14	4.915%
K = 15	5.882%

Description. For each level of N and K fifty landscapes were created and local peaks – within 1 mutation distance – were counted exhaustively. Numbers shown on panel A, corresponds to the mean number of local peaks found and the standard deviation (below). Panel B shows the proportion of local maxima in respect to the total number of positions in the landscape for every N,K value.

Interpretation. As K increases it becomes easier for the agents to get trapped into local maxima, making more difficult an incremental improvement strategy.

In NK landscapes the number of local peaks grows exponentially as K grows (Table 2) and their grow ratio increases with N (Figure. 1). But as N increases, a second regime can be observed, the ratio of local maxima versus total number of points for K maximal (K = N-1) is 1/N+1 and this percentage decreases with a ratio 1- 1/N as N increases (Table 2). So, local maxima become perceptually scarce as the landscape grows.

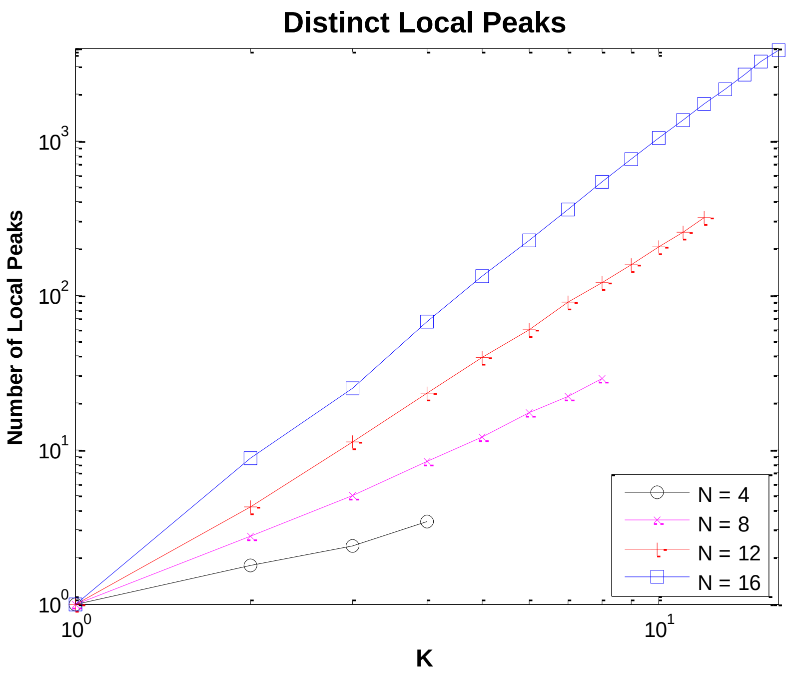

Figure 1. Distinct Local Peaks.

Description. For each level of N and K fifty landscapes were created and local peaks – within 1 mutation distance – were counted exhaustively. A figure with a log/log representation of the results is shown for every level of N.

Interpretation. The number of local peaks grows exponentially with K, but as N grows they are a fraction of the total 2^N points.

For NK landscapes as N and K grow, two regimes can be observed. As K grows for a certain N, the landscape becomes rugged and it is easier for the agents to get trapped into local maxima, resulting in a lower success for an incremental improvement strategy.

On the other hand as N grows, the size of the landscape grows faster than its number of local maxima, providing larger traveling spaces where incremental improvement agents can bet on more strategies without getting immediately trapped into a local peak.

One very well known characteristic of NK landscapes is that local peak height decreases as K increases (Table 3) effectively flattening the landscape.

This effect can be avoided normalizing by $\sqrt{N}$ if desired, but in many cases it is not relevant. For example, if we are using a greedy search strategy where the highest peak is the one selected, the relative height of peaks does not have any effect. On the contrary, if our agents use a fitness strategy, where peaks are selected on the basis of their relative height (or the difference in height with respect to our position) then differences in relative peak height will result in different probability distributions.

Table 3 – Peak Height

	N = 4	*N = 8*	*N =12*	*N =16*
K = 0	**0.669** (0.04)	**0.669** (0.02)	**0.668** (0.07)	**0.670** (0.04)
K = 3	**0.649** (0.09)	**0.663** (0.06)	**0.661** (0.05)	**0.657** (0.04)
K = 5		**0.654** (0.06)	**0.657** (0.05)	**0.659** (0.04)
K = 7		**0.649** (0.06)	**0.647** (0.05)	**0.648** (0.04)
K = 9			**0.647** (0.04)	**0.645** (0.04)
K =11			**0.638** (0.05)	**0.639** (0.04)
K =13				**0.636** (0.04)
K = 15				**0.630** (0.04)

Description. One hundred landscapes (random interactions) were created for different levels of N and K and local peaks– within 1 mutation distance - were examined exhaustively. The mean peak height is shown in bold and below the standard deviation of the average is shown in parentheses below each data point.

Interpretation. The average height of local maxima falls as K increases, or as the landscape becomes more complex. This effect must be taken into account in simulations and can be corrected normalizing by $\sqrt{N}$.

It is difficult to asses if this fall of peak height reflects in any way a real world economic characteristic where more complex and interrelated strategies result in lower rewards (fitness) than simpler ones. Simpler strategies have usually lower entry barriers that result in more crowded points with higher concurrence levels than strategies with a higher degree of epistatic interactions. These differences in concurrence levels due to lower entry barriers make it difficult to asses if in real economies, a higher level of interaction between strategy components result in lower local peak fitness. Either way, this effect is not relevant to the simulations and the work carried out in this paper, but must be taken into consideration for future work.

The distribution of local maxima in NK landscapes is a relevant characteristic that will clearly affect how agents perform search. We will use the Hamming distance (Hamming, 1986), known as the difference in information components, strategy components in that case, between to bit strings (strategies in that case). So if two strategies difference is in 1 component, its Hamming distance will be 1.

As we can see in Table 4, the average distance between local maxima approaches N/2 as K increases which clearly corresponds with the random distribution upon which the NK spaces are built. One striking factor, already reported in (Kauffman, 1993) is the fact that for K low (K=1, K=2) peaks are closer, approaching N/3. This could be consistent with many real world situations where for very focused sectors, one or two components dominate their strategy (low cost flights, low cost retailing, etcboth with logistics and cost being the dominant strategy players) producing dominant strategies that are close together because they share the main dominant factors.

Table 4 – Distance between Local Maxima

	N = 4	***N = 8***	***N =12***	***N =16***
K = 0	**0** (0) 0 (0)	**0 (0)** 0 (0)	**0 (0)** 0 (0)	**0 (0)** 0 (0)
K = 1	**1.49** (0.14) 1.28 (0)	**2.66 (0.47)** 1.56 (0)	**3.58 (0.17)** 1.88 (0)	**5.54 (0.08)** 1.88 (0)
K = 2	**2.49 (0.23)** 2.05 (0.29)	**3.78 (0.51)** 2.09 (0.14)	**4.01 (0.29)** 2.00 (0)	**5.89 (0.07)** 2.00 (0)
K = 3	**2.20 (0.19)** 1.95 (0.04)	**4.05 (0.26)** 2.04 (0.06)	**5.65 (0.30)** 2.17 (0.27)	**5.96 (0.11)** 2.00 (0)
K = 4		**3.95 (0.23)** 2.03 (0.08)	**5.74 (0.27)** 2.09 (0.18)	**6.16 (0.25)** 2.00 (0)
K = 5		**3.98 (0.21)** 2.04 (0.13)	**5.78 (0.19)** 2.08 (0.22)	**6.82 (0.47)** 2.00 (0)
K = 6		**3.91 (0.17)** 2.00 (0.01)	**5.77 (0.14)** 2.02 (0.05)	**7.74 (0.14)** 2.11 (0.26)
K = 7		**3.88 (0.16)** 2.00 (0)	**5.88 (0.12)** 2.05 (0.17)	**7.70 (0.14)** 2.01 (0.11)
K = 8			**5.83 (0.10)** 2.00 (0)	**7.83 (0.08)** 2.04 (0.14)

K = 9	**5.86 (0.08)** 2.0 (0.03)	**7.85 (0.06)** 2.04 (0.15)
K= 10	**5.83 (0.08)** 2.00 (0.02)	**7.89 (0.05)** 2.01 (0.05)
K =11	**5.88 (0.07)** 2.00 (0)	**7.92 (0.04)** 2.01 (0.05)
K =12		**7.89 (0.03)** 2.00 (0.04)
K =13		**7.92 (0.03)** 2.00 (0)
K = 14		**7.93 (0.02)** 2.00 (0.01)
K = 15		**7.96 (0.03)** 2.00 (0.02)

Description. For each level of N and K fifty landscapes were created and local peaks – within 1 mutation distance – were counted exhaustively. Once found the average (above in bold) and the minimum (below in normal) distance between each local maxima and all the others was obtained using the Hamming distance as a measure (number of bits – strategy components – different from one strategy with respect another one. The result corresponds to the average and standard deviation (between parentheses) of the 50 landscapes tested.

Interpretation. We can see how as K increases, mean distance approaches N/2, beginning for K=1 with approximately N/3. A very interesting phenomena is that the minimum distance is always close to 2, but for K=1 that is even closer. That means that given any peak we can find another one really close, or that any peak carries information relevant not only to itself but to another one.

What is also interesting on the data of Table 4 is that the minimum distance between two peaks – the distance to the closest peak – is always around 2 (except for K=1 that is even lower). That means that given any peak we can find another one at a distance of two or lower in any case (note that standard deviation is always 0.2 or lower). This is also consistent with the real world experience that not all factors weight the same and some are dominant, around these dominant factors we can find several strategies resulting of the interchange of equally weighted, let us call them, secondary factors.

But this fact has also an important consequence for the collective behavior of the agents and their collective learning process. That is that the fact of being in one strategy local maxima carries information valid to other points, information that can potentially lead to find a different peak.

Table 5 – Mean Walk Lengths to Local Optima

	N = 4	N = 8	N =12	N =16
K = 0	**1.996** (1.005)	**4.013** (1.418)	**5.999** (1.741)	**7.979** (2.003)
K = 1	**1.682** (0.977)	**3.467** (1.379)	**4.976** (1.624)	**6.803** (1.876)
K = 2	**1.354** (0.869)	**2.813** (1.305)	**4.292** (1.603)	**5.773** (1.892)
K = 3	**1.159** (0.806)	**2.448** (1.266)	**3.705** (1.572)	**5.060** (1.838)
K = 4		**2.077** (1.111)	**3.214** (1.439)	**4.383** (1.753)
K = 5		**1.821** (1.041)	**2.801** (1.342)	**3.797** (1.614)
K = 6		**1.589** (1.003)	**2.524** (1.329)	**3.401** (1.515)
K = 7		**1.418** (0.961)	**2.233** (1.181)	**3.077** (1.400)
K = 8			**1.987** (1.081)	**2.795** (1.326)
K = 9			**1.832** (1.047)	**2.559** (1.302)
K= 10			**1.643** (1.029)	**2.340** (1.224)
K =11			**1.510** (1.010)	**2.154** (1.130)
K =12				**1.973** (1.064)
K =13				**1.804** (1.025)
K = 14				**1.684** (1.010)
K = 15				**1.560** (1.005)

Description. For each level of N and K one hundred landscapes were created and 100 agents released in each landscape. Incremental walk lengths performing a greedy search were recorded. The average walk length is shown in bold and the average of the standard deviations of walk lengths for each landscape is shown between parentheses.

Interpretation. Mean walk length begins with N/2 and as K increases approaches 1 reflecting an increasingly rugged landscape. Mean walk lengths have also implications in how long a system will settled down and how much time will be available for diffusion between agents

Correspondence to the real world is in that case quite direct. Complex, very interrelated strategies make the economic agents very prone to get trapped into local maxima, many times forgetting key factors that are suddenly rediscovered by a new competitor. We have many examples of that where in mature sectors like flight companies or banks, complex strategies were carried out and companies craved niches around them until a new competitor simplified the strategic approach and was able to attain a higher maximum.

But the shortening of walks due to the increasing complexity of the environment has also two important implications in a dynamic system where economic agents are interrelated and interdependent.

The first one is diffusion. A shorter path results inevitably in less time available to diffuse discoveries and to assimilate them.

The second one is equilibrium, with a shorter path length equilibrium can potentially be reached earlier given the fact that the system will settled down when all agents have attained their maxima with regard of the positions of other agents.

We can see, and we will present in the next sections several models of collective discovery where a group of agents guided only by local information and their greedy interest will in fact collaborate in the discovery of the highest peaks in the NK space attaining a situation that will be globally better than the one achievable without interrelation.

This is a process of collaborative pattern learning, where the agents will try to discover patterns in the NK space construction that result in a higher fitness, these are nothing else than the ones that have the highest value in the K+1 gene table used originally to obtain the fitness of each point.

3 Strategic Interaction in NK Landscapes

3.1 Introduction

An important unresolved question in technology strategy is whether a firm should take a closed approach to innovation, making all choices regarding product development, or to the contrary, should it open its technology and adopt elements or subsystems developed by other players. The literature has approached this question by pointing to a fundamental trade-off between adoption and value appropriation (West, 2003). Shapiro and Varian (1999), for example, reason that by reducing the risk of supplier hold up, openness fosters adoption and feeds network effects, improving user value created. However, opening a technology often hampers the strength of property rights and impairs the developer's ability to capture value thus affecting incentives to invest (David and Greenstein, 1990).

Work empirical in nature such as that of Cusumano et al. (1992), von Burg (2001), Chesborough (2003), von Hippel (2005), or Boudreau (2006) provide insights through detailed case descriptions and analyses of open innovation (the embracement of external ideas and knowledge in conjunction with internal R&D)[1] that suggest that openness does not only determine the trade-off between adoption and appropriability but that it also influences the development trajectories that technologies follow over time: openness can stimulate innovation by combining the efforts of a large and diverse pool of complementary firms leading to increased product diversity and better matching of products and consumer preferences. Greenstein (1996), on the other hand, points out that openness increases coordination costs because it requires the cooperation of multiple suppliers and/or complementors.

The purpose of this paper is to contribute to work in this area through the analysis of a simulation model that allows careful consideration of a trade-off that emerges from this body of literature: the benefits of discovery of new combinations of product features brought about by open innovation versus the costs of suboptimal coordination due to divergent objectives.

Our argument begins with the observation that when a product or system is opened to outside suppliers or complementors, some choices that could have been made by the original system designer are now undertaken by independent firms that pursue their own interests. Devolving control in this manner has two main effects. First, the system developer loses some freedom to establish the technological trajectory of the system. Restraining this freedom is costly as it amounts to operating under constraints that

[1] Chesborough (2003).

could have been avoided with a closed approach. Indeed, suppliers and complementors are likely to maximize their own payoffs, not those of the original designer. And while there may be some positive correlation between the interests of different industry players, goals will generally not be perfectly aligned. We refer to this effect as “divergence.”

Second, because independent suppliers and complementors will generally be engaged in product development paths different from those of the original system developer, they are likely to innovate in ways that the system developer would not have chosen. Opening the system may allow the original designer to discover new combinations of product features that would otherwise be hard to foresee. By opening the system up, it may be possible to use knowledge of suppliers and/or complementors to end up with a better product. We call this effect “discovery.”

“Divergence” and “discovery” work in opposite directions: there is a trade-off between the cost of losing control of the product’s technological trajectory and the benefit of aggregating knowledge from other players to promote innovation. Assuming that other factors are held constant, this trade-off determines whether the original developer will want to open its system or, to the contrary, take a closed approach to innovation.

We present a model that captures these two effects. In a world where firms act to optimize their own payoffs, one is tempted to conclude that firms should do better with closed innovation (full internal control of the product development path). Somewhat surprisingly, we find that the trade-off between discovery and divergence is resolved differently depending on the underlying complexity of the mapping between firm’s choices and the willingness to pay for the product (or perceived value) by customers. In particular, we find that open innovation is generally superior to closed innovation when complexity is not high.

This paper complements existing theories by introducing a novel trade-off. To make progress, however, we must abstract from other important factors already addressed by the literature (such as network effects, supplier or complementor hold-up, and the effects of property rights on incentives to invest). Formal modeling requires the imposition of important simplifying assumptions.

Close to our view, Chesborough (2003) argues through case evidence that an open approach to innovation encourages firms to incorporate new ideas into their businesses. Moreover, open innovation results in increased competition for resources as internal researchers must compete with external players. While related to Chesborough’s, our approach is different in that we present a formal model. Moreover, the simple trade-off that we derive suggests that open innovation is not uniformly superior to closed innovation.

Our theory provides an explanation for why very basic and very complex telephones are designed by companies following a closed approach to innovation. When the level of complexity is intermediate, networks of companies in charge of development come up with better products. More generally, product innovators that push the design frontier, for the most part, follow a closed approach. For example Apple has followed a closed innovation strategy with the iPod, a product that not only has brought the company back from death but that has been acclaimed as best product of the year. Similarly, Nintendo has engaged in closed innovation for its new videogame system, the Wii. Nintendo's Wii is certainly more innovative than Microsoft's Xbox 360 or Sony's PlayStation 3 (in the sense delivering new combinations of product features highly valued by customers, such as the role and use of controls).

3.2 The Model

Our model is a simple extension of NK fitness landscapes. Phil Anderson (1983, 1985) devised the NK framework to model spin-glass physics and Stuart Kauffman (1993) adapted it to the study of evolutionary biology. Applications to Strategy began with the work of Levinthal (1997) and Levinthal and Warglien (1999) and was followed by important work by Rivkin (2000), Rivkin and Siggelkow (2002), Ethiraj and Levinthal (2004), Lenox et al. (2006), and others.

To capture as simply as possible the notions of open and closed development, we consider a product composed of two subsystems, α and β. For example, if the product is a PDA, α might represent hardware and β software.[2] Each subsystem can be thought of as a set of features configured in ways chosen by firms. Hardware features may include processor speed, number of pixels in the display, number of color bits, random access memory available, weight, volume, et cetera, while software features may include user-friendliness of the GUI, the presence of communications utilities or productivity applications, and so on.[3]

The final product, which we represent by $\langle\alpha, \beta\rangle$, has N features and each subsystem is composed of N/2 features. Following the NK framework, each feature can take on one of two possible configurations, 0 or 1. The values 0 and 1 do not necessarily mean the absence or presence of a given feature, but just two different ways in which a particular feature can be configured. A more general model would allow for more than

[2] A more general model would allow for more than two subsystems. Having two subsystems only, captures in a tractable way the essence of the phenomenon that we study.

[3] Clearly, each one of these features could itself also be considered a subsystem made up of other product features. For example, at a broad level of aggregation the presence or not of GUI can be seen as a feature of a given PDA. A more detailed view would consider specific features of the GUI such as the possibility of having several windows open at the same time or the ease by which the user can browse through different open windows.

two configurations per feature. The usual 0/1 assumption delivers the simplest, most tractable model.

We assume that different combinations of product features lead to different “willingnesses” to pay for the product. That is, there is a mapping between product features and how individuals evaluate the product. For simplicity, we assume that this mapping is fixed and does not evolve over time. For some products the mapping is complex, while for others it is simple. By “complex” we mean that minor changes in bundles of features result in drastic changes in perceived value. By “simple” we mean that the mapping is smooth. As usual in Strategy applications of NK fitness landscapes, we consider landscapes exogenous and fixed. However, we should note that with modularity, firms can often offer large bundles of features to customers and then individual customers can choose which features to use. By following this approach, the landscape can be simplified significantly. A discussion of this issue is offered in Section 3.5.1.

There are many ways in which firms may search for better positions on the landscape. Following the literature, we assume that firms look at all alternatives that are one step away from their current position and select the best alternative.[4] Local search is the simplest search heuristic that captures the idea that firms do not have full knowledge of what are the combinations of features most valued by potential customers. With local search, companies move on the landscape by varying one product feature at a time. This search strategy has its roots in optimization, believing that if every product feature can be optimized or exactly tuned to market needs, then the organization will be able to attain optimal performance. With local search, product design is prone to get trapped onto local maxima when the landscape is rugged.

Formally, a product <α, β> is represented by a vector of N features <s1, s2, …, sN> where each si is an element of {0, 1}. Assuming that N is even, subsystems α and β are:

$$\alpha = \langle s1, s2, \ldots, sN/2 \rangle \quad \text{and} \quad \beta = \langle sN/2+1, sN/2+2, \ldots, sN \rangle.$$

The landscape is constructed as usual. There are 2N possible product configurations. The contribution ci of each product feature si to willingness to pay depends on other K components. For each of 2K possible combinations, a value is drawn from a uniform probability distribution on [0,1]. The overall willingness to pay associated to <s1, s2, …, sN> is the average over the N value contributions,

[4] This search strategy is sometimes called “incremental improvement search” or “greedy search.”

$$WTP(s_1,\ldots,s_N)=\frac{\sum_{i=1}^{N}c_i(s_i;s_{i_1},\ldots,s_{i_K})}{N},$$

where s_{i_j} j={1,…,K} are the configurations of the K features with which si interacts. We assume random assignment of dependencies (ij are determined randomly in the model).

Having presented the construction of NK landscapes and the mechanics of local search, we are now ready to introduce our models of open and closed innovation.

Closed vs. Open Innovation

Our model of closed innovation has firms choosing all features of both subsystems, α and β. In other words, the configuration of every feature of the final product <α, β> is chosen by the firm that brings that product to market. We refer to this regime as closed innovation because the firm has full internal control to determine exactly where on the landscape it ends up.

Under open innovation firms specialize in either the α or the β subsystem and then combine to produce the final product <α, β>. We refer to a firm specializing in α as a "firm α" and one specializing in β as a "firm β." For firm α to have a complete product it needs to bundle its subsystem with that of a β firm. Firm α, however, has no control over the configuration of features that make up β since these are chosen by the other firm. Obviously, the willingness to pay for the final product <α, β> depends on how all of its features are configured: those chosen by firm α and those chosen by firm β. Therefore, the willingness to pay for <α, β> depends on actions taken by two separate firms.

We refer to this regime as open innovation because firms devolve control (partly) of the final product's technological trajectory to other industry players. For example, when Sony decided to adopt IBM's microprocessors for its new generation videogame console, some choices affecting Sony's position on the landscape would be made by IBM.

At time zero, firms are all distributed randomly on the landscape. In the case of closed innovation firms search locally for better positions until they reach a (local) maximum. The case of open innovation is a little bit more involved. We must specify: (a) how α and β firms are paired and (b) the payoffs to both firm types.

(a) Pairing firms. We consider two alternative mechanisms for pairing α and β firms. Both have firms randomly paired at time zero but differ in what firms are allowed to do over time. Under "Fixed Partnerships" firms stick to the randomly assigned partner over the entire simulation. Under "Flexible Partnerships" firms are allowed to change partners: at every stage we allow firms to look at a subset of available partners and pair with the one that leads to highest fitness.

These two mechanisms are extremes in a continuum. In most cases, reality falls in between: firms do not change partner(s) everyday but new relationships are built when it becomes clear that there is a better alternative. For example, for many years Apple computers were shipped with IBM PowerPC microprocessors, but in 2006 Apple began using Intel processors. To a large extent, Apple's decision to switch was based on the better integration and performance of its OS X on Intel architecture microprocessors.

(b) Payoffs. In the case of closed innovation, the payoff associated to product <α, β> corresponds to the height of the landscape at the N features that define it. Formally, the payoff associated to <α, β> (≡ <s1, s2, …, sN>) is

$$WTP(s_1,\dots,s_N) = \frac{\sum_{i=1}^{N} c_i(s_i; s_{i_1},\dots,s_{i_K})}{N} \tag{1}$$

In the case of open innovation, a given firm α incorporates a β subsystem (or, equivalently, a β firm incorporates an α subsystem) and brings the complete product <α, β> to market. In this case, firm α (or firm β) cares about the willingness to pay for the complete final product (composed of N features). Thus willingness to pay is computed just as in the case of closed innovation (eq. 1).[5]

Note that payoffs to partners do not coincide typically. A given firm α (call it firm α1) may incorporate the β subsystem produced by firm β1 and bring product <α1, β1> to market. That particular β firm (which we refer to as firm β1) may incorporate a different α subsystem in the product it commercializes, perhaps that of firm α2 (≠ α1). If this is the case, firm β1 will sell product <α2, β1>. As a consequence, the willingness to pay for the products brought to market by firms α1 and β1 will typically not coincide as, in most cases, the products will be different.

An example of our model of open innovation is that of motor coach manufacturing which is divided into two central activities: the construction of the chassis (α) and the construction of the bus body (β). Bus chassis' manufacturers sell the chassis complete with the engine to a bus body manufacturer who adds the top section and completes the interior of the coach. In recent years, the separation of the two activities has

[5] More formally, consider firm α. Suppose that it configures α as $<s_1, s_2, \dots, s_{N/2}>$ and that it is paired up with a firm β that has configured β as $<s_{N/2+1}, s_{N/2+2}, \dots, s_N>$, then the willingness to pay for the product that firm α brings to market (the combination of α and β) $<s_1, s_2, \dots, s_{N/2}, s_{N/2+1}, s_{N/2+2}, \dots, s_N>$ is $WTP(s_1, \dots, s_N)$ (as in equation 1).

become more widespread, with larger companies supplying the chassis and making agreements with bus body manufacturers with whom to partner.[6]

- A product is composed of N = 16 features.
  - s_i represents feature i $\in$ {1, 2, …, 16}.
  - Product features can take one of two possible configurations: $s_i \in \{0, 1\}$.
  - Thus a product is a sequence of sixteen digits taking values 0 or 1.
    For example, <s_1, s_2, s_3 …, s_{16}> = <1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 1> is one product.
    - There are 2^{16} = 65,536 possible products.
- Product features are divided into two groups: features 1 through 8 and features 9 through 16. These groups represent two different subsystems. Two subsystems put together is a final product.
  - The subsystem composed of features 1 through 8 (<s_1, s_2, s_3 …, s_8>) is called α and that composed of features 9 through 16 (<s_9, s_{10}, s_{11} …, s_{16}>), β.
  - There are three types of firms
    - A closed firm is one that controls all 16 product features.
    - An α firm is one that controls an α subsystem.
    - A β firm is one that controls a β subsystem.
      - An α firm must incorporate the subsystem produced by a β firm to have a final product for sale (and *vice versa*).
- Every product <s_1, s_2, s_3 …, s_{16}> has some willingness to pay associated with it.
  - The contribution to willingness to pay of a particular product feature s_i, depends on the configurations of K other features. (0 ≤ K < N).
    - The particular K features that interact for willingness to pay are assigned randomly.
  - The contribution to willingness to pay for the final product of subsystem α is:

$$WTP(s_1,\ldots,s_8 \mid s_9,\ldots,s_{16}) = \frac{\sum_{i=1}^{8} c_i(s_i; s_{i_1},\ldots,s_{i_K})}{N}.$$

  - The contribution to willingness to pay for the final product of subsystem β is:

$$WTP(s_9,\ldots,s_{16} \mid s_1,\ldots,s_8) = \frac{\sum_{i=9}^{16} c_i(s_i; s_{i_1},\ldots,s_{i_K})}{N}.$$

  - The willingness to pay for the final product is:

$$WTP(s_1,\ldots,s_{16}) = WTP(s_1,\ldots,s_8 \mid s_9,\ldots,s_{16}) + WTP(s_9,\ldots,s_{16} \mid s_1,\ldots,s_8) = \frac{\sum_{i=1}^{16} c_i(s_i; s_{i_1},\ldots,s_{i_K})}{N}.$$

- At the beginning of each simulation, products are randomly assigned to firms. Firms then search incrementally for better positions on the willingness to pay landscape. Their goal is to have a product with as high willingness to pay as possible.
  - Firms are allowed to reconfigure one feature at a time (amongst those features that they control). Firms stop searching when incremental search does not lead to a product with higher willingness to pay.
- *Innovation* takes place as firms search for and find better positions on the landscape.
  - Closed innovation is modeled by a closed firm searching for better positions by fully controlling internally *all* of the 16 product features.

[6] See Casadesus-Masanell, Ramon, and Jordan Mitchell. "Irizar in 2005." *Harvard Business School Case* 706-424.

- Open innovation is modeled by an α firm (paired with a β firm) searching for better positions by controlling internally features 1 through 8 only. (Similarly for a β firm.)

Table 6. Model Summary and Main Assumptions

Table 6 presents a summary of the model, its main elements and assumptions. The performance measure that we use to compare closed and open approaches to innovation is average fitness.

An example of an industry where open and closed innovation have occurred simultaneously is personal digital assistants (PDAs).[7] In the mid-1980s, Psion released the Psion Organizer. It included 2K of RAM, 4K of applications in ROM. The idea was to provide a portable machine that would have the ability to retain data. Psion offered additional packs, which included a programming language as well as mathematical and financial functions. Entry intensified by the late 1980s both with DOS clone devices by HP and Compaq and electronic organizers by Sharp and Casio. By the end of 1991, Sharp and Casio led the market for electronic organizers. All of these products had been designed and released without involvement from outside firms. Each manufacturer was seen to take a closed approach to innovation.

In the open innovation front, several large electronics enterprises, computing companies, and venture capital firms formed alliances to further the development of 16-bit handheld computers. Amongst them, IBM backed financially the young start-up GO Corporation in the late 1980s to develop PenPoint, a pen-based OS. Later, GO Corporation partnered with AT&T, although that partnership ended due to mistrust, time delays in meeting targets, and disagreements on product development. At the same time, IBM set its sights on developing a handheld computer with phone capabilities. It worked with BellSouth to develop Simon. However, the device was seen to be too heavy and was ineffective in administering phone calls and computing functions at the same time.

All of these early open development efforts failed. According to an industry observer:[8] "It's kind of like a rock-and-roll group. You get five guys and they all start off with the same goal, but sooner or later somebody wants to do his own thing. Competition [within the alliance] can make things difficult, and sometimes whatever they're rallying around doesn't prove to be what they thought it was going to be."

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[7] For a detailed description of the PDA industry, please see R. Casadesus-Masanell, K. Boudreau, and J. Mitchell. "Palm (A): The Debate on Licensing Palm's OS (1997)." Harvard Business School Case 708-514. The case description in the paper draws heavily from this teaching case.
[8] Caroline A. Duffy, "Alliances form to build PDA capabilities," *PC Week*, April 19, 1993, p. 32.

The success of Sharp's Zaurus and Casio's BOSS in the early days of the industry, suggests that closed innovation was a superior development approach at the time. We will see below that open innovation is generally inferior to closed innovation when complexity is high and in Section 5.1 we argue that complexity (as perceived by the firms) is likely to decrease with technological progress.

3.3 Simulation Mechanics

All simulations have N=16. For each K=1…15, we do the following fifty times: generate a landscape and release one hundred firms that search for highest fitness under both, closed and open innovation. For any given landscape, let CLO be the average fitness of firms engaged in closed innovation and let OPE be the average fitness of firms engaged in open innovation. For each landscape we compute the difference in average fitness, OPE–CLO. Because for each K we have fifty landscapes, we generate fifty differences in average fitness (OPE–CLO). We compute the average and variance of OPE–CLO for each K. A positive and significantly different from zero average indicates superiority of open innovation.

Closed Innovation

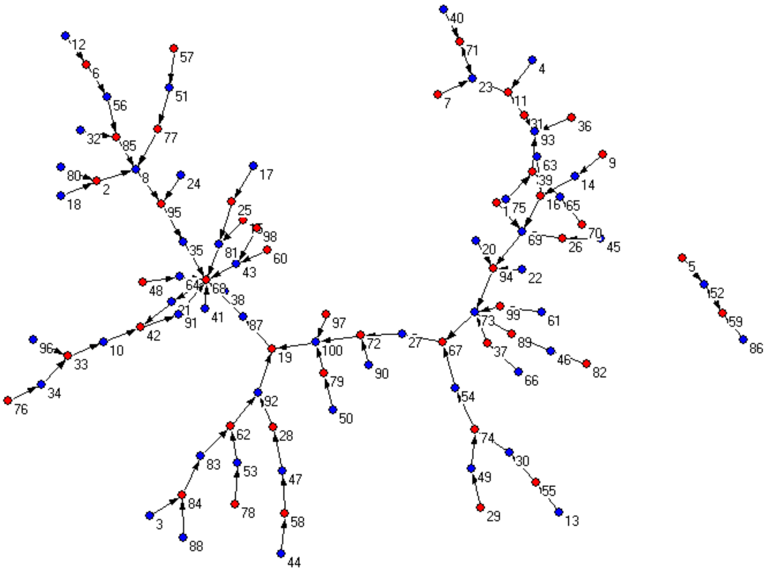
For every landscape, one hundred firms are released at random locations. Firms search for better positions by evaluating all local alternatives and adjusting any one of N product features. The simulation ends when all 100 firms settle down; that is, when no firm has the desire to further modify product features.

Open Innovation – Fixed Partnerships

For every landscape one hundred firms are released at random locations. Each firm is one of two possible types, α or β. Firm type is assigned randomly (0.5 probability of either type). Therefore, about 50 of 100 firms are of type α and about 50 of type β. In most cases, however, the split is not perfectly symmetric (because it is probabilistic).

To have a complete product, a firm α must pair with a firm β, and vice versa. We assume that the pairing (which occurs at time zero) is random and that once paired, the two firms remain together for the entire simulation. We assume that each firm searches to maximize its own fit, without taking into consideration how its choices affect the fit of its partner. In every iteration firms search for higher positions by evaluating all local alternatives (for those features that they control) and adjusting any one of the available N/2 product features.

In this simple model firms have one partner only. But because partners are assigned randomly, a given firm can be partner of more than one firm. As a consequence, we have relatively large networks of firms being formed. The figure below shows one such possible network. The blue nodes are α firms and the red nodes β firms:



Picture 1: Random Network of Firms

Once every firm has modified one product feature (staying put is also a possibility), products <α, β> are assembled. The fitness levels associated to the new products are recorded. At this point a new iteration begins. Notice the implicit assumptions that (a) choices are made simultaneously by all agents and that (b) each firm takes the other firm's prior choices as given in evaluating alternatives.

The procedure is repeated until the system settles down (no firm desires to reconfigure product features under its control). At this point the simulation stops and endpoint fitness is recorded. Since this model does not always settle down, the simulations are stopped after 200 iterations if needed (this happens occasionally and only when K is high).[9]

Open Innovation – Flexible Partnerships

In this case, in every iteration and before firms choose whether or not to modify product features, they are allowed to change partners. The set of available partners (which we call "partner opportunity set") is composed of all firms of complementary type.[10] That is, α firms are allowed to choose any one of about fifty β subsystems to

[9] Cases where the simulation reaches 200 iterations never occur in the model of flexible partnerships or for closed innovation. In the case of fixed partnerships, the simulations sometimes reach 200 iterations. The results considering only the runs where all 100 firms settle down are similar to those where all runs are considered.

[10] Below we investigate the effect of having smaller partner opportunity sets.

combine with their product.[11] Similarly for β firms. Notice the trivial fact that firm α's desire to partner with a given firm β does not necessarily imply that that firm β prefers that particular firm α over all firms with an α product. The model of flexible partnerships possibly generates a different network in every iteration: the network evolves over time as new desirable partnerships are formed.

3.4 Results

We begin by comparing the outcomes of closed and open innovation when partnerships are fixed. In Section 3.4.3, we consider the case of flexible partnerships.

3.4.1 Open vs. Closed Innovation when Partnerships Are Fixed

When partnerships are fixed, open innovation outperforms closed innovation for low and medium-low levels of complexity. Devolving control to industry players appears to be a better approach to product development when the landscape is rugged (Fig. 1). We also find that when complexity is high, closed innovation is a superior development approach. Specifically, when K approaches N/3 the performance of open innovation decays abruptly. From that point on, the best approach to product development is closed innovation.

[11] There are *about* fifty β subsystems available because there are one hundred firms and each has .5 probability of being of either type.

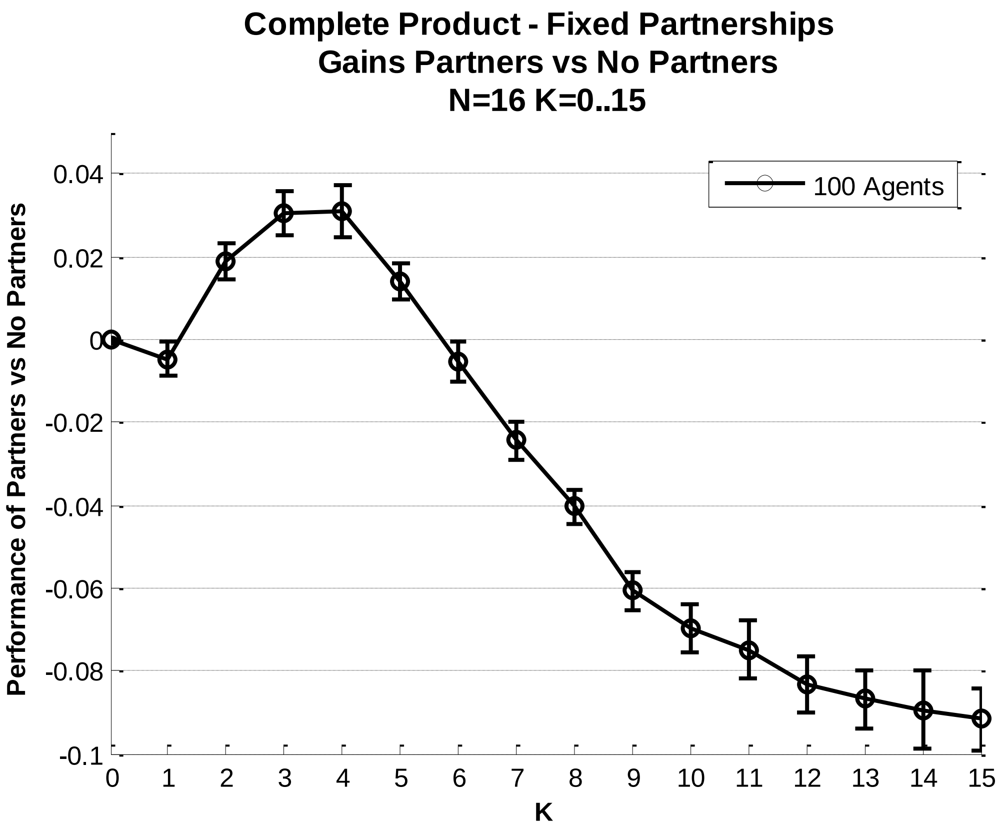


Figure 2. Complete Product - Fixed Partnerships. Gains Partners vs. No Partners.

Description. For each K=1…15, we do the following fifty times: generate a landscape and release one hundred firms that search for highest fitness under both, closed and open innovation (fixed partnerships). Let CLO be the average fitness of firms engaged in closed innovation and OPE the average fitness of firms engaged in open innovation. For each landscape we compute the difference in average fitness, OPE–CLO. Because for each K we have fifty landscapes, we generate fifty differences in average fitness (OPE–CLO). The figure plots the average of OPE–CLO for each K. At K=3, for example, average fitness under closed innovation is 0.9014 (with variance .00075) and under open innovation it is 0.9317 (with variance .00098). The difference is .0303. The t-statistic of OPE–CLO is 5.59 and thus it is significantly different from zero. The bars are standard errors of the mean.

Interpretation. Open innovation outperforms closed innovation for low-mid values of K.

We note that this result is consistent with the observation by Boudreau (2006) who, citing the work of Teece (1996), Novak and Eppinger (2001), Christensen, et al. (2002), Brusoni (2005) and Macher (2006), asks if opening a technology to outsiders stimulates innovation and concludes that for innovations that require “changes involving the interactions and dependencies among components [corresponding in our model to large K], the consensus is that it does not.” He concludes that innovations where there is high interdependency between components require “a guiding hand that can internalize externalities, centralize authority, and promote knowledge sharing among various development activities."

3.4.2 Discovery and Divergence: Benefits and Costs of Open Innovation

We now investigate the comparative benefits and costs of open innovation. With open innovation the original product developer loses some control compared to closed design. This devolving of control has two main effects:

Discovery. Open innovation may allow the system designer to discover new combinations of product features that would otherwise be hard to foresee.

Divergence. The system developer loses freedom to establish the product's willingness to pay trajectory: there are product features that the firm might want to reconfigure but it is unable to do so because they are controlled by another firm that acts to maximize its own payoffs.

The trade-off between discovery and divergence determines the desirability of open vs. closed innovation.

We now proceed to quantify discovery and divergence to gain insight on what drives the result that open innovation may sometimes outperform closed innovation. To make progress, we introduce a supercharged firm. This is a firm engaged in closed innovation that can see beyond incremental change. Specifically, the supercharged firm is allowed to make one change in the first N/2 choices and one change in the second N/2 choices (simultaneously). The supercharged firm may reconfigure one product feature only if it desires to do so.

Let SCH be the performance of the supercharged firm, CLO be the performance of firms engaged in closed innovation, and OPE be the performance of firms engaged in open innovation. We quantify discovery and divergence as follows:

$$\text{Discovery} = \text{SCH} - \text{CLO}$$

$$\text{Divergence} = \text{OPE} - \text{SCH}$$

What do these definitions capture? Consider discovery first. Closed firms can reconfigure one product feature only in each period, while open firms can make two decisions in each period.[12] For example, let's use N = 4 for ease of notation. If the firm currently sits at 0000, a closed firm can only move to 1000, 0100, 0010, or 0001. In contrast, the open firm could move to 1001, for instance. Clearly, the difference in

[12] To simplify the exposition, we refer to firms engaged in closed innovation as *closed firms* and to those engaged in open innovation as *open firms*.

performance between supercharged firms and closed firms is a measure of discovery as generated by the ability to make changes that are not entirely incremental.

The supercharged firm does not perform like the open firm either, since in this case the individual firms (α and β) care about their own performance, rather than about firm performance. This performance difference then is a measure of divergent objectives or divergence (as we call it).[13]

The total effect of open innovation is the discovery benefit plus the divergence cost:

Total effect = Discovery + Divergence = (SCH – CLO) + (OPE – SCH) = OPE – CLO.

The figure below shows discovery and divergence for the four model specifications. The blue line corresponds to discovery, the red line to divergence, and the black line is the total effect: discovery plus divergence.

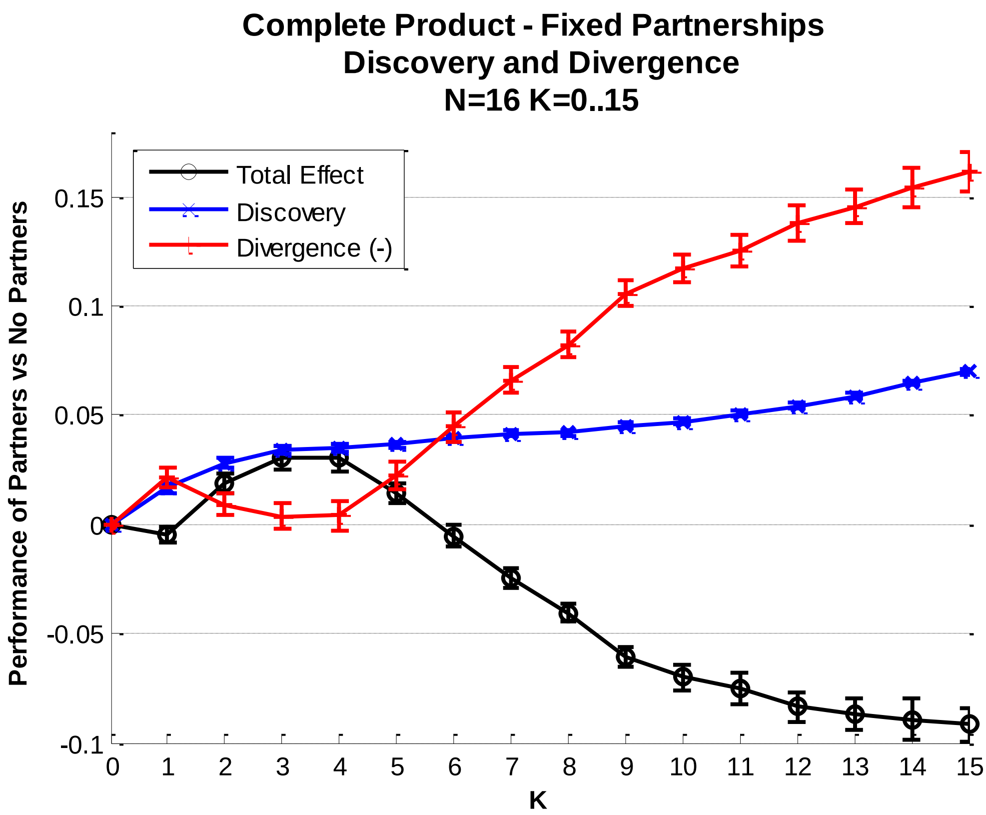


Figure 3. Complete Product - Fixed Partnerships. Discovery and Divergence

Description. For each K=1…15, we do the following fifty times: generate a landscape and release one hundred firms that search for highest fitness under closed innovation, open innovation (fixed partnerships), and as supercharged firms (see Section 4.2 for a description).

[13] We thank an anonymous reviewer for suggesting these definitions and the introduction of the *supercharged* firm.

Let CLO be the average fitness of firms engaged in closed innovation, OPE the average fitness of firms engaged in open innovation, and SCH the average fitness of supercharged firms. For each landscape we compute *Discovery = SCH – CLO* and *Divergence = OPE – SCH*. Because for each K we have fifty landscapes, we generate fifty data points for discovery and divergence for each level of complexity. The figure plots average discovery (in blue) and average divergence (in red) for each K. We also plot the total effect: *Total Effect = Discovery – Divergence* (in black).

Interpretation. The benefits of discovery and the costs of divergence increase with K.

Notice that discovery is always positive. This is expected as the supercharged firm could always replicate the actions of the closed firm: if it chooses different feature combinations it must mean that such combinations lead to higher fitness.[14] Discovery grows with the ruggedness of the landscape. As K grows, being able to "see" two steps ahead prevents the firm from being trapped onto low local maxima more and more often because the number of local maxima increases with K.

Contrary to discovery, divergence is sometimes positive (a benefit) and sometimes negative (a cost), i.e., in some instances divergence results in better performance than the supercharged firm. The reason for this is that there are two (countervailing) effects at work for the open firms. One, the problem of not coordinating across the firms. The second effect, however, is a positive one: being parochial can lead to more discovery. (See Rivkin and Siggelkow, 2003.)

Notice that the divergence cost could, in some instances, be overcome by the focal firm offering its partner a higher price to make specific changes. This would happen only when the specific changes led to superior total value created; that is, the reduction in the partner's product willingness to pay from configuring features in a way that is suboptimal from its viewpoint, must be more than offset by the increase in willingness to pay of the focal firm's product (after the additional changes have been made). Of course, if we allowed the focal firm to identify changes in the partner's product that were beneficial in this global sense, then it would be as if the focal firm could "see" the landscape around the partner's location. Our assumption, however, is that each partner can only see the effects on willingness to pay of changes on the features that they control. Also, allowing negotiation for feature configuration when mutually beneficial, would move us away from a world where each firm chooses product features to further their strict best interest. Finally, consideration of money

[14] A constrained optimization problem has a better solution the fewer the number of constraints. In our NK setting, allowing two changes instead of one in every period is tantamount to dealing with a constrained optimization problem with fewer constraints.

transfers would introduce considerations of value capture and bargaining that, for tractability, we have sidestepped.

3.4.3 Open vs. Closed Innovation when Partnerships Are Flexible

Figure 3 shows that with flexible partnerships the gains are larger than in the case of fixed partnerships. In fact, open innovation outperforms closed innovation even for large K.

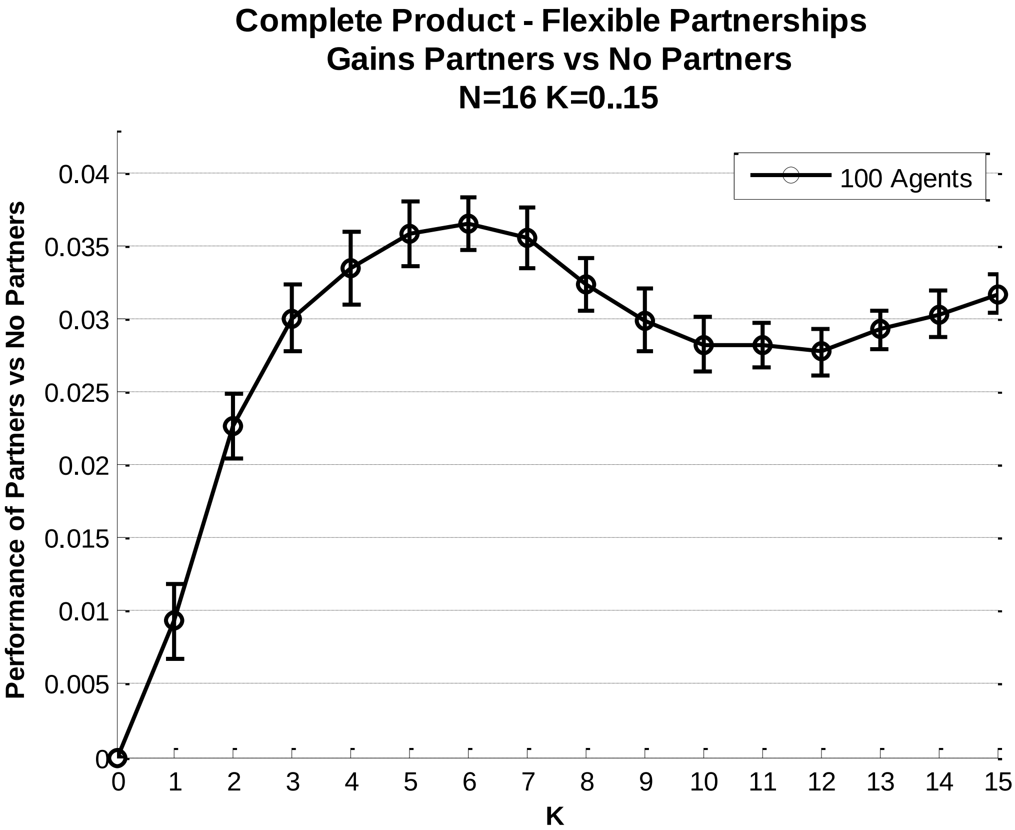


Figure 4. Complete Product - Flexible Partnerships. Gains Partners versus No Partners

Description. For each K=1…15, we do the following fifty times: generate a landscape and release one hundred firms that search for highest fitness under both, closed and open innovation (flexible partnerships). Let CLO be the average fitness of firms engaged in closed innovation and OPE the average fitness of firms engaged in open innovation. For each landscape we compute the difference in average fitness, OPE–CLO. Because for each K we have fifty landscapes, we generate fifty differences in average fitness (OPE–CLO). The figure plots the average of OPE–CLO for each K. The bars are standard errors of the mean.

Interpretation. Open innovation with flexible partnerships outperforms closed innovation for all levels of K.

The advantage of open innovation with flexible partnerships can be explained with a simple thought experiment. Imagine that we separate the product into N parts (one part for each decision) with each firm doing one part (i.e., we have N firms in any partnership, not just 2 firms). We create two firms for each of the N parts and have those two firms do that part differently. Then, we let each firm recombine with the best possible partners. If we did this, we would effectively be allowing each firm to optimize over N-1 decisions through partner selection. That should get us pretty close to the optimal performance even at fairly high N, only being beat by a firm that hits the optimal over all N decisions. Thus, the more finely we cut up the product, the closer we will get to global optimization. Splitting the decision in two and allowing partial flexibility in choosing partners (as we do in the paper) is just one step closer to optimization.[15]

Splitting the firms, then assuming they recombine optimally or nearly optimally, is equivalent to allowing firms to select the right partners externally. Our model of closed innovation, on the other hand, implicitly assumes that firms have very limited ability to select the right complementary practices internally (by “complementary practices” we mean the bundle of product features configured by the partner firm). The reason why such complementary practices are hard to select internally is that often they are “far away” from current internal practices (which are assigned randomly at time zero and evolve through local search) and local search does not typically lead to such optimal configurations.

The advantage of open innovation with flexible partnerships that we find in this model is from the assumption that firms are better at selecting complementary partners than they are at selecting complementary practices. One way to think about the limitations imposed by closed innovation is that firms cannot “imagine” all the possible bundles of complementary practices. All that they can imagine are those complementary practices that are one step ahead from current configuration. Open innovation allows firms to see beyond current practice and understand that important improvement can be realized.

The model of flexible partnerships effectively says “if you can’t figure out how to put the pieces together internally (configure two subsystems optimally), it is critical to have lots of different pieces (complementary subsystems) to choose from and know how to put them together externally.” The more pieces that are there to choose from (as implied by a larger partner opportunity set), the better open innovation will perform. Consistent with this reasoning, Figure 4 shows that when the partner opportunity set is opened, the improvement in performance is due to less severe divergence costs.

[15] We thank an anonymous reviewer for presenting this argument.

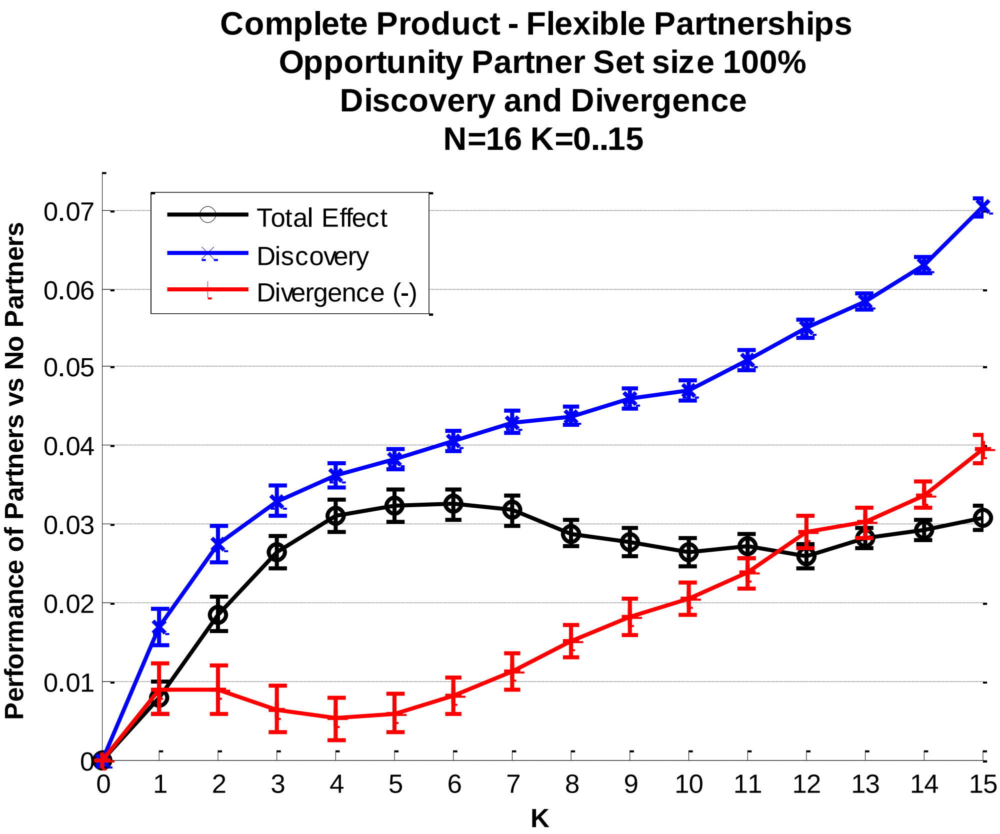


Figure 5. Complete Product - Flexible Partnerships - Discovery and Divergence

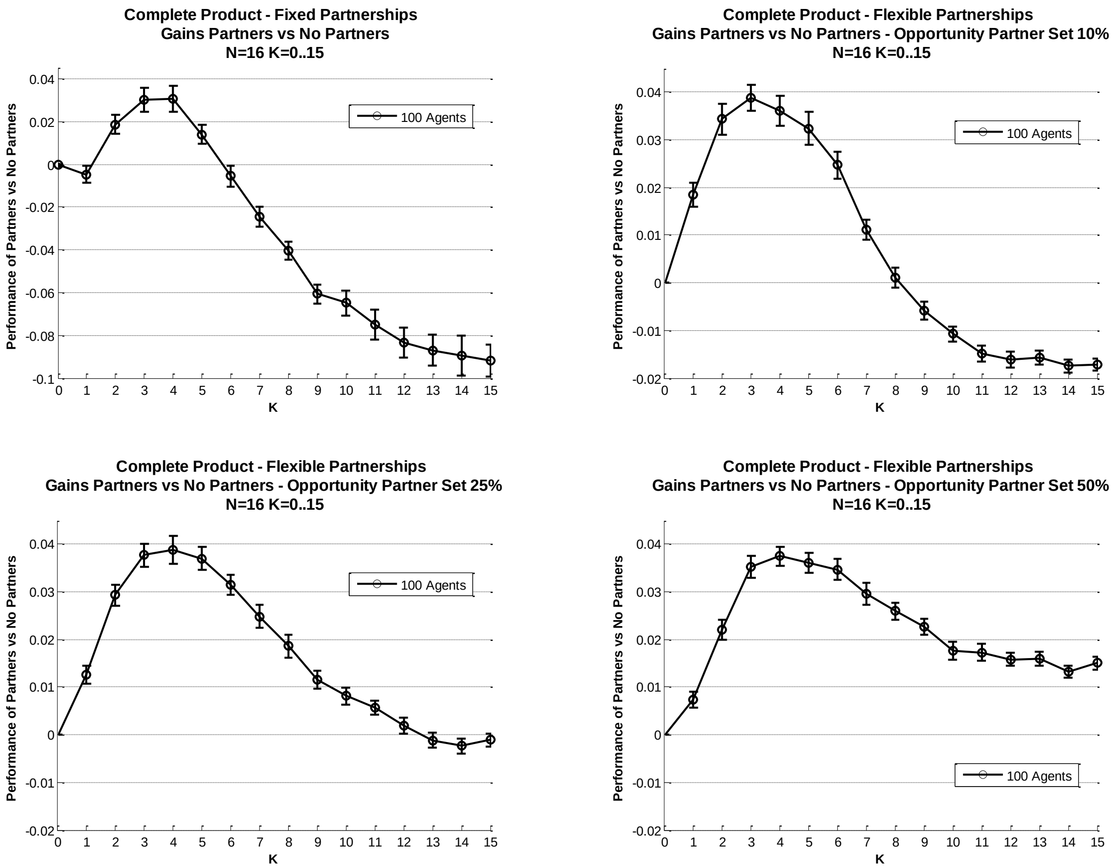
Description. For each K=1…15, we do the following fifty times: generate a landscape and release one hundred firms that search for highest fitness under closed innovation, open innovation (flexible partnerships), and as supercharged firms (see Section 4.2 for a description). Let CLO be the average fitness of firms engaged in closed innovation, OPE the average fitness of firms engaged in open innovation, and SCH the average fitness of supercharged firms. For each landscape we compute *Discovery = SCH – CLO* and *Divergence = OPE – SCH*. Because for each K we have fifty landscapes, we generate fifty data points for discovery and divergence for each level of complexity. The figure plots average discovery (in blue) and average divergence (in red) for each K. We also plot the total effect: *Total Effect = Discovery – Divergence.*

Interpretation. The benefits of discovery increase with K. Comparing to Figure 2, we see that the negative effects of divergence decay substantially when the partner opportunity set grows from 0% to 100%.

3.4.4 Fixed vs. Flexible Partnerships – Two Ends of a Continuum

Open innovation with flexible partnerships performs better than when partnerships are fixed. Our model of flexible partnerships is extreme in that the opportunity set of possible partners consists of all firms producing complementary products. In other words, a given firm α is allowed to partner with any one of about fifty firms β, and vice versa. In reality, physical distance, capacity constraints, reputation, and the like will reduce the cardinality of this set. We now investigate how sensitive the results of flexible partnerships are to changes in the cardinality of this set.

Towards this end, we re-ran the models of flexible partnerships with randomly selected groups of 10, 25, 50, and 75 per cent of complementary firms. Notice that the cases of fixed partnerships and flexible partnerships analyzed above are particular cases corresponding to opportunity sets of 0 and 100 per cent, respectively. Figure 5 shows the progression from fixed to flexible. Notice that in the simulations with 100 firms, when the partner opportunity set increases to 10%, closed innovation beats open innovation only for K ≥ 9 and as the partner opportunity grows larger, so does the minimum K such that closed innovation beats open innovation.



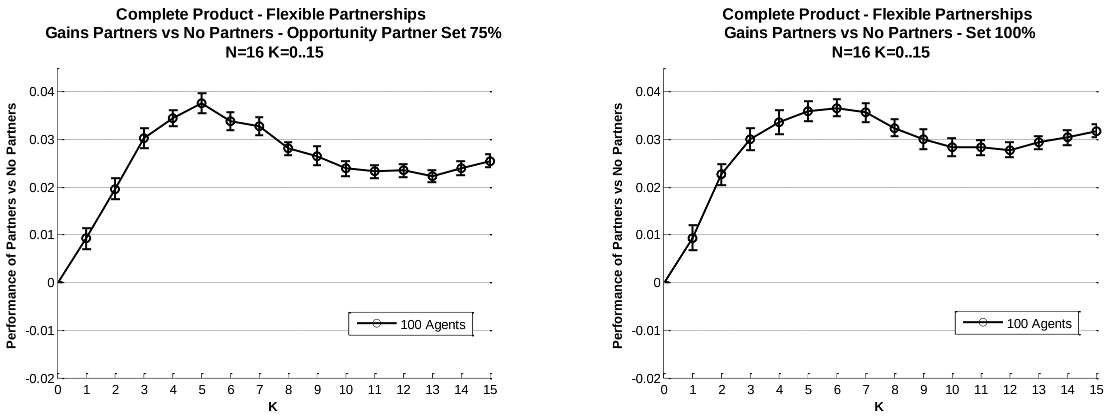


Figure 5. Complete Product at Different Opportunity Sets

Description. We consider the effect of different cardinalities of the "partner opportunity set." The graphs are for partner opportunity sets of 0% (fixed partnerships), 10%, 25%, 50%, 75% and 100% (flexible partnerships). For each K=1…15, we do the following fifty times: generate a landscape and release one hundred firms that search for highest fitness under both, closed and open innovation. Let CLO be the average fitness of firms engaged in closed innovation and OPE the average fitness of firms engaged in open innovation. For each landscape we compute the difference in average fitness, OPE–CLO. Because for each K we have fifty landscapes, we generate fifty differences in average fitness (OPE–CLO). The figure plots the average of OPE–CLO for each K.

Interpretation. As the partner opportunity set expands, so does the minimum level of complexity such that open innovation leads to better performance than closed innovation. Open innovation does better than closed innovation for all levels of K when partnerships are open to a randomly selected group of 50% of complementary firms. We also note that the evolution of performance of open innovation for low values of K is not monotonic.

3.4.5 Summary

We end Section 4 with succinct statements of our two main results:

Result 1: Suppose that it is not possible to change partners (either it is too costly or there are no other potential partners with whom to do business). Then, open innovation leads to better performance than closed innovation when complexity is low.

Result 2: Suppose that it is possible to change partners. Then, as the partner opportunity set expands, so does the minimum level of complexity such that open innovation leads to better performance than closed innovation.

3.5 Discussion

3.5.1 On the Evolution of Complexity

We have assumed that the mapping between product features and willingness to pay is objective and does not change over time. It would seem natural to assume that even when the true mapping is complex, firms may want to think of it as if it was simple. How can firms think of a complex map as simple? Firms could just configure all product features to their “maximum” as having “more of everything” should always be desirable to customers. That is, even if some of the features are not valued much by customers, making them available should not detract from willingness to pay. The optimal strategy in this case is: configure all product features individually as completely as possible.

While this approach may be valid in some instances, quite often “simplifying the complex” in this manner is not feasible. The reason is that the state of technology forces trade-offs between features. As new features are added, the product is likely to become less desirable in some dimensions. For example, adding powerful, long-lasting batteries (a desirable feature) generally means having a more voluminous PDA (an undesirable feature). When the firm is forced to make these sorts of trade-offs, a complex mapping between features and willingness to pay cannot be simplified as suggested above. When technological trade-offs force the firm to offer specific bundles, complexity has a bite.

As the state of technology improves these trade-offs become less binding, allowing firms to offer more complete products (with “more” of all features). From the firm’s viewpoint, technological evolution can have the effect of simplifying the landscape. Consider, for example, the case of PDAs. When PDAs were first brought to market, technology limitations forced heavy compromises between features, most obviously between hardware and software. As technology evolved, trade-offs became less severe. In the extreme, one could imagine a day when processing speed, RAM, storage, battery life, and other features become unlimited (for all practical purposes), if this ever happens the mapping as evaluated by the firm will have become “simpler” even if it truly remains complex.

We conclude that K (as perceived by the firm) is likely to decrease with technological progress (better written software, modularization…). The model’s predictions are in this sense consistent with the stylized facts documented by Boudreau (2006) who finds that early in the life of a system, closed development leads to more successful innovation and that later, when complexity lessens, open development is generally more successful. Specifically, when complexity is low, all industry participants agree on what the “right” design should be. As a consequence, the cost of devolving control is low as partnering firms will want to make choices similar to those the original system developer would have made in the first place. And even when the choice is not exactly the same, willingness to pay for the system is close to that of the best design because landscape ruggedness is low. Moreover, the additional learning that comes from having others co-develop the system (discovery) is low. In this case, there will be near indifference between open and closed development. Both approaches will fare equally well.

3.5.2 On Competitive Interaction

Because payoffs are interdependent, the models of open innovation that we have considered have firms interacting. Notice that the position on the landscape of a firm α is partly determined by its own choices (features 1 through 8) and partly by choices of the firm β with which it is paired (features 9 through 16). Moreover, we have assumed that every firm configures product features under its control to maximize its own fit.

The approach is thus similar to game theoretical models of competitive interaction. Our model of open innovation can be seen as a modest attempt to bring closer together strategic interaction (à la game theory) and NK fitness landscapes in line with arguments in Levinthal and Warglien (1999).[16] One important critique to the application of NK fitness landscapes to the study of business strategy is that it was originally devised for the study of physics and genetics, not strategic interaction. Most applications to strategy thus far have not explicitly considered strategic interaction between players: the actions of a player do not affect the position of other players on the landscape. One important exception is the work of Lenox et al. (2006).[17] We believe that the integration of NK fitness landscapes and game theory is a promising area of research that can potentially inform many aspects of firm strategy that have thus far been analyzed assuming away the effects of competitive interaction.

[16] There are important differences between our approach and standard game theory. Most importantly, firms are assumed not to see the entire landscape but only their local environment. In addition, firms do not try to anticipate their partners' behavior when making their own choices.

[17] In their model, firms make two decisions. First, they choose a set of activities that determine their marginal cost. Second, they compete in the market place by choosing quantities. Marginal cost is modeled as the height of an NK landscape. An important difference with the present paper is that Lenox et al. (2006) model competitive interaction as a Cournot game.

3.6 Extension: Sale to OEM

We now study an alternative way to pairing α and β firms. In this extension, which we name "Sale to OEM," firms α and β sell their subsystems to OEMs who assemble them together into a final product that is sold to consumers.

3.6.1 Simulation Mechanics

The simulations are just as those of the benchmark model studied above. The main difference is that, because firms sell the subsystems to the OEM, we assume that component manufacturers are concerned about the contribution to willingness to pay of the N/2 features that they directly control. For example, in the case of a firm α, this is computed as follows:

$$WTP(s_1,\ldots,s_{\frac{N}{2}} \mid s_{\frac{N}{2}+1},\ldots,s_N) = \frac{\sum_{i=1}^{N/2} c_i(s_i; s_{i_1},\ldots,s_{i_K})}{N} . \qquad (2)$$

Note that the contributions $c_i(s_i; s_{i_1},\ldots,s_{i_K})$ i=1…N/2 may depend on configurations of product features outside the control of i. This happens when one or more features in <s1, s2, …, sN/2> interact(s) with features of the β subsystem.[18] Thus, the value of a particular α subsystem to a given OEM depends on the particular β subsystem with which it is combined to generate the final product.

In equation (2) we have divided the sum by N. This is a normalization. We could have divided the expression by N/2. That would scale the landscape up but its shape would be unchanged. With this, we have

$$WTP(s_1,\ldots,s_N) = WTP(s_1,\ldots,s_{\frac{N}{2}} \mid s_{\frac{N}{2}+1},\ldots,s_N) + WTP(s_{\frac{N}{2}+1},\ldots,s_N \mid s_1,\ldots,s_{\frac{N}{2}}) ,$$

where

$$WTP(s_{\frac{N}{2}+1},\ldots,s_N \mid s_1,\ldots,s_{\frac{N}{2}})$$

is the WTP for the β subsystem (produced by a firm β) and it is computed similarly to that for α. Table 7 summarizes the differences between the various models of open innovation that are considered in the paper.

[18] Likewise for contributions $c_i(s_i; s_{i_1},\ldots,s_{i_K})$ i=N/2+1…N.

	Complete Product	Sale to OEM
Fixed Partnerships	• Pairings maintained over time • Firm x incorporates product y and sells complete bundle	• Pairings maintained over time • Firm x and Firm y sell subsystems to OEM who sells final product
Flexible Partnerships	• New partnerships can form over time • Firm x incorporates product y and sells complete bundle • New partners are chosen by x and y	• New partnerships can form over time • Firm x and Firm y sell subsystems to OEM who sells final product • New partners are chosen by the OEM

Table 7. Four Models of Open Innovation

What are the particular α and β subsystems assembled by OEMs in this model? Under fixed partnerships, subsystems α and β are given to the OEM at time zero. The OEM is stuck with those particular systems for the rest of the simulation. Under flexible partnerships, each component manufacturer looks at all manufacturers of complementary subsystems and picks the one such that a combination with its product will result in the most valuable complete system. For example, a given α firm picks the β firm such that <α, β> results in the highest possible fit. The reason for this pairing is that if a particular OEM picked that specific α, it would be pairing it with precisely that β subsystem because that combination leads to maximal fit. In choosing what product features to modify, however, firm α considers only the contributions of features 1 through N/2 (those features that compose the product that the firm sells to the OEM).[19] In the model of flexible partnerships, payoffs are computed twice: once by the suppliers (this computation guides search) and once by the OEM (which guides supplier pairing). In the first computation, equation (2) is used; in the second, equation (1) is used.

[19] With this process, when the simulation ends, we wind up with *several different* subsystems α and β available. If the OEMs could see all the α and β subsystems that are available, they would all choose the same combination. This is likely to lead to little value capture by OEMs. As mentioned in the Conclusion, this paper focuses on value creation through configurations of α and β subsystems and not on value capture. We do not consider how competition between OEMs may influence the incentives by α and β firms to innovate.

3.6.2 Results

OEM assembly from fixed pairs of firms leads to disastrous performance, regardless of complexity (Fig. 6). To see why, recall that in the model of the OEM, no attempt is made by firms α and β to coordinate product designs. A given firm α, for example, does not take into account how the configuration of the components under its control affect the contributions of the N/2 product features under the control of the β firm with which it is paired (because these do not enter its payoff).[20] The OEM is stuck with two interdependent subsystems that evolve independently of one another, resulting in ruinous performance.

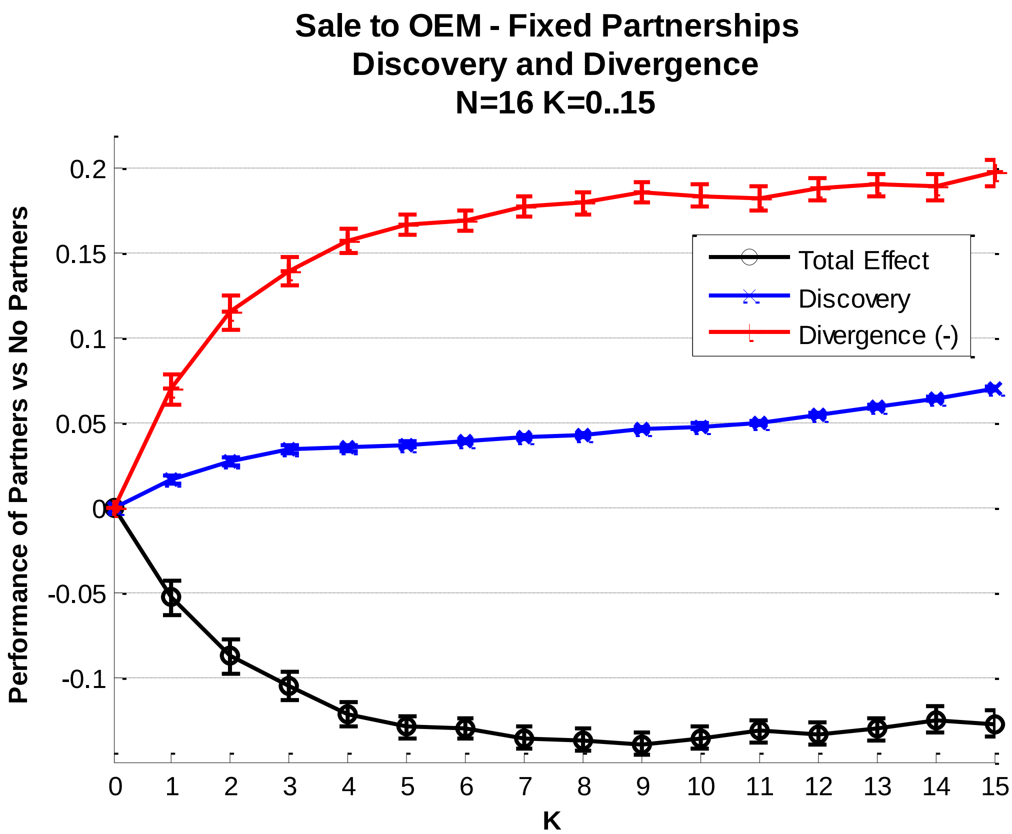


Figure 7. Sale to OEM - Fixed Partnerships

Description. For each K=1…15, we do the following fifty times: generate a landscape and release one hundred firms that search for highest fitness under closed innovation, open innovation (Sale to OEM and Fixed Partnerships), and as supercharged firms (see Section 4.2 for a description). Let CLO be the average fitness of firms engaged in closed innovation, OPE the average fitness of firms engaged in open innovation, and SCH the average fitness of

[20] To see the difference with the benchmark (complete product) model notice that while each firm acts to maximize its own fit, fit depends not only on the contributions of the product features under their control but also on the contributions of those under the control of the firm with which it is paired. As a consequence, in the model of complete product firms α (β) consider how their N/2 choices affect not only the contributions of the features under their control but also those chosen by the β (α) firms with which they are paired.

supercharged firms. For each landscape we compute *Discovery = SCH – CLO* and *Divergence = OPE – SCH*. Because for each K we have fifty landscapes, we generate fifty data points for discovery and divergence for each level of complexity. The figure plots average discovery (in blue) and average divergence (in red) for each K. We also plot the total effect: *Total Effect = Discovery – Divergence* (in black).

Interpretation. Open innovation (Sale to OEM & Fixed Partnerships) underperforms closed innovation for all levels of K.

When OEMs can choose which components to assemble, the model delivers superior performance (compared to closed innovation) when K is large (Fig. 7). In this case, even as subsystems α and β evolve independently, OEMs choose the best possible match at every stage. When K is high, the model generates many assemblies and disassemblies of α and β components and, thus, lots of variability in the available subsystems for assembly. A consequence of all this variation is that better systems can be assembled leading to superior performance. When K is low, there are few local maxima and firms settle quickly. The firm ends up at conditional local maxima. The quality of these maxima would be high if there was a large set of possible configurations of the conditioning features (those controlled by the other firm) to choose from (by switching partners). Because K is low, however, there is not much variability. As a consequence, performance ends up not being great for the open firm.

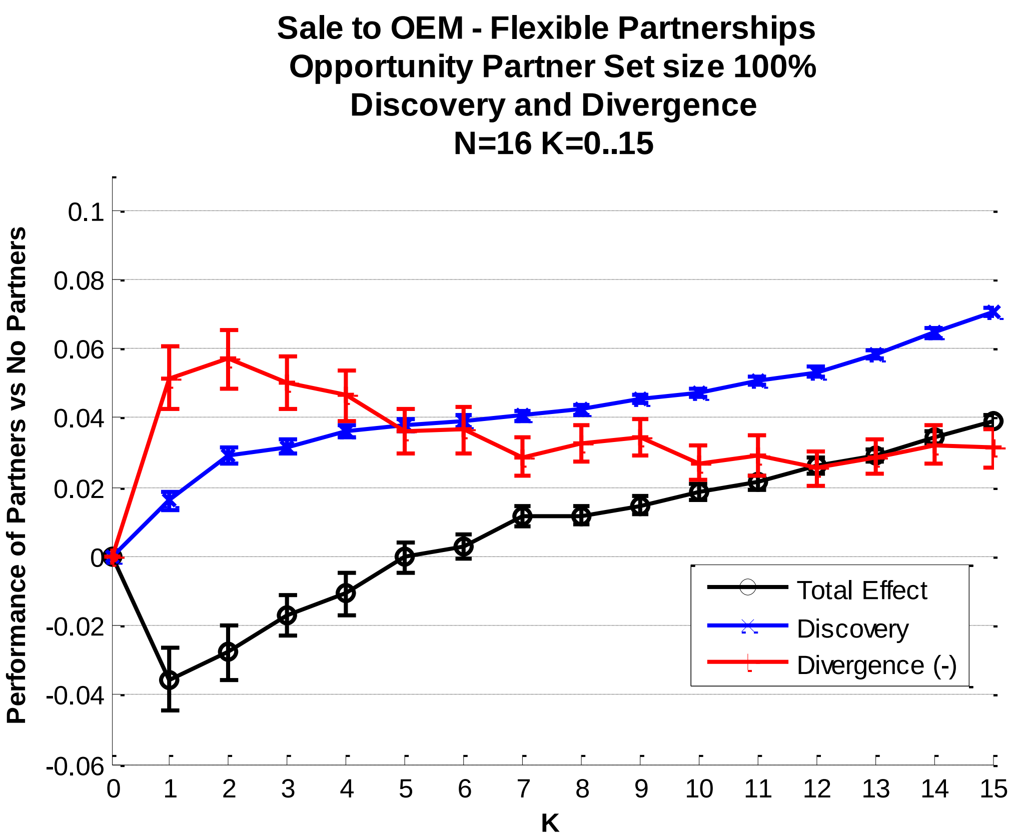


Figure 8. Sale to OEM - Flexible Partnerships

Description. For each K=1…15, we do the following fifty times: generate a landscape and release one hundred firms that search for highest fitness under closed innovation, open innovation (Sale to OEM and Fixed Partnerships), and as supercharged firms (see Section 4.2 for a description). Let CLO be the average fitness of firms engaged in closed innovation, OPE the average fitness of firms engaged in open innovation, and SCH the average fitness of supercharged firms. For each landscape we compute *Discovery = SCH – CLO* and *Divergence = OPE – SCH*. Because for each K we have fifty landscapes, we generate fifty data points for discovery and divergence for each level of complexity. The figure plots average discovery (in blue) and average divergence (in red) for each K. We also plot the total effect: *Total Effect = Discovery – Divergence* (in black).

Interpretation. Open innovation (Sale to OEM & Flexible Partnerships) outperforms closed innovation when K is high.

In addition to comparing the performance of “Sale to OEM” to closed innovation, it is useful to compare the two models of open innovation, the benchmark model (where partners bring complete products to market) and “Sale to OEM” (where OEMs assemble components produced by independent firms). The simulations show that the benchmark model outperforms the model of “Sale to OEM.” This is somewhat puzzling because when partnerships are flexible, OEMs pick the single best possible combination of two partners. Why would the best combination of two partners ever be outperformed by any other mix of partners?

In the benchmark model, each firm takes into consideration the choices made by its current partner (thus searching for improvements that enhance the whole given the partner). The “Sale to OEM” model is at the other extreme: firms do not take into consideration the choices made by its current partner in searching for improvements to the product. In reality, firms that sell to an OEM will take such choices into consideration and optimize accordingly. If in the model of “Sale to OEM” we allowed partners to consider each others’ feature configurations when making their choices, we would end up with a model very similar to the benchmark.

The result that the benchmark model outperforms the model of “Sale to OEM” may depend on the total number of firms in the industry. As the number of firms rise, so rise the odds that OEMs can find combinations of partners that result in products with high willingness to pay (even though component firms have not coordinated in any way). However, firms innovating through the benchmark model with a complete product will also be able to combine with more partners and end up at better positions. Therefore, there is no clear-cut prediction as to the evolution of relative advantage of each model of open innovation when the number of potential partners increases.

3.7 Concluding Remarks

We have presented a model that suggests that discovery might arise not from the exercise of full strategic freedom (being able to choose all N product features), but from restricting the available choices and learning from those made by others. An open innovation strategy allows the firm to discover areas of the product landscape that would be hard to imagine otherwise. As partners seek better positions, the focal firm discovers locations on the landscape that it may have never reached had it been in charge of all choices. In a sense, the search that our models of open innovation generate is similar to the cognitive search in Gavetti and Levinthal (2000). These authors allow firms to search by performing long jumps to regions of the landscape that are characterized, on average, by high fitness. In our case, the non-incremental moves on the landscape are not the result of better cognition but, rather, of making use of other players' knowledge.

We end by pointing out that the model has important limitations. Most importantly, our model is one of value creation, not value capture.[21] Questions such as: might it not be much more profitable to be an average closed firm than one beholden to a specific supplier or set of suppliers? and: how would this affect both the advisability of different approaches and the likelihood that firms adopt one approach or another? cannot be addressed with our model. To properly address issues of value capture we would need to make assumptions regarding (a) bargaining power between customers and firms, (b) intensity of competition between firms as a function of how similar their products are (how far or close on the landscape the products are), and (c) bargaining power between α and β firms that are paired together. The increased complexity may blur the mechanism for value creation that we have fleshed out (the trade-off between discovery and divergence). The study of value capture is important but complex and we relegate it to a different paper.

By focusing on the trade-off between discovery and divergence, we have assumed away other factors that affect the relative attractiveness of open vs. closed innovation. These include: (1) user adoption and network effects (2) the opportunity to refocus internal resources on finding, screening, and managing implementation, (3) the sense of urgency for internal groups to act on ideas or technology, and (4) the creation of a culture that fosters innovation. The upside of limiting the analysis in this way is that it allows us to understand in depth one mechanism affecting the choice between both approaches to innovation. In applying our results to real managerial settings, however, one must be careful not to discount other factors affecting the attractiveness of each development method. These factors interact, sometimes non-trivially, with the mechanism introduced in this paper.

[21] We thank an anonymous reviewer for pointing this out.

Our model suggests that researchers investigating user-driven innovation (see, for example, the work by Jeppesen and Molin (2003), Franke and Shah (2003), Jeppesen (2005), and Chatterji and Fabrizio (2007)) looking into the relationship between collective knowledge sharing, product development, and innovation may find it helpful to consider the complexity of the mapping between product features and customer value created as a factor that can potentially moderate the effects of user contributions to product innovation. Likewise, our model (which has firms, not users, innovating) could be extended to a setting where ideas generated by users can be incorporated into the product. Obviously, the distinction between user-driven innovation and innovation by firms becomes especially important if value capture was explicitly considered.

The presence of strong network effects may lead to a dynamic of winner-take-all. In this case, generating differential willingness to pay fast is especially important. The literature has considered a number of mechanisms to raise willingness to pay in such settings, including: (i) the deepening of network effects (through low prices, wider distribution, and the like) (Arthur, 1989, 1994; Shapiro and Varian, 1999), (ii) managing expectations to draw adoption by customers and complementors (Farrell and Klemperer, 2007, Church and Gandal, 2004), and (iii) investing to produce a higher quality product (Rangan and Adner (2001), Jacobson and Aaker, 1985, and Sethi, 2000). Our argument suggests that one additional mechanism that is available (when complexity is not too high) is open innovation. To the extent that there is a large pool of firms that are available to act as innovation partners (which increases the likelihood that open innovation will generate large increases in value) open innovation may neutralize efforts by competitors to raise willingness to pay through other mechanisms.

One implication of the models with flexible partnerships that we have presented is that having a large network of firms ready to collaborate for innovation can be highly beneficial, regardless of the level of complexity that characterizes the mapping between product features and willingness to pay. As a consequence, having a capability for managing such networks is essential for our arguments to apply. Ecosystem-promoting actions such as Intel's set up of Intel Capital (a venture capital company formed in the early 1990s to stimulate advances in computing by investing in start ups), not only have the benefit of potentially strengthening indirect network effects, but also should lead to improved innovation (as Intel benefits from the diversity of knowledge of firms in the portfolio). In other words, large ecosystems of firms around a platform not only help exploit network effects, but also result in enhanced product innovation when the platform has a capability to manage such relationships.

4 Statistical Inferences vs. Patterns

4.1 Introduction

Exploration has always been central to market economies, because trough it, innovation, strategy, grow, competition - to name a just few processes - get articulated.

This is a process where heterogeneous agents with limited capacities and competences face a commonly large space of solutions where there is a repeated appearance of novelties as a result of technological and organizational innovations created by the agents themselves, and where market (and other arrangements) operate as a selection mechanism.

This process of exploration, is driven by a continuous succession of hypothesis generation and testing that can also be described as a learning process, where economic agents confront two basic challenges: the Knightian uncertainty (Knight, 1921) of a large search space and their own cognitive and path dependent limitations.

In order to better understand the mechanisms behind exploration, modeling has revealed as a useful technique able to deal with the complexity of the interactions that we attempt to understand.

A first class of models portray agents that respond to some local characteristics of a given population. Agents connected to their neighbors that observe them and by interacting with them, "learn" (Kirman, 1997, David, 1992, Dalle, 1994). Key to this arrangement is a notion of distance, $d(i,j), i,j \in Agents$, where

$$\Gamma_i = \{j \in A : d(i,j) \leq d^*\}$$

In this class, collaboration (Almirall and Casadesús-Masanell, 2009) and imitation (Rivkin, 2000), copying the behavior of others based on their popularity of pay-off is probably the best well known mechanism and has been widely studied in areas like diffusion of innovations.

Also Markov Fields, assuming that agents stochastically select their action depending on the states of their neighbors (An and Kiefer, 1995, Dalle, 1994) has been profusely explored.

Nevertheless, other models rely in the capacity of the agents to learn from the environment or the population of agents, either by directly probing the search space such in the case of incremental search (hill climbing), reinforcement (Arthur, 1993), imitation (Rivkin, 2000), etc. or by observing some global characteristics. Already Arthur in 1987 (Arthur, 1987) presenting the interpretation of frequencies as free public information while Dosi (Dosi, Ermoliev et al., 1994) assumed that agents estimate frequencies by observing a sample of the population.

Another stream of research relies on directly modeling the outcomes rather than attempting to describe even a stylized version of the mechanisms. This is the case of evolutionary models where learning takes place at population level by means of a selection process that favors strategies with higher pay-offs, increasing their share in the population of agents.

Evolutionary models, pioneered by Maynard Smith (Maynard Smith, 1982) are the prime representatives of this line. There, being p_i^t the fraction of players playing strategy i at time t, the replicator dynamic equation, operationalizing the selection principle that strategies with a higher pay-off are increasingly sampled in the population, takes the form,

$$\dot{p}_i^t = p_i^t \, g\left(\pi_i^t - \overline{\pi}^t\right)$$

being π_i^t the pay-off of strategy i at time t and $\overline{\pi}^t$the average pay-off across the population at time t.

However, all these three approaches contrast with the existing exploration process in modern economies. In fact, these societies have endowed themselves with institutions whose mission is to pursue the understanding of the social and economic mechanisms in general together with aspects as concrete as, for example, the impact of technological developments in specific sectors.

In fact, Business Schools, academic institutions research agencies, the business and economic press and media, consultants and in general, a large number of organizations, devote their energies to observe, analyze and sense the business and economic outlook, developing theory and extracting best practices that companies will adopt and test thereby assessing its validity.

Two major practices performed by these institutions can be distinguished. On one side we have organizations that try to find the most promising patterns by collecting best practices and from there, inferring causalities and mechanisms that can provide insights on the rules governing their behavior. On the other, we find other researchers that rely on statistical inferences, applying analytical tools such as regression analysis, Structural Equation Models, etc.

For the purpose of modeling them in the framework of NK spaces we will designate the first type, resulting from the generalization of "Best Practices" represented by binary stings as "Patterns" because the generalization process will extract the most common patterns, bit substrings. On the other side, we will use multiple linear regressions as the most representative tool for statistical inferences, to conclude which substrings perform better.

In both cases, the results from regressions and distilled best patterns are provided to the agents, who by adopting and incorporating them to their current strategies provide the raw materials that will guide the next iteration of research.

However, this process is either left outside of the model, as in the case of local learning, treated as exogenous, in some of the cases of models that incorporate global characteristics or considered only in its aggregate form in the case of evolutionary models. Nevertheless, we know that agent strategies and institutions co-evolve (Young, 1988), shaping each other.

We argue that if we seek an understanding of the process of exploration, the mechanisms used by the institutions to extract theories, either in the form of best patterns or correlations, from the information available in the agents, must be incorporate in the models.

By doing that, we will not only gain some insights into the appropriateness of the process of collecting and processing information and on the best way to use it by the agents, but we will also gain some understanding of the social and distributed aspects of this process where agents, by adapting the theories proposed by Business Schools and other organizations, will validate or falsify them and by exploring new strategies, merging the proposed with the existing ones, will create new mutations that will provide at its turn, opportunities for discovering new theories either in the form of correlations or patterns.

Exploration becomes therefore, an iterative and distributed process that takes part both on the agents and on the institution, converging until the best theories are obtained and validated.

A determinant aspect of this process, is the complexity of the space of solutions to be explored. In order to assess this, agents are situated in an NK space where the level of complexity can be easily tuned by varying the number of epistemic linkages between its components. That way, we can go from a simple space with only one local maxima, a space that can be easily solved using hill climbing, to an extremely complex one, where the value of each component depends on the combination of all the other components and where multiple local maxima exist.

With these tools we aim to explore three research streams:

1) The modeling of the mechanisms of pattern-based discovery.

2) The mapping of this mechanism into and NK space, uncovering questions such as how many best cases should be collected, how comprehensive they should be, of what and when patterns from best cases perform better than insights obtained from regression analysis.

3) Uncovering the co-evolutionary aspects between agent and institutional exploration process, providing insights on how many resources should individual agents devote to exploration and how much they can rely on the advice of institutions such as Business Schools.

4.2 Model-Based Learning

Economic agents in their search for better strategies and innovations, enjoy nowadays a richness of information and analytical tools that our ancestors could not even dream of. However, they are bound by the same two basic limitations: the fact that human beings are limited in their cognitive abilities and the Knightian (Knight, 1921) uncertainty that characterizes markets and in general social settings.

Because acquiring information by individual learning is costly, natural selection has favored learning mechanisms that rely on extracting adaptive information: strategies, best practices, heuristics and beliefs, from the social group at a lower cost than alternative individual mechanisms based on trial and error.

This characterization of strategy search as driven by similar mechanisms than social learning appeals to the first strand of research that has influenced our work: evolutionary psychology.

Once individuals begin to learn from others, it is obviously wise to be selective and preferentially pay attention to and learn from those who are highly successful or particularly skilled subjects (Henrich and Gil-White, 2001), being the probability of imitation correlated with the observed difference in payoffs (Alpesteguia, Huck and Oeschssler, 2005; Schlag 1998, 1999).

However, in this form of model-based cultural learning assessing from whom to learn is not a straightforward task. This is why we rely on cues such as competence, success and prestige and we devise and build social mechanisms that promote their emergence.

Therefore, in a social setting that makes use of competence and success signals, highly skilled individuals will be in high demand and a selection pressure leading to a deference mechanism will appear (Gurven, 2001). Naive entrants can therefore look at the existing pattern of deference in order to solve the costly information problem. Consequently, solving the problem of from whom to learn is reduced to aggregating information from the distribution of deference.

A well known social mechanism to perform this aggregation is "*conformist transmission*" (Boyd and Richerson, 1985; Henrich and Boyd, 1998), that can be described as copy the majority or copy what the majority understands as best practices.

Moreover, conformist transmission is known to be the best route to adaptation in information-poor environments (Henrich and Boyd 1998; Kameda and Nakanishi, 2002). Hence, when individual ambiguity due to low accuracy of the information obtained through individual learning increases, so does the reliance on conformist transmission (Henrich and Boyd, McElreath, Lubell, et al. 2005; Smith and Bell, 1994; Wit 1999).

This is certainly the case of high complexity environments such as selecting the best strategy in free competitive markets, innovating or embracing new and yet untested innovation in the form of new products, services or processes.

This leads us to the second strand where our research is indebted with: diffusion of innovations. As Rogers summarizes in his massive review

> *"most people depend mainly upon a subjective evaluation of an innovation that is conveyed to them from other individuals like themselves who have previously adopted the innovation ... suggest that the heart of the diffusion process consists of the modeling and imitation by their network of partners who have adopted previously" (Rogers, 1995 p. 18).*

Rogers describes these individuals as: 1) locally high in social status, 2) well respected, 3) widely connected and 4) effective social models.

Our last strand of research that we are indebted for is cognitive science that sees pattern-matching as central to reasoning and learning. The two predominant cognitive models, the connectionist that sees the brain as a computer (Donald, 2001) and the evolutionist (Dosi, Marengo and Fagiolo, 2003) that postulates a process-based in somatic selections, view the brain as employing pattern-based reasoning, rather than abstract logical reasoning, which is essential for explaining how we make choices in a world of uncertainty. "Thinking occurs in terms of synthesized patterns, not logic and for this reason it may always exceed in its reach syntactical or mechanical relations" (Edelman and Tonini, 2001, p. 152).

This pattern-based reasoning mechanism also influenced Institutional Economics. In fact, when dealing with the process of economic change, Douglas C. North, indicates:

"Much of learning comes from absorbing and adjusting to subtle events that have an impact on our lives, incrementally modifying our behavior ever so slightly. Implicit knowledge evolves without ever being reasoned out. In fact we are relatively poor at reasoning compared to our ability to understand problems and see solutions. We are good at understanding and comprehending if the issue is sufficiently similar to other events that have happened in our experience. Ideas to far from the norms embodied in our culture cannot easily be incorporate in our culture. Ideas are adopted if and when they share a kind of cohesion that does not take them too far from the norms we possess. Pattern-matching is the way we perceive, remember and comprehend. This is the key to our ability to generalize and use analogy. This ability makes us good not only at modeling “reality”, but also at constructing theories in the face of real uncertainty." (North, 2005, p. 26-27).

However, even if the underlying mechanisms that drive behavior of economic agents are similar to the ones that drive cultural learning, it will be naive to pretend that a simple and direct transposition could be a fair representation of the actual mechanisms in the real world.

There is, in fact, a substantial and important difference. The aggregation of information in order to infer patterns is not solely accomplished by agents, but has been institutionalized.

Business Schools, the research community, the economic press, governmental and public agencies, etc. devote a great deal of energy to produce models of successful strategies, innovations, by extracting the common traits that presumably are at the root of their success. These common traits that constitute our set of best practices or suggested courses of action is what we call in the present work, patterns.

4.3 Modeling Pattern-Based Strategy Search

Broadly speaking, theoretical models have depicted strategy search as either using incremental search or imitation as their main mechanisms. In incremental search, agents are allowed to change one component of their strategy at a time and they “know” the resulting fitness or at least are able to sense which change can lead to a higher fitness level. In imitation, agents copy, although potentially imperfectly, the strategy of another more successful agent. Also, besides these two main methods, others have been studied, like long jumps or the use of genetic algorithms.

Incremental improvement captures the notion that agents possess bounded visibility by limiting its scope to one strategic component. That way, agents will choose the strategy with a better fitness in 1-component range performing a greedy search. This search strategy has its roots in optimization, believing that if every aspect of the strategy can be optimized or exactly tuned to market needs, then the organization will be able to attain its maximum performance level. With local search, economic agents are prone to get trapped onto local maxima when the landscape is highly rugged (high K).

Drawing on the insights of section two, we aim to introduce a pattern-based discovery mechanism that captures and represents in a more realistic although stylized way of how exploration is performed in social groups. In order to implement it, an institution representing Business Schools, research agencies, the economic & management press, etc. that for a matter of concision we will label as Business Schools in this paper, will obtain and aggregate the common patterns of the population of agents at each round of the simulation. Patterns will be represented as a subset of the strategy vector.

Following the insights of section two as well, even if we will focus on "best cases" conformist transmission, other strategies will be laid out for comparison. Concretely, best cases conformist transmission will be implemented by counting the number of agents, from the subset of best performers, that actually have a particular pattern in their strategy vector.

In our model an agent is endowed with a vector of binary choices representing unique strategy components, $a_s = \{s_1, s_2, \ldots, s_n\}$ which can take a value of either 0 or 1. This vector is directly mapped to a position in the NK space, and through this mapping, a fitness value, corresponding to the fitness of this position in the NK space, for each agent is obtained. Agents move through the NK space performing individual search strategies either incremental or patterned search.

Incremental search is implemented by performing a hill climbing algorithm where agents are allowed to freely move between 1-component range seeking the best fitness.

A pattern is a group of binary choices composed by one or more components. Therefore all possible patterns of length l can be described as combinations of $C_N^l\ 2^l$.

For example given N=4, $s=\{s_1, s_2, s_3, s_4\}$, the possible patterns that could be derived from all possible combinations of length two of the two components of the strategy s are,

s_1, s_2   **s_2, s_3**   **s_3, s_4**

s_1, s_3   **s_2, s_4**

s_1, s_4

each of them can take any of the possible 2^l combinations of s_i, $s_i \in \{0,1\}$, therefore

s_1	s_2
0	0

0	1
1	0
1	1

Agents aim to discover the best patterns in the population of agents in order to incorporate them into their strategy and improve their fitness.

In order to map the role of "Business Schools" we assume that they periodically scan the universe of existing strategies, select and study the best cases among them and make their results public to the entire population of agents. Therefore in this model these institutions are mapped as performing three different functions:

1. Monitor the position of the agents in the landscape at each iteration
2. Rank the agents according to their fitness and select a percentage of best performers (governed by a parameter ρ, $\rho \in (0..1]$) as best cases
3. Collect the patterns among these best cases and rank these patterns according to one of the following strategies

    a. the average fitness of the pattern. Representing a rational agent with complete and exact knowledge of the fitness of the rest.
    b. their popularity. Mapping the mechanism of conformist transmission.

For the sake of the example let us assume that there are only 4 agents with N=4 and ρ=1, thus we consider the entire population as best cases.

$a_1 = \{ 0\ 1\ 1\ 0 \}$

$a_2 = \{ 1\ 0\ 1\ 0 \}$

$a_3 = \{ 1\ 1\ 1\ 0 \}$

$a_4 = \{ 1\ 0\ 1\ 1 \}$

	0 0	***0 1***	***1 0***	***1 1***
s_1, s_2	0	1	2	1
s_1, s_3	0	1	0	3
s_1, s_4	1	0	2	1
s_2, s_3	0	2	0	2
s_2, s_4	1	1	2	0
s_3, s_4	0	0	3	1

following the previous table, the ranking of patterns according to their popularity as best cases will be established as

Strategy components	*Pattern*	*Number of Cases*

s_1, s_3	1 1	3
s_3, s_4	1 0	3
s_1, s_2	1 0	2
s_1, s_4	1 0	2
s_2, s_3	0 1	2
s_2, s_3	1 1	2
s_2, s_4	1 0	2
s_1, s_2	0 1	1
s_1, s_2	1 1	1
s_1, s_4	0 0	1
s_1, s_4	1 1	1
s_2, s_4	0 0	1
s_2, s_4	0 1	1
s_3, s_4	1 1	1

building that way a structure of patterns p as a set of tuples $<c_i, v_i, o_i, a_i, f_i>$ where c_i stands for the set of components that the pattern considers, v_i for their binary value, o_i for the number of occurrences in the population of best cases considered (in case that we use the popularity classification), a_i for the average fitness of each pattern (in case that we use the average fitness classification) and f_i for the maximum fitness of the pattern, taken as the one of the best performing agent endowed with that pattern.

Moreover, agents are endowed with a memory $m_a = \{s_{a,1}, \dots , s_{a,n}\}$ which contains all strategies known by the agent because they have been previously applied. Therefore agents will only apply strategies that are either unknown or being known lead to a fitness higher than the current one.

Agents consider this structure as an input in their search for the best strategy. In our model, this process is mapped using the following algorithm (Algorithm 1),

Algorithm 1 Apply Best Patterns to an agents

Input: agent.{s,f} - *agent's strategy (agents.s) and fitness (agents.f)*
Input: P - set of patterns collected by the institution
Output: agent.{s,f} - *agent with adopted pattern*

funciton *ApplyBestPattern :* (agent, P) → agent

P' = sort(P, v, 'descend') - *Sort patterns by # votes*
for each p ∈ P'
  if p.f ≤ agent.fitness - *pattern has lower fitness than the agent*
  then
    continue

```
            end

            if  p ⊂ agent.s   -pattern exist in the agent's strategy vector
             then
                    continue
            end

            xs= apply(p, agent.s)

            if xs in agent.mem and xs.fitness ≤ agent.fitness
             then
                    - strategy has been applied and has a lower fitness
                    continue
             else
                    agent.s = apply(p, agent.s)          - apply pattern
                    agent.mem = include(agent.mem, agent.s)
                    - include in memory
                    return agent
            end
        end
        return agent
    end
```

Therefore, in every round of the simulation each agent considers the existing selection of patterns sorted by popularity (or alternatively by the average fitness of the agents endowed with them) until one pattern if found and applied or all patterns have been discarded by any of the following conditions:

1. The strategy of the agent already includes the pattern.
2. The best performer-agent with this pattern has a fitness lower or equal than the one of the agent.
3. The position resulting from applying the pattern to the strategy of the agent is already in the memory of the agent with a lower or equal fitness (the appliance of the pattern does not result in a gain for the agent).

Consequently, agents participate in the exploratory process in three distinctive ways.

First, they contribute to pattern discovery with their strategies that constitute the raw materials for obtaining the best patterns. This process aims to represent the collection of best practices done by Business Schools, research organizations, economic press, etc...

Secondly, they perform a selection process. Patterns, in fact, are not applied blindly by the agents. Agents select patterns by comparing the fitness of the best performer-agent endowed with the pattern with their own fitness and adopting it only in the case that the maximum fitness attainable by adopting the pattern, is higher than the one that they already have.

Therefore, we assume that a fitness estimation, representative of the pattern is public. This aims to model the common scenario where best practices are exemplified and presented with the aid of a real stellar performer. We can find multiple examples of this widespread practice, such as the case of Toyota for lean manufacturing or P&G for Open Innovation (Chesbrough, 2003).

Obviously agents lack the capacity and the information to produce a fair appraisal of the pattern - in contrast to the institution distilling them -, but because patterns represent real world practices, it is in the best interest of the organizations that elaborate them to present one or several representatives in order to: a) persuade about the selection process by presenting a sample of it, b) present evidence of the quality of the best practice, and c) provide a concrete examples for pedagogical reasons.

This selection process comes naturally, product of common sense, in the real world where a practice whose results seem to be worse than the ones obtained by other practices in use, is normally discarded. However, has important implications in the selection process, because that way, popular but non-performing practices are rapidly discarded allowing the exploration of potentially better ones.

This is the case, for example, of the initial states of the simulation where the strategies of the agents are randomly picked and their level of popularity does not correspond to a selection process socially evaluating their performance but to an initial random arrangement.

The second mechanism of selection with which the agents are endowed is their memory. As we will discuss later in this paper, the size of the memory has important implications on the resulting performance of the system. However, the main effect of memory is to prevent the agents to fall into traps and to avoid circular loops.

This, of course, has the undesired effect of averting some jumps which have to find an alternative route. For illustration purposes, let us assume positions a, b and c in the landscape, with fitness f_a, f_b and f_c respectively, such as $f_b < f_a < f_c$, and f_c optimal maxima. Given that a path existed between a and c through b, agents will have to experience a reduction in their fitness when reaching position b. If b is in the memory of the agent, this fact will prevent that movement and position c could not be attained through this path. Fortunately, an alternative route to c will be found in most of the cases (with lower probability as k increases because the diameter of the basins of attraction determining the different ways to access the maxima, decrease). In addition to that, as we will discuss later, the process of discovery progresses through successive generations of alleged best practices, rendering important parts of the memory obsolete.

Memory has therefore this dual effect of avoiding traps, but at the same time limiting discovery. In the business literature, we can find many examples of this paradox, especially in areas related to change and change management.

Finally, there is a third mechanism of exploration driven by the agents: a variation of crossover. Agents generate potentially new strategies by adopting new patterns. Let us for the sake of the example, consider an agent with strategy 01110 (N=5) adopting pattern p=< component={2,4}, value={0,0}>. Once adopted the agent will hold strategy 00100 as a result.

Even if pattern adoption drives discovery, it is also true that the progressive adoption of the most popular patterns reduces the level of heterogeneity among the population of agents. As we will discuss later on, this effect can be counteracted by a proactive exploration on the side of the agents.

4.3.1 Aggregating Information: Average Fitness vs. Conformist Transmission

Conformist transmission is based on popularity and this can obviously raise some skepticism around its goodness as an indicator of the performance of a pattern. Therefore, in order to assess its level of performance as a measure we chose two additional measures for comparison.

First, and as a baseline, incremental search, where agents engage in a greedy search of 1-component range.

And secondly, we can imagine an institution that could know with exact precision the fitness of all the agents selected as best cases. Such an institution could therefore average the fitness of the agents endowed with a certain pattern producing that way a potentially pretty good estimate of their quality.

We then compared these two strategies with our modified version of conformist transmission, popularity, where the institution selects not the whole population as input, but a subset of best cases.

In figure 2, we can appreciate the results of this exercise. There the best 25% performers among the population of agents has been selected as best cases from where to infer patterns (we will see later on that these results are consistent for a lower set of best cases).

We can observe that the strategies corresponding to the use of the average fitness or popularity (number of agents endowed with a certain pattern) lead to results roughly equivalent. Results that are, however, much better than the ones obtained by the use of incremental innovation, where agents easily fall and get trapped into local maxima.

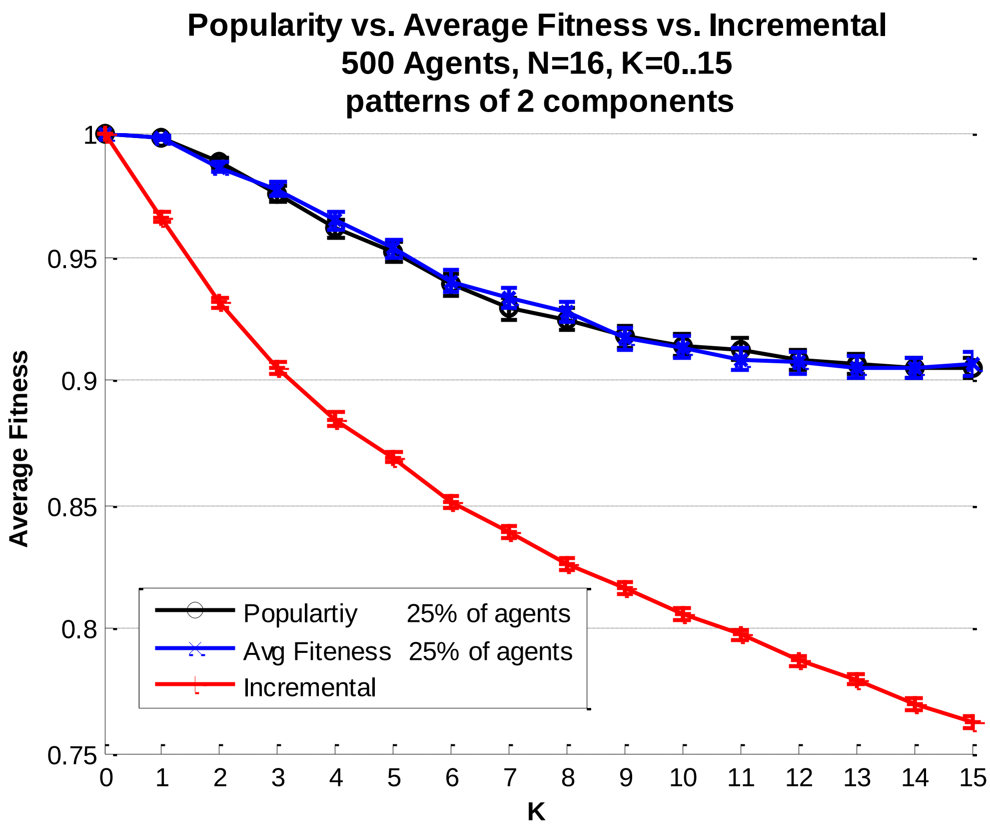


Figure 9. Comparing three strategies: Popularity, Average Fitness and Hill Climbing

Description. 500 agents performing patterned search are released in a NK landscape, 100 tries are performed and results are averaged. Three different approaches are used for selecting the pattern that agents will apply: a) the popularity of a pattern among a set of Best Performers, b) the average fitness of the agents endowed with that pattern and c) incremental search (hill climbing) where agents can change one component at a time . Error bars correspond to the standard error of the mean.

Interpretation. We can observe that popularity is an heuristic as good as average fitness, although less costly and more easily observable. Both of them produce better results than performing incremental search with their distance increasing as complexity does. These results confirm the validity of the methodology pursued by Business Schools collecting best practices and inferring propositions from a selected group of Best Cases.

We also have to consider the operational efficiency of the mechanism. Compared to obtaining an accurate measure of the average fitness, popularity is easily observable and very cheap to assess because it only involves counting. This is even more true in cases where the uncertainty of the economic or technological environment possesses greater challenges to an accurate assessment of fitness, in these cases, popularity among best cases continues to be an easy, simple and fast measure.

As we have seen, results of this heuristic are similar to using average fitness for a set of cases involving a 25% of the population of agents and both clearly superior to incremental innovation (hill climbing).

Finally, let us discuss the mechanisms with some more detail.

Proposition 1. Accuracy of ordering depends on the size of the set of best cases (in the case of average fitness ordering) and on the selection process.

Let us consider first the case of ordering by average fitness. Following (1) we can consider that the fitness f_i of point i, as divided in two parts, $f_i = f_{i\in p} + f_{i\notin p}$, the fitness corresponding to components included in the pattern p, $f_{i\in p}$ and the fitness of the components not belonging to p $f_{i\notin p}$. As the size of the set of best cases considered increases, this second part will tend to reflect the mean of these components because the fitness of the components are drawn from a uniform random distribution. Equally, the first part will tend to reflect the quality of the pattern.

However, if the sample selected does not correspond to a random sample of the agents (as in the initial state), ordering will be driven by the selection process.

This is also the case for popularity, which initially is completely random and later on is solely driven by the selection process.

Proposition 2. Pattern selection is a social process - between the agents and the institution - affected by the quality of the patterns and the quality of the ordering, which is more relevant as the average fitness of the set of best cases considered decreases (larger sets of best cases).

Adoption of a pattern by an agent is governed by the ranking of the patterns, the offering of patterns and the agent's fitness. In fact the condition for adoption is $P_{adopted} = P \mid P.f > a.f \; \forall \; a \in Agent$, therefore only patterns with higher representative fitness will be adopted.

However, ranking can affect pattern adoption, *e.g.* given two patterns p_i and p_j with $p_i.f>p_j.f$, a certain ordering can effectively mask p_i preventing its adoption and ultimately disappearing of the set of best cases being replaced by the inferior pattern p_j.

In order to find out the relative importance of ranking, let us consider the case where only the best patterns are selected. Obviously ranking in that case will be completely superfluous. On the contrary, if heterogeneity is very high, the number of different patterns will also be higher (sets with more noise and smaller differences in ranking), in that case, ranking quality will be very relevant in order to prevent masking . Therefore, the importance of the ranking is directly correlated with the level of quality of the set of best cases, so is their fitness.

The offering and ranking of patterns in the next iteration will nevertheless depend on the ones selected by the agents in the previous one together with crossovers. In that sense pattern adoption is a social process where agents play a fundamental role by choosing to adopt and selecting patterns on the base of their own fitness.

4.3.2 Less is More

In the model being presented, institutions infer and generalize which are the combinations of strategy components that could result in a better fitness by using patterns. They infer these patterns considering a number of "*Best Cases*" among the overall strategies of the agents. The percentage of "*Best Cases*" under consideration is implemented in the present model by the ρ parameter.

Therefore, a question that immediately arises is about the most appropriate magnitude for ρ, or formulated in other terms, how many "*Best Cases*" should be considered to infer relevant conclusions? Will we get better results if we examine all cases? –contrary to current practice – or a small number of the best ones is sufficient to achieve similar results?

In order to answer these questions, we will first go back to our rational agents that rely on the exact fitness of each pattern to draw their conclusions.

Figure 10 shows how different magnitudes of ρ perform. There, we can observe how this heuristic works better for small subsets of best cases and how its performance decreases as the set of agents considered enlarges. Obviously, the differences are significant for low and medium levels of complexity, however when complexity is too high, patterns encounter difficulties deciphering the landscape and its performance decreases.

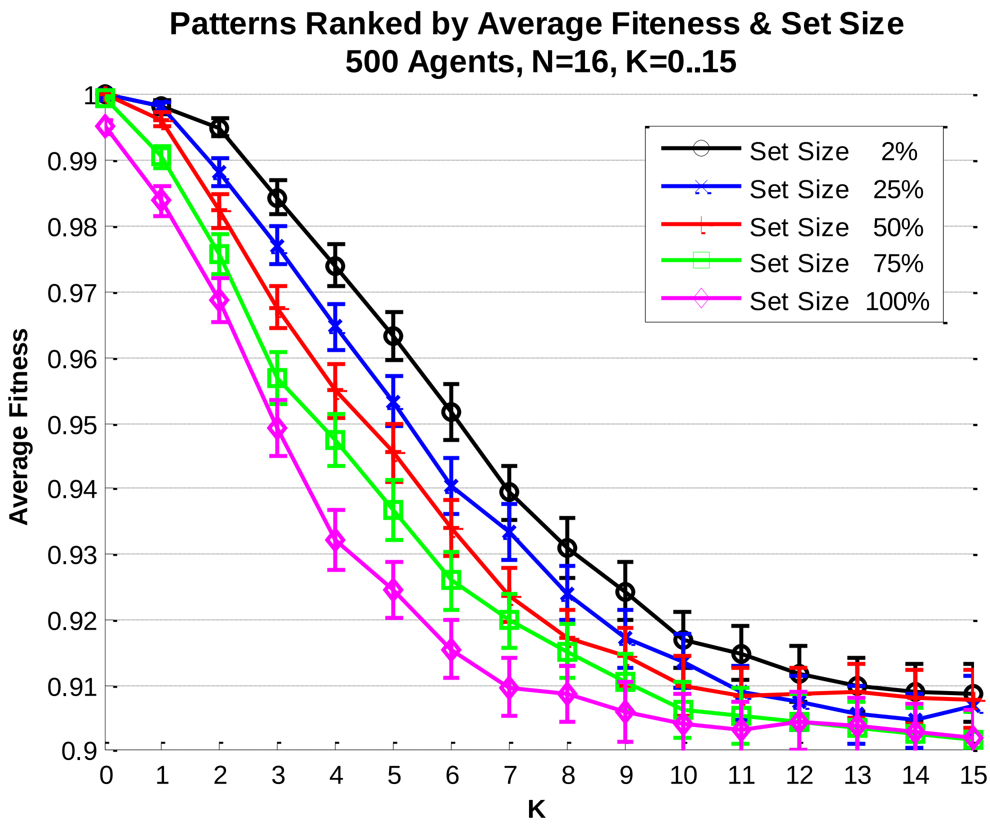


Figure 10. Variation in performance for different set sizes using average fitness for pattern ranking

Description. A set of 500 agents performing patterned search with patterns ranked on the average fitness of each pattern, are released in a NK landscape, 100 tries are performed and the results averaged. The experiment is repeated for different sizes of the set of best cases, ranging from 2% (10 best cases) to 100% (500 best cases). The mean and its standard error are presented.

Interpretation. We can observe how selecting a small number of cases produces better results than a larger one. (To an extent, as we will see later, the number of cases has to be sufficient to contain enough information to allow the deciphering of the landscape.)

Will this characteristic maintain with our simple heuristic based on counting? In Figure 11 we have the answer to this question. There we can observe that popularity performs similarly to average fitness.

Definitely, *less is more*, a small and well-selected number of best cases produce better results than a larger one or the use of the whole population, and this result is valid for any level of complexity.

Nevertheless, we can also observe some differences when comparing with the heuristic based on the average fitness. Even if for a small set of best cases, results are roughly similar, as the size of the set of best cases increases, we can observe how, in popularity-based ranking, the degradation of results is more pronounced, compared to the strategy based on average fitness that appears to be more robust respect to variations on the size of the set.

Therefore, when using the popularity of patterns as the guide for pattern selection and adoption, its accurate selection, given the small size of the best performing set, appears to be of great relevance.

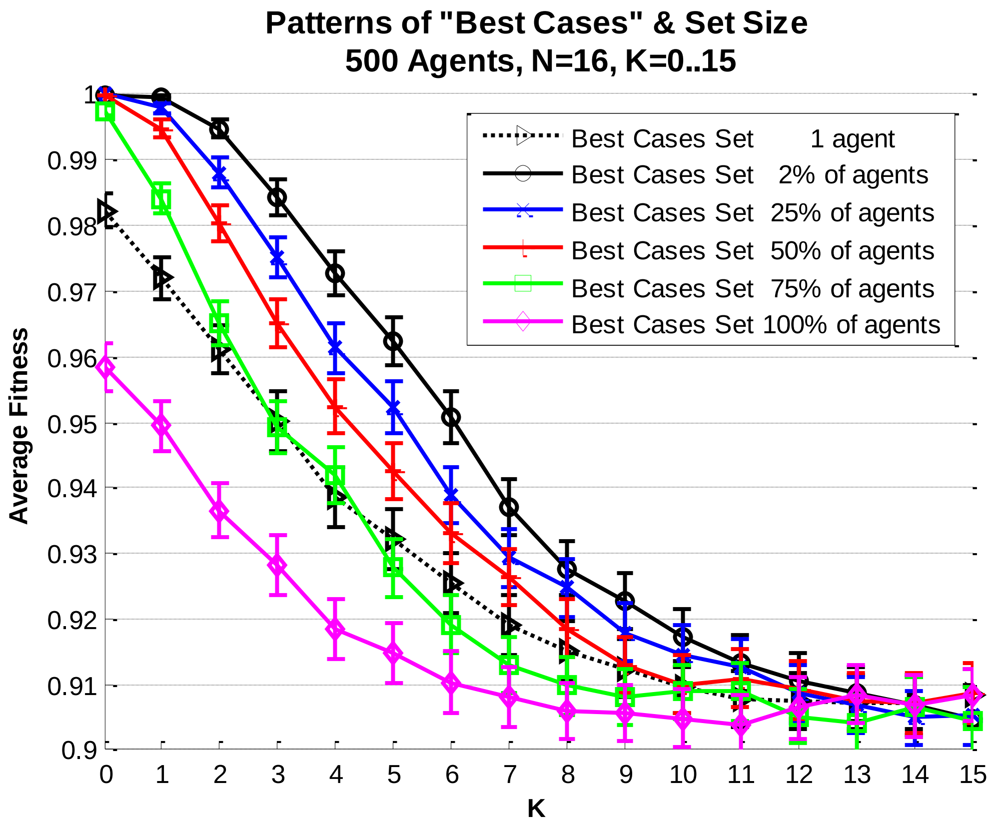


Figure 11. Variation in performance for different set sizes pursuing a pattern popularity strategy

Description. Again a set of 500 agents performing patterned search based, in this case, on the popularity of each pattern, are released in a NK landscape, 100 tries are performed and the results averaged. The experiment is repeated for different sizes of the set of best cases. The mean and its standard error are presented.

Interpretation. We can observe a similar behavior as in the case of using the average fitness as a selection method. However, in that case the system is even more sensible to set size, resulting in a faster and deeper degradation as set size increases, compared with Figure 10.

Proposition 3. Performance of pattern driven search increases inversely to the size of best cases sampled by fitness in decreasing order (considering only set sizes with enough information to decipher the landscape).

Because of proposition 2 we know that the average quality of the patterns presented to the agents is more relevant than the ordering because of its inaccuracy (proposition 1). Obviously the better the cases selected the better the quality of the patterns.

Therefore, less noisy sets with a higher pattern accuracy will perform better. Smaller sets of best practices sampled by fitness fit better this characteristic than larger sets.

Proposition 4. The size of the set of best cases sampled by fitness is more relevant in the case of ordering by popularity than in the case of ordering by average fitness.

Because of proposition 1 we know that the accuracy of the ordering increases as the set of best cases grows in the case of ranking by average fitness. And because of proposition 2 we know that the accuracy of ranking by popularity decreases as the set enlarges.

Therefore, larger sets will benefit from a ranking by average fitness and suffer from a ranking by popularity.

Given the results just described, the reader may be tempted to think that if less is more, maybe one is enough. In fact, as Figure 12 shows, results with only one agent are clearly worse and as we will discuss later on, there is an optimal range for set size, that even if small, must be significant.

The next question that we can ask ourselves could be around the consistency of these results across a diversity of population sizes. Do larger populations of agents benefit for a larger collection of best cases? Figure 11 provides the answer to this question. There we can observe how smaller sets continue to produce better results than larger ones for diverse cardinalities of the agent set. Concretely we present two examples, one with 100 agents and another one with 30 times that size, 3000 agents, where we observe similar behaviors.

However, as the size of the population increases we can witness two additional effects. First patterns are more accurate, and we are able to obtain high levels of average fitness. And secondly, the gap between set sizes closes, the system is therefore less sensitive to the number of best cases involved in inferring patterns. Obviously, a larger set of agents has more possibilities of finding the best positions in the landscape than a smaller one. This implies that case selection may be less critical in larger populations, because the lack of accuracy can be traded for using a larger set of cases.

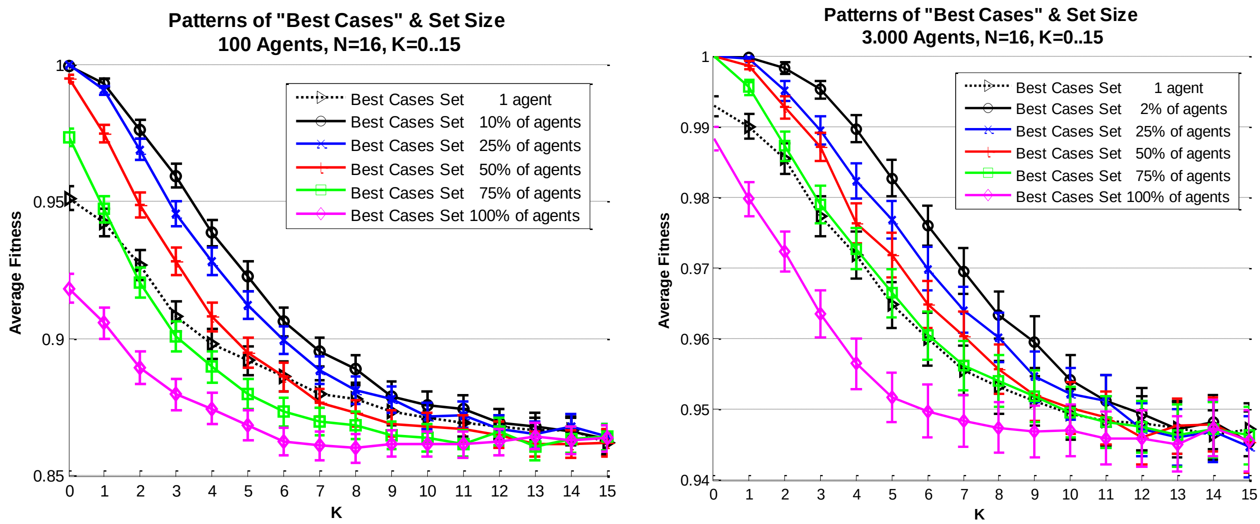


Figure 12. Comparison between two populations of 100 and 3,000 agents respectively

Description. Results of the average fitness of two populations of agents, comprising 100 and 3,000 agents respectively are presented. In both cases, 100 tries were performed with random generated landscapes in each try. Population average fitness and standard error are plotted in the graph.

Interpretation. We can observe a similar pattern of behavior, where smaller set sizes obtain better results than lager ones, together with two additional effects: a) lager populations allow the inference of better patterns leading to better results and b) the gap between set sizes decreases as population size increases.

Having established that a smaller set of cases leads to better results than a larger one, being however, the number of cases significant enough to allow inferences that could be generalized, the next question should be about determining the optimal number of best cases, or at least providing some useful insights about it and answering questions like if this number depends on complexity or not. This is the objective of the experiments presented in Figure 13.

There, we can observe how, if it is not really possible, to find an exact number of cases where the system performs at its peak, there is a range that clearly leads to better results. In our case and for 100 agents and a landscape of N=16 (2^{16} possible points) it can be situated between 5 and 15.

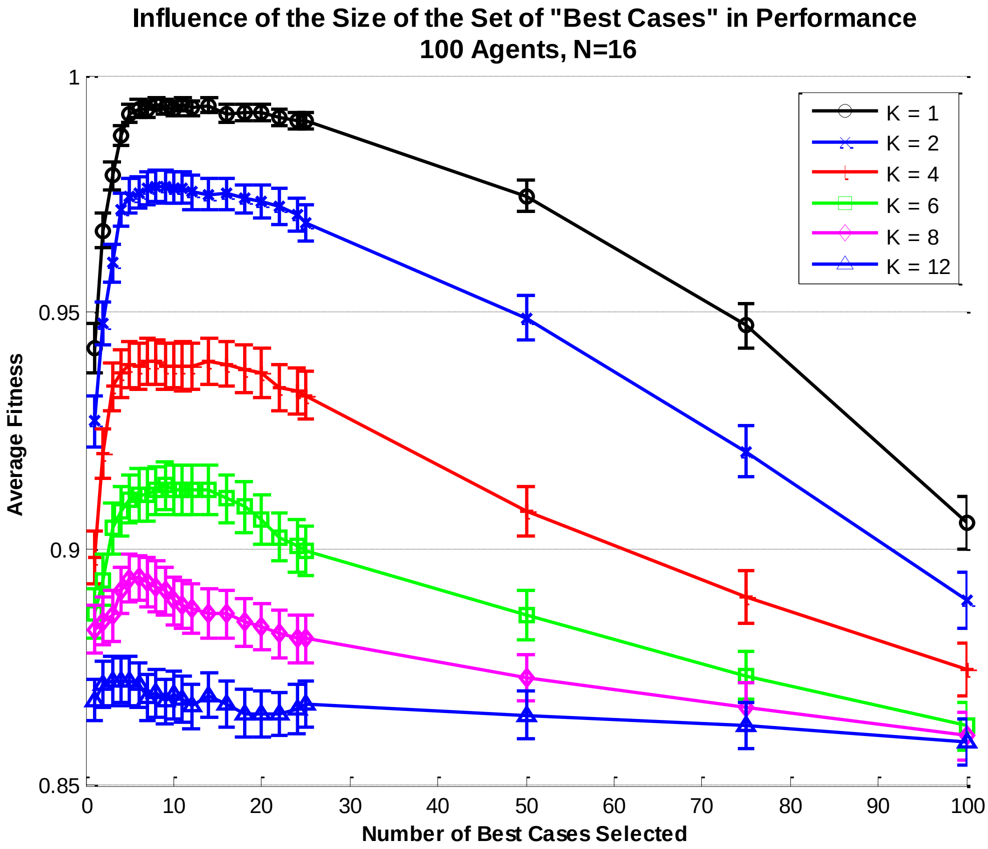


Figure 13. Determining the optimal number of best cases

Description. A number of experiments with different sizes of the best case set, ranging from 1 agent to 100 agents, over a total population of 100 agents, are conducted. Results on population average fitness and standard error of 100 random experiments are plotted.

Interpretation. We can observe that even if it is not possible to point out an exact number of optimal cases, there is a range, between 5 and 15 where the system performs at its peak.

In fact, the optimal number of best cases to collect in order to be able to infer relevant information in the form of patterns is a balance between information and noise. A smaller set of best cases ensures us low noise but at the cost of lower amounts of information. Following this reasoning, one may be tempted to believe that higher levels of complexity will require a larger set of best cases in order to capture a level of information that is big enough to "*solve*" the landscape. Unfortunately, with more information comes more noise, reducing that way its effectiveness and leading to worse results. Later on, in this paper, we will discuss how the pro-active exploration and selection by the agents partially solves this problem.

4.3.3 Pattern Complexity

Until now, we have restricted our experiments to patterns of two bits. However, we can also imagine patterns of 1 bit or in general, patterns of any length.

However, as pattern length increases, so does its number. In the case of binary patterns of 2 bits we have $C_2^{16}\ 2^2 = 480$ patterns, while for 3 bits $C_3^{16}\ 2^3 = 4{,}480$ patterns exist, for 4 bits $C_4^{16}\ 2^4 = 29{,}120$, and for 8 bits $C_8^{16}\ 2^8 = 3{,}294{,}720$ patterns.

This massive increase on the number of possible patterns implies that every agent will possess a larger number of them, potentially lessening the focus on the really good ones and promoting a dispersion of the popularity votes over a larger set.

It seems therefore that we have to find a balance between two forces: larger patterns could be potentially more exact, while smaller ones will result in less noisy sets and focused population votes (due also to its smaller number).

In Figure 14, we can observe the results of the experiments carried out in order to obtain additional insights about this balance. There, for two populations of 100 and 500 agents we can observe how patterns of size between 2 and 4 bits have similar levels of performance, especially at low complexity levels. Although smaller patterns (patterns of 2 bits) tend to marginally outperform larger ones, especially as complexity increases.

Again, patterns can be small, but to an extent, patterns of 1 bit, although they perform quite well at low complexity levels, abruptly fail as complexity increases.

It can also be observed how larger populations of agents lead to better fitness results than smaller ones. Nevertheless, as the population increases so does the gap of performance between patterns of 1-bit and the rest, especially at higher complexity levels.

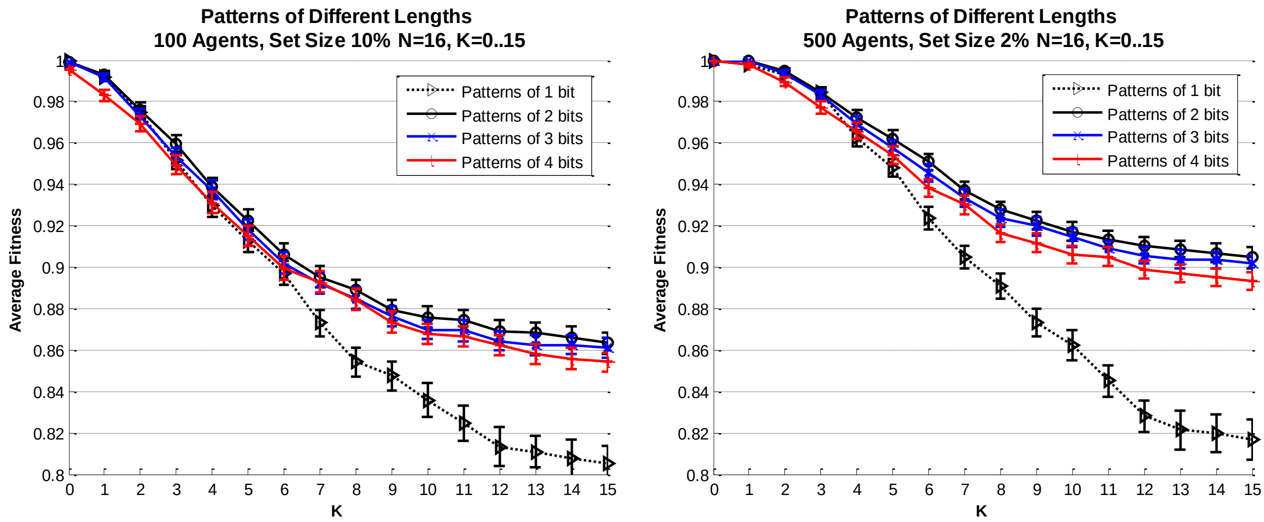


Figure 14. Performance of patterns of different lengths and different population sizes

Description. Patterns of lengths from 1-bit to 4 components are used by two populations of 100 and 500 agents respectively. Results from 100 randomly created NK landscapes, average population fitness and its standard error are presented.

Interpretation. We can observe how patterns of 2-bits to 4-bits perform roughly similar, with a marginal advantage for the smaller 2-bit pattern. All beat the 1-bit pattern who abruptly fails as complexity increases.

4.4 Modeling Statistical Inferences

In the previous section of the paper, we presented and discussed a novel approach to modeling the process of aggregating and processing information from best cases done by Business Schools, consultants, the economic press, etc.

We explored the parallelism of this process with conformist transmission, a well-known mechanism on which humans have relied for millennia. There, humans or groups of humans adopt the dominant strategy, in terms of popularity, of the group or of a selection portion of a group. In a similar way, patterns are inferred by collecting the best practices of the best performing agents and ranking them by popularity in this best performing group.

However, beyond aggregating best cases and relying on agent adoption for their ranking, there are other instruments that the research community has been successfully employing for decades, such as regression analysis, structural equation modeling (SEM), principal component analysis (PCA) or more elaborated ones like neural networks or support vector machines (SVM), etc., to name just a few.

They choose a more scientific approach based on statistical analysis in order to uncover the causal relationships hidden in the data. Obviously, statistical analysis has a bigger and better developed arsenal of tools and the contest will be completely unfair if it was not because of the very specific conditions that characterize the problem.

The most obvious of these conditions is the complexity of the landscape. As we have discussed before, the number of possible patterns of two is $C_2^{16}\ 2^2 = 480$, which increases rapidly to 4,480 for three, 29,120 for four and so on. The natural mapping of these patterns will be the number of independent variables in an analytical model, which is clearly a daunting but yet affordable task, especially with instruments like neural networks or SVM.

There is, however, a second problem. In fact the amount of data available is necessarily limited to the points traveled by the agents, who represent a very small fraction of the landscape. Moreover, not only the sample is limited in size, but also it is biased because of the maximization behavior of the agents.

For the purpose of our experiments, we choose to model statistical inferences with one of their most common approaches, robust linear regressions (DuMouchel, 1989, Holland, 1977).

Patterns of one component have a fairly straightforward translation to linear regressions of one variable, resulting in,

$$y_i = \beta_0 + \beta_1 x_{1i} + \dots + \beta_p x_{pi} + \varepsilon_i$$

with p independent variables corresponding to each one of the N strategy components of the agent (or to the components of a position in the NK landscape), $s, s \in \{0,1\}$, therefore $x \in \{0,1\}$.

However, as in the case of patterns, the use of a single component is not enough to untangle the landscape and like in the case of patterns, we will resort to two variables representing two strategy components in order to capture the effects of the interaction among the components of an NK space.

Because any set of two strategy components can have four different values, we will use four different interaction variables to represent each one of them.

s_1	s_2	x_1	x_2	x_3	x_4
0	0	1	0	0	0
0	1	0	1	0	0
1	0	0	0	1	0
1	1	0	0	0	1

Therefore, given any two components of a landscape position, $s_1, s_2,\ s \in \{0,1\}$, we will use four interaction variables x_1, x_2, x_3 and x_4 to represent each one of the possible combinations of s_1 and s_2, e.g. if s_1, s_2 hold the combination 0 0, then the interaction variable x_1 will be set to 1 and x_2, x_3, and x_4 to 0, and so on.

Components are chosen sequentially producing 8 sets of four interaction variables each for a N=16 landscape. According to this construction, our model will use 64 interaction variables for a N=16 (2^{16}) landscape.

Distinguishing which one of the four interaction variables will lead to higher fitness is accomplished by checking their β coefficients, taking advantage of the fact that we are using linear regressions, and choosing the one with a maximum positive value (if none is positive the pattern is skipped in the iteration). Resulting patterns are ranked using the values of these β coefficients.

However, the objective of the institution is to provide the agents with a ranked set of best patterns, combination and value, to apply in order to obtain the best performing strategy (reach the highest point in the landscape). Unfortunately, regressions are designed to find the best fit to a set of data and not to the set of values that will maximize it, or the positions of the agents in the landscape in our case.

We try to overcome this problem in two ways.

First, the set of data is not a random sample of the positions of the landscape but of some of the best positions, because agents only adopt a pattern if, potentially, it could lead to a higher position. They accomplish that by checking the maximum fitness of the pattern (the highest fitness of the set of agents endowed with this pattern) and only adopting it if it is higher than their current fitness.

Therefore the data set improves as agents iterate, although not monotonically because sometimes regressions fail to find better patterns. In order to facilitate this process, once enough points are gathered, we use the last 10,000 (arbitrarily chosen). However, frequently the simulation settles down before reaching that limit, especially in low complexity landscapes.

Secondly, we oversample the pattern with the highest fitness in the dataset by inserting multiple copies of it in the regression model. Instead of using a single observation, a number of observations could also be used. However, using multiple observations poses a problem with landscapes with low K, having a small number of peaks - one in the case of K=0 - because this strategy could result in oversampling underperforming positions. Using a single observation allows us to simplify the model and use the same number of oversampled observations for all K values.

However, the number of oversampled observations that produce better results can only be obtained experimentally. Figure 15 presents the results of the experiments conducted, where an oversampling number around 500-1,000 seems to lead to better results. In our model, we resorted to using 1,000 for oversampling.

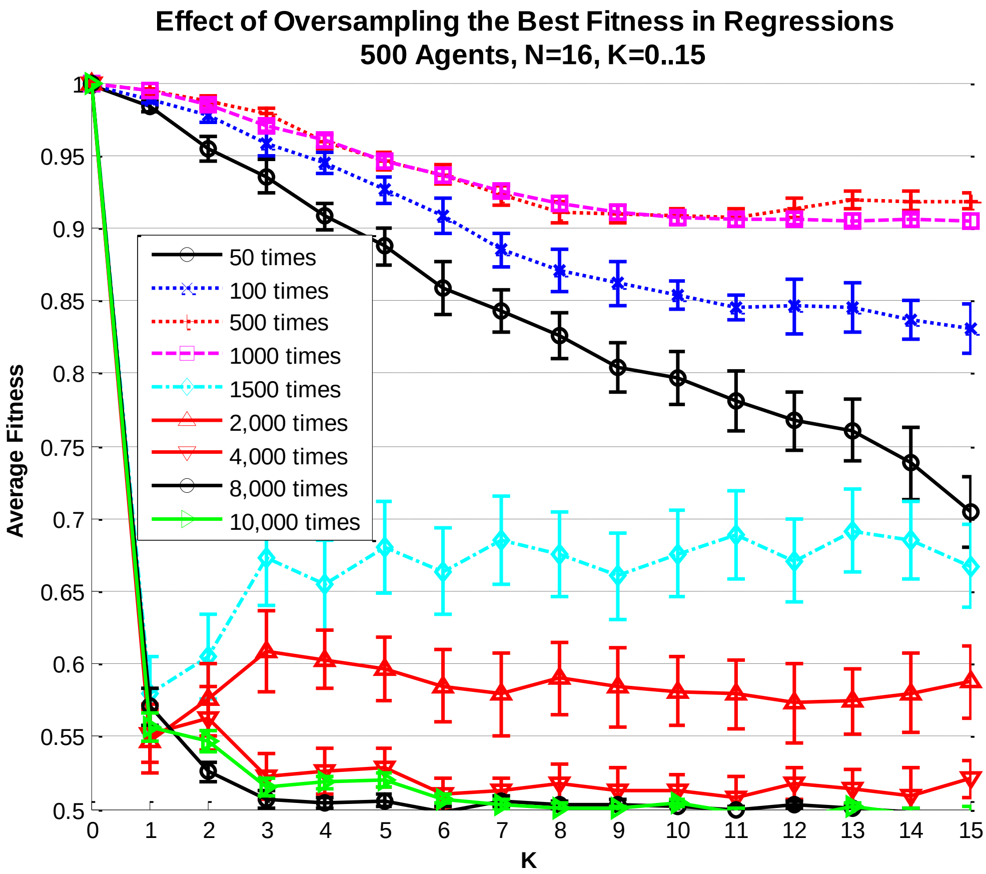


Figure 15. Effect of oversampling in regressions

Description. Regressions of two strategy components represented by four interaction variables each pair of components, are used to learn the set of patterns that could potentially maximize the positions of the agents. Different amounts of oversampling (inserting multiple copies in the regression model) of the best performer element, were tested. Results of 100 experiments with randomly generated landscapes are presented, plotting the resulting average fitness and the standard deviation of the mean.

Interpretation. We can observe that the experiments show that the best results can be obtained by setting oversampling around 500-1000 copies of the best performer element.

4.5 Statistical Inferences versus Patterns

Until now we have been assuming that agents are endowed with an unlimited amount of memory. This memory allowed them to avoid circular loops and to skip underperforming positions that they were able to “learn”. Also the memory helped the agents to make up for inaccurate rankings.

However, this unlimited memory scenario assumes a level of cognitive capacities of the agents that might be pretty unrealistic.

First, because the unlimited memory assumption not only supposes that the agents will be able to recall any strategy from the past but to identify it in a different context.

Secondly, because in real scenarios, strategies do not appear in its pure form but surrounded by noise.

And finally because in a changing world and especially when the rate of change is fast, agents could assume that their memories became obsolete even in the case where they are still valid.

Because of these reasons, it is certainly interesting to investigate the behavior and sensibility of our models to different memory sizes.

In Figure 16 we can appreciate how patterns behave at different memory levels. There we can observe first that memory is more relevant as K increases, and secondly how results cluster around certain memory configurations.

Concretely, no memory or a single memory position seem to lead to very poor results even at low K values, which stresses the importance of memory in the case of patterns.

However, from two-three positions of memory and up, results are pretty close at low and medium K values. Only at medium-high and high K values the distance between 2-3 and more memory positions increases substantially. Above three memory positions, there is no improvement.

These results provide a heavy contrast with the ones coming from regressions in the same Figure 16. There we can observe that from two positions and up results are completely equivalent (with no memory or 1 memory position the behavior of the system is similar to patterns - not presented in Figure 16).

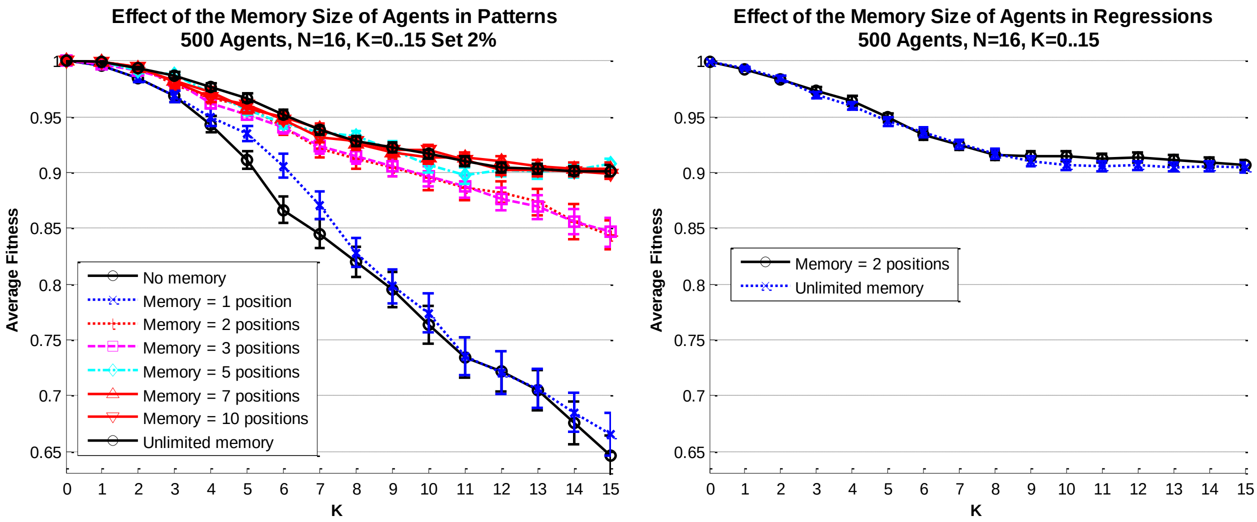


Figure 16. Effect of memory size in Patterns and Regressions

Description. One hundred experiments with populations of 500 agents using pattern search and regressions are performed. In each set of 100 experiments, agents are endowed with different memory sizes, from 0 to unlimited. Results in terms of average fitness and standard error of the mean are presented.

Interpretation. We can observe how the pattern-based mechanism is very sensitive to the size of memory. Although, from two positions and up results are equivalent for K low and medium, if K is higher, we need 3 memory positions for matching the unlimited memory results. Contrary to that, results from regressions are equivalent from 2 memory positions and up for all K values (with no-memory and 1-memory position results are equivalent to the ones in patterns - not shown).

In order to explain these differences in behavior, we must first consider both mechanisms and *how ranking* is obtained. In the case of regressions, observations are accumulated at each iteration and all of them (up to 10,000 and beyond that, only the last 10,000) are considered in the process of discovering and ranking theories. Therefore, their ranking is increasingly more accurate as the number of iterations grows.

Patterns however, only consider the immediate last round of observations to distil both the patterns and their rankings.

Therefore, in the case of patterns, agents play a more important role in guiding the process and avoiding bad patterns, while in the case of regressions, their role in collecting observations is more noteworthy.

Therefore, when comparing regressions with patterns, these considerations around the size of the memory of the agents, must be taken into account. It will be completely unrealistic to imagine agents without memory, but it will also not be realistic to imagine agents endowed with an unlimited amount of memory. Consequently, we have two frontiers that could set the limits of the behavior and performance of the agents using pattern-based search. In our case, we considered that two memory positions as the lower bound and unlimited as the upper one, could be appropriate in terms of comparison.

In Figure 17, we can observe the results of this exercise of comparing the mechanism of patterns with our version of regression analysis for different levels of complexity.

There, we can distinguish three different scenarios. When complexity is low, patterns do perform better, even with limited memory. In fact, when complexity is very low, patterns are almost optimal.

As complexity increases analytical methods gain advantage over patterns, that still perform better, but only if memory levels are high. Also, in real world scenarios we have to consider aspects like the rate of change and the noisiness of the environment that will effectively put limits on the use and validity of memory.

Finally, if complexity is very high, regressions perform as well as patterns when endowed with unlimited memory and much better than patterns with limited memory.

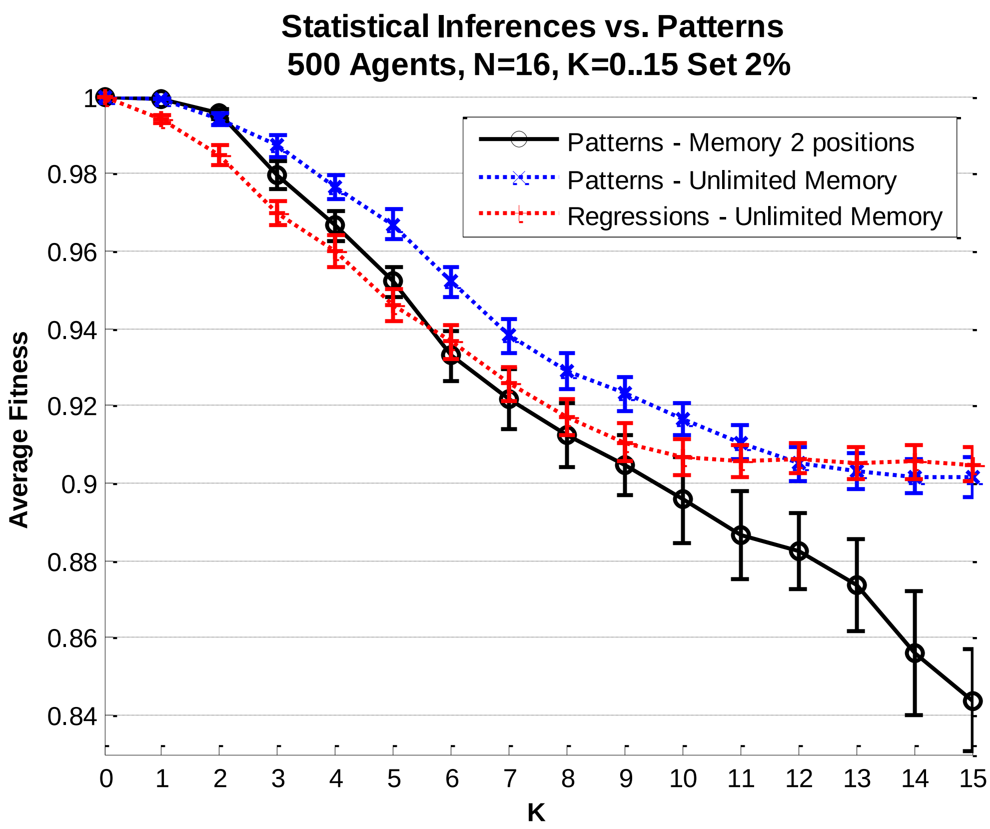


Figure 17. Statistical Inferences versus Patterns

Description. Three different mechanisms are compared: multiple linear robust regressions, patterns based on popularity with agents endowed with 2 memory positions and patterns with unlimited memory positions. Experiments are repeated 100 times and results are averaged. Average fitness and its standard error are presented.

Interpretation. The graph clearly shows three different scenarios: a) in low complexity environments, patterns perform better, b) when complexity is medium, regressions outperform patterns in low memory situations or when memory becomes partially obsolete, e.g. rapid changes, c) when complexity is high, regressions outperform patterns with limited memory, producing results equivalent to the ones of patterns configured with unlimited memory.

Figure 17 compares patterns with regressions in terms of performance, however, another aspect that must be considered is the amount of resources necessary to obtain this performance and in that aspect it is quite obvious that patterns are extremely economic. In fact, patterns obtain these results by probing a very small percentage of the population, 10 agents in the case under consideration, at each iteration and letting the agents rank them.

In comparison, regressions use all (or the last 10,000) points traveled by the agents, together with their exact fitness (patterns only count them).

Without any doubt, the frugality of patterns, largely contrasts with the high needs, in terms of data, of regressions.

This frugality, can be explained by taking into account the roots of both mechanisms. Regression analysis and in general statistical tools have its roots in the physical and engineering world of controlled experiments and high demands for precision while patterns evolved from the social mechanism of conformist majority, so well suited to environments where getting precise information is costly and uncertainty is high. Looking at them from this perspective, is probably easier to understand why patterns perform so well in low-medium complexity environments and why regressions do better when facing high complexity. In many ways, it is written in their roots.

Nevertheless, this discussion around the two mechanisms would not be complete without addressing what they have in common: both are social mechanisms because none of them relies on a single iteration random sample to infer theories, but on repeatedly sampling the space of solutions explored by agents that base their decisions on the propositions of the Business Schools build upon the results and consensus provided by the agents themselves.

In fact, in both cases the institution elaborates and presents images about causality relations to the community of agents and it is this community, by adopting them, that validates or falsifies these hypotheses.

We can stress the differences and argue that in the case of patterns, the agents play a bigger role in the process, and that the amount and quality of information that the institution has to manage is lower than in the case of regressions. However, in both cases, adoption is key, because without adoption, there is no validation of falsification, and without adoption mutations do not occur, the system does not evolve, does not converge and the optimal points will not be found.

In fact, both systems manage to work because of the intrinsic motivation of greedy agents voluntarily engaged in a conscious process of growth. The quality of the result, will be therefore, determined by the intensity of the engagement.

4.6 The Importance of Diversity

Until now, we have produced experiments with populations of agents that rely solely on the output of the institution: patterns or regressions, as their mechanism of exploration. Moreover, as we all are aware, this is not a fair representation of the real world. Actual economic agents also engage in explorative activities on their own. This is especially true for incremental innovation, because being experts in their fields, they normally have a good assessment of the potential fitness of incremental improvements.

Therefore, in fig. 10 we compare the results of three different populations. One engaged solely on incremental innovation. A second one, engaged in popularity-based patterns. And a third one, where agents take advantage of their knowledge of the potential fitness, if performing incremental improvements, to decide if they use patterns (in the case that a pattern exists with better max. fitness than the one attainable with an incremental improvement) or perform an incremental improvement. We have limited our exploration to incremental innovation, however, any other type of innovative engagement on the side of the agents will produce similar results.

As we can observe, results increasingly favor the mix of patterns with incremental improvement as complexity (K) increases. What we can call active populations or populations actively engaged in innovation. The reason why this happens is because of the increase in exploration that incremental improvements bring to the system, that also results in an increase in diversity.

In fact, as we have discussed before, both patterns and regressions are socially constructed. For example, in the case of patterns, business schools and universities, propose to the population of agents a certain pattern that, given the information provided by the best cases selected, looks promising. It is however, the population of agents who verifies or falsifies this hypothesis with its adoption, being the pattern discarded or reinforced.

If the exploration process performed by the agents, relies solely on the patterns provided by the institution the only new information in the system is the one that comes from the crossover of the actual strategies of the agents with the proposed patterns, this new information is however limited, and the system converges fast to a very small number of strategies. This process of diversity creation is greatly enhanced by the active participation and engagement of the agents in an exploratory process.

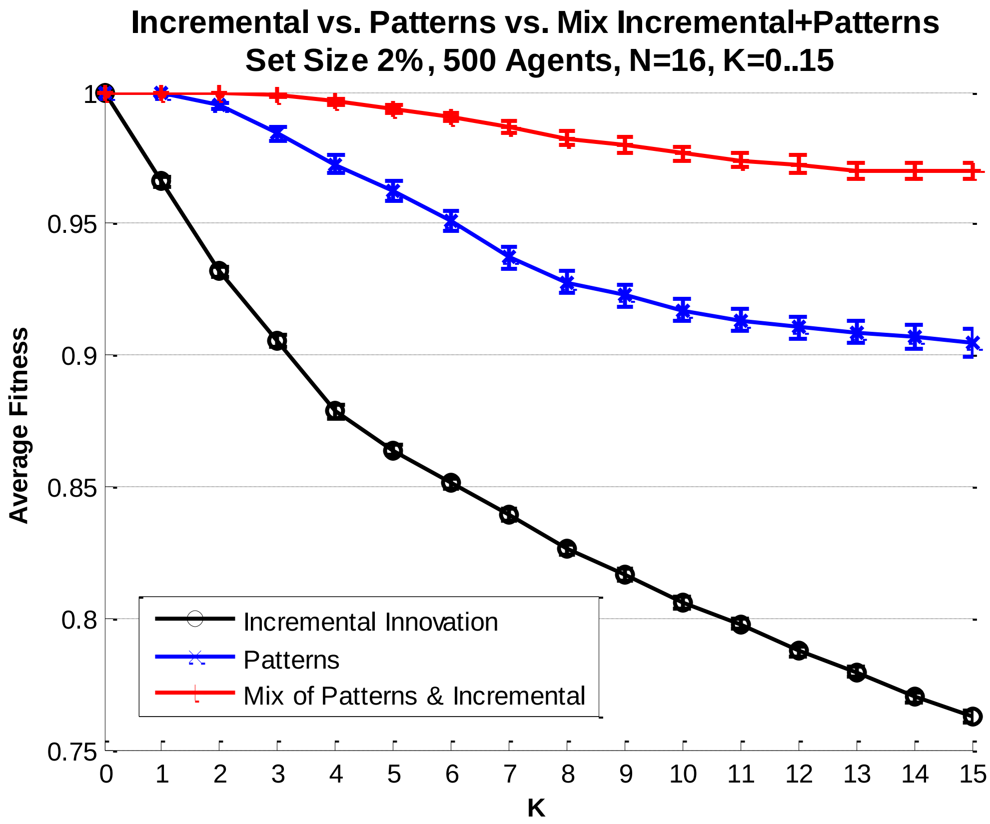


Figure 18. Comparison between three mechanisms: incremental, pattern-based and mix.

Description. Three different experiments with populations of 500 agents performing three different strategies are presented: incremental, patterns based on popularity and mix. In the mix strategy, agents use their knowledge of the potential fitness of incremental innovations to decide which strategy to follow if incremental or pattern-based.

Interpretation. We can observe how a mix strategy is clearly superior because it relies on a larger amount of relevant information upon which better patterns can be inferred.

The next question is, if in this richer environment - information-wise - still less is more, or if we need larger sets of best cases in order to infer relevant patterns. Fig. 19, attempts to answer this question by depicting the performance of several populations of agents with different set sizes. There we can observe that if agents are actively engaged in incremental innovation and not only in following the advice of Business Schools adopting the patterns suggested to them, the size of the set of *Best cases* is mostly irrelevant (if big enough).

The reason behind this change is the fact that by engaging in a mix of patterns and incremental innovation and by using the information provided by their knowledge of the immediate neighborhood to direct pattern selection, the agents themselves manage to reduce noise by avoiding irrelevant strategy configurations while increasing exploration and providing new opportunities for uncovering new and better patterns.

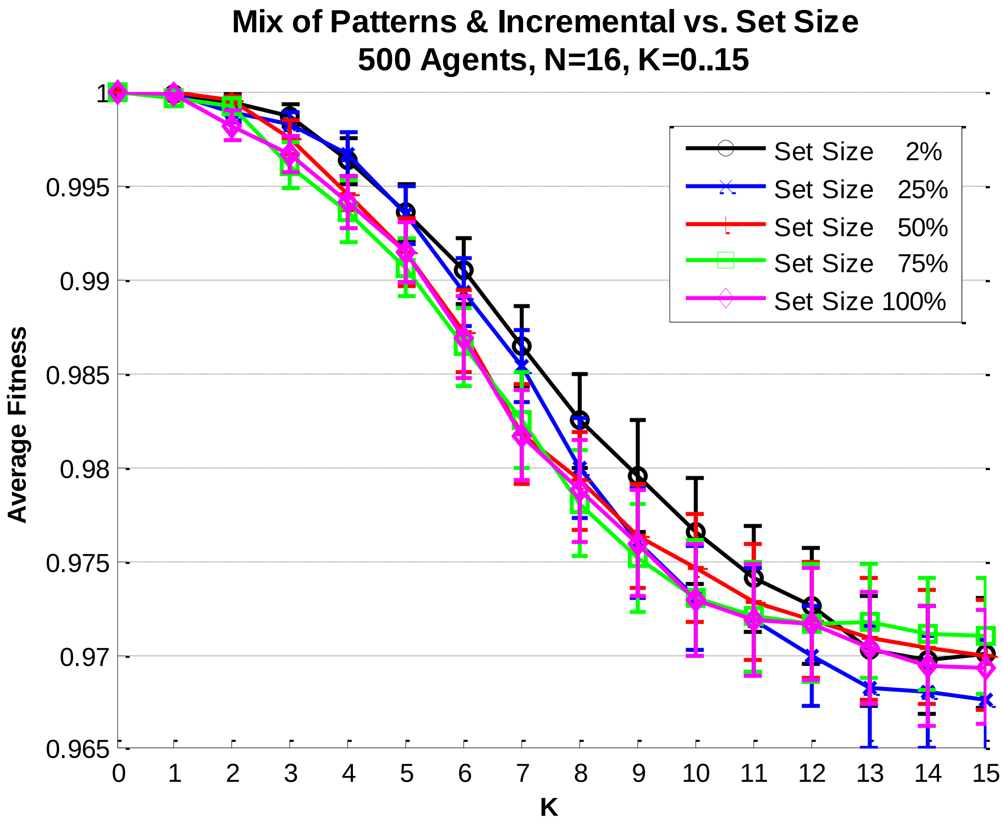


Figure 19. Relevance of set size when agents engage in a mix strategy.

Description. A population of 500 agents engages in a mix strategy, using the information of incremental search to decide which strategy to follow: incremental or patterns. Experiments are performed 100 times and the average fitness and its standard error are plotted.

Interpretation. We can observe if agents actively perform a mix strategy, set size is mostly irrelevant (although is still marginally better the smaller one). The reason behind this is that agents themselves manage to clean unwanted patterns while increasing the process of exploration.

However, innovation and exploration are costly and only if successful, they add to the bottom line. Companies, at least the historical structure of companies, are in many respects better suited to having a structure that prioritizes effectiveness over being continuously engaged in exploration.

Therefore, a relevant research question is whatever it will be possible to obtain good results by primarily following the advice of the Business Schools, limiting the amount of exploration. Knowing the answer of this question will allow companies to focus their resources in other areas, such as development, productivity, etc. without losing the advantages of acquiring new strategies, leveraging that way on the results provided by the institution.

Figure 20, aims to provide an answer to this question. There we can observe how, if companies rely 25% of their time on the advice provided by Business Schools without even looking at their incremental opportunities and perform a mix of pattern - theory-based search and incremental the remaining 75% of their time, they achieve similar results as if they were fully engaged in exploration 100% of their time.

What is more relevant, is the fact that the level of engagement needed in incremental innovation, depends on complexity. In fact for lower levels of complexity, the engagement in smaller amounts of exploration seems to be a viable alternative.

Even for higher levels, engaging only 50% of the time in a decision of whether to bet on incremental or patterns while relying the other 50% solely on insights provided by Business Schools or other organizations, seems to be a fairly good alternative that still reverts in important gains close to maximum.

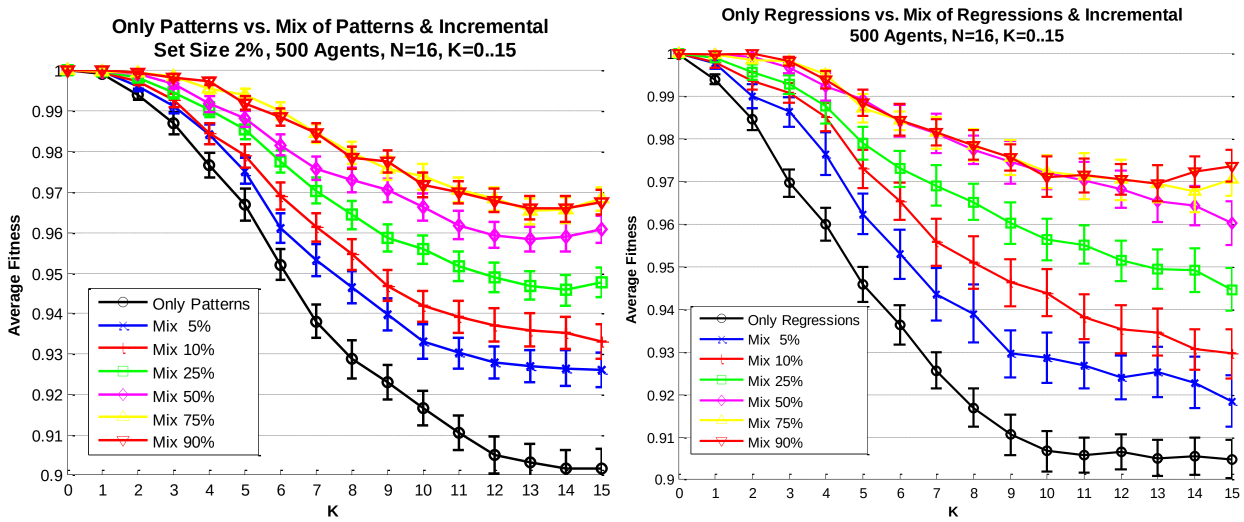


Figure 20. Relevance of the incremental engagement of the agents on patterns and regressions

Description. Different percentages of a mix strategy (patterns - regressions or incremental) are included in a pattern-theory driven strategy selection. Percentages range from 5% to 90% of forced mix strategy. Experiments are conducted using a set corresponding to the best performing 2% of the population of agents. Averaged results of 100 experiments per mix are presented. Average fitness and standard error of the population are plotted.

Interpretation. We can observe how, for a low level of complexity, the complete reliance on insights coming from patterns or regressions, produces results that are very close to mix strategies. However, as complexity increases, the need for a percentage of mix strategies in exploration becomes evident. Still, we can witness how a reliance of 50% on patterns provided by the Business Schools, leaving the other 50% to mix strategies, produces results very close to maximum. We can also notice that beyond 75% of reliance in mix strategies there is no improvement.

4.7 Conclusions

There is certainly no lack of literature about innovation and strategy. Yet, it is a discourse that moves in two levels. On one side, at macro level, where systems of innovation and relationships among the different actors are emphasized. On the other, at micro level, where a lot of effort is put on trying to understand how companies innovate and what the mechanisms for exploration are.

In terms of modeling, at macro level, innovation is many times considered exogenous to the model, while at a micro level, the focus is on either mechanisms for individual exploration of the dyadic relationships between agents, situated or not in a network.

Little effort has been put into trying to understand the role that organizations like Business Schools, the economic press, etc. play in this process. And many times, this role has been somehow diminished under the label of diffusion, arguing that these organizations do not discover new strategies, the agents do, they only contribute to their diffusion.

With this work we attempt to contribute to this strand of research presenting innovation as a collaborative process that co-evolves and where both parts, the institution and the agents play an essential role.

We have done that by first uncovering a new mechanism that we called pattern-based exploration, based on a traditional behavior in human societies: conformist majority. Discussing it has helped us in understanding sampling in social mechanisms. Understanding *how* sampling works in pattern-based search allowed us to find some valuable insights on how to determining *how* many *Best Cases* should Business Schools examine and *how* comprehensive this sampling should be.

A central contribution of our work in this field is comprehending and comparing the two main mechanisms presented: patterns and statistical inferences from a theoretical perspective but also referring to more practical questions, such as *which one* works better *where*. In this respect, we found that patterns work surprisingly well in contexts of low and medium complexity while statistical approaches gain advantage as complexity increases.

In these days of global crisis and fierce competition between America, Asia and Europe, innovation is many times seen as the *Holy Grail* that business should pursue at any cost. However, understanding innovation as a collaborative endeavor where both institutions and individual agents play a significant role in the process sheds new light on when and in what circumstances resources of companies are better employed in the core business, when a significant effort should be diverted to innovation and when the exploration that comes as a result of incorporating the best practices suggested by Business Schools and other organizations, is enough to capture a substantial part of the value, both at individual and societal level. We found that, again, complexity plays a significant role in this discussion.

However, this work only scratches the surface and many questions are left unanswered. The societies that we modeled present stylized worlds where agents do not cooperate nor compete among them. All agents are equal and able to reap equal benefits of their exploration and evolutionary dynamics is presented in terms of adoption and not as new entrants and closures. Obviously, these systems lack structure, better dynamics, competition and diversity. Modeling these characteristics will certainly provide new insights that could not only contribute to a better understanding of the causality relationships underneath and the dynamics or the system, but also inform policy.

5 Collaborative Innovation in Practice: The Living Labs approach

When on December 25, 2006 Time magazine (Time, 2006) selected the user as the person of the year for its front page, it was doing nothing more than publicly acknowledging the increasing importance of user involvement and participation in generating contents and ultimately in innovation.

Even if users are the final recipients of the innovation process, their participation in the process itself has been precluded by the inability to reach and use the technologies needed to innovate. Regardless, during the past decades and especially since the emergence of the personal computer, technology has experienced a process of democratization (von Hippel, 2005) that translated into two streams: access and the virtualization capacities of information technologies (Dogson et al., 2005). This process of democratization together with the connectivity and coordination capacities of the Internet (Shirky, 2008) have been driving and fueling the growth of user involvement.

However, user involvement has taken a variety of approaches such as users as creators, as in the case of lead users (von Hippel, 1986) or Open Source; co-creators in practices such as Design Thinking (Brown, 2008), participatory or user-centered design or simply being treated as passive subjects whose insights are captured and introduced in the innovation process, such as in the case of applied ethnography, usability, human interaction or market validation exercises.

Living Labs trials and organizations are situated in this fertile middle ground of considering users as equal partners in the process of innovation and actively involving them in materializing their own needs, aspirations and wishes in their real-life context.

This research aims to examine some of the leading methodologies in the Living Labs community, trying to find out through its comparison, where are their strengths situated, what spaces of inquiry are they addressing, that by capturing the imagination and insights of users, could foster innovation. Thus, in our study we address the following research questions:

1. Where can Living Labs methodologies be situated in comparison with other innovation practices?
2. What is the new contribution of Living Labs methodologies that differentiate them from the existing ones?

3. Where are Living Labs methodologies more appropriate in terms of the innovation problem being addressed?

The understanding of these questions is highly relevant, not only for the agents directly involved in innovation, such as companies or researchers that must select methodologies to address innovation problems, but also to policy makers because of the Open nature of Living Labs, their capacity in developing the Information Society and the importance of the public sector in their development.

5.1 What are Living Labs?

Living Labs are commonly characterized as both a methodology that stresses user involvement in innovation projects and the organizations that focus on its use.

Living Labs are driven by two main ideas: a) involving users as co-creators on equal grounds with the rest of participants and b) experimentation in real world settings. Living Labs therefore provide structure and governance to user participation in the innovation process (Almirall and Wareham, 2008).

There is nothing that prevents the use of Living Labs methodologies in private companies or closed settings. In fact, some well known companies have largely explored its use. Living Labs organizations are possibly even more interesting because of its open nature and its role as intermediaries in an Open Innovation environment (Almirall and Wareham, 2008).

Living Labs organizations, thanks in part to the support of the EU, have grown fast in the last two years and a network comprising 129 members from Europe, Brazil, South Africa, Mozambique, China and Taiwan has been established.

Our research took this network as the point of departure and examined the most established methodologies, drawing from a combination of secondary sources and field research derived from the active participation in the network and in Living Labs projects during the last three years.

5.2 Living Labs Methodologies

5.2.1 3.1 CDT. Luleä, Sweden

FormIT (Bergvall-Kareborn et al., 2006) is the last iteration of the most used Living Lab methodology in CDT, Luleä (Sweden) (http://www.cdt.ltu.se), one of the oldest and more developed Living Labs.

FormIT tries to put users at the center of the process by involving them through different methods and tools, mostly qualitative. In FormIT, three states of product/service development are differentiated: the design of concepts, the design of prototypes, and the design of the final system. The methodology evolves in spiral through these three stages.

In each stage we can find a three-step process that begins with the appreciation of existing opportunities in applying a new technology, process or product. Once the opportunities are clearly established, the process continues with a collaborative design of concepts, prototypes and the final system, depending on the stage. Real life environment validation is maintained through the whole process as much as possible. This three step process is repeated until the results is considered satisfactory.

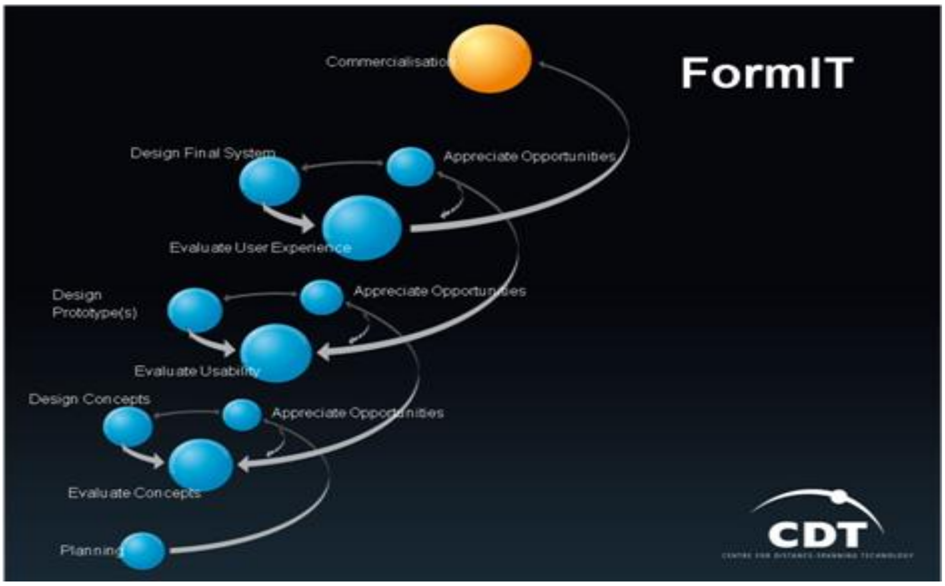


Figure 21. FormIT methodology

5.3 iLabo – IBBT, Belgium

iLabo in Belgium (http://www.ibbt.be/ilabo) also uses a three-step methodology plus a feedback phase (Ballon and Pierson, 2007). In this case, probably the most salient aspect is the importance given to the context. This is in a way similar to the appreciation of opportunities phase that we encounter in the previous methodology, but here a special focus is devoted to the technological and socioeconomic context.

The first phase is contextualization that after appreciating the technological and socioeconomic context evolves to user selection, finding groups of users whose insights could be relevant in this context.

The second phase is concretization, where departing from an initial measurement, the concept is developed.

The third phase corresponds to its implementation and testing in real life environments using a combination of logging analysis and traditional qualitative methods.

Finally, an ex-post measurement is conducted and on the basis of the final report a new evolution of the project could be carried out, if appropriate.

Similar to the previous case, each phase can be conducted iteratively, but in this case each phase can lead not only to the previous one but to contextualization.

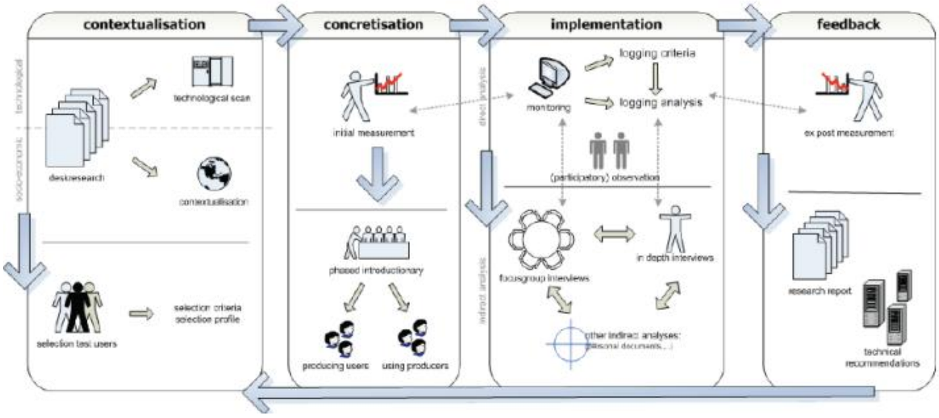


Figure 22. IBBT, iLabo methodology

5.4 CKIR, Finnish Living Labs

To our accounts, a developed conceptualization of Living Lab methodologies in Finland is not published yet. Therefore we will rely on initial versions presented in conferences that try to summarize current practices (Mikkelä, 2008).

In this case, the methodology is guided by pre-defined scenarios that lead the focus of the project. It is again a three-phase methodology that evolves in a spiral.

In the first phase, called the grounding phase, a similar process as in the previous contextualization one, is conducted, identifying stakeholders and selecting the group of users.

The second phase, interactive and iterative co-design, covers the definition of concepts and the design of prototypes in a co-creative manner.

Finally, the third phase, appropriation and implementation is where public trials occur and feedback is gathered.

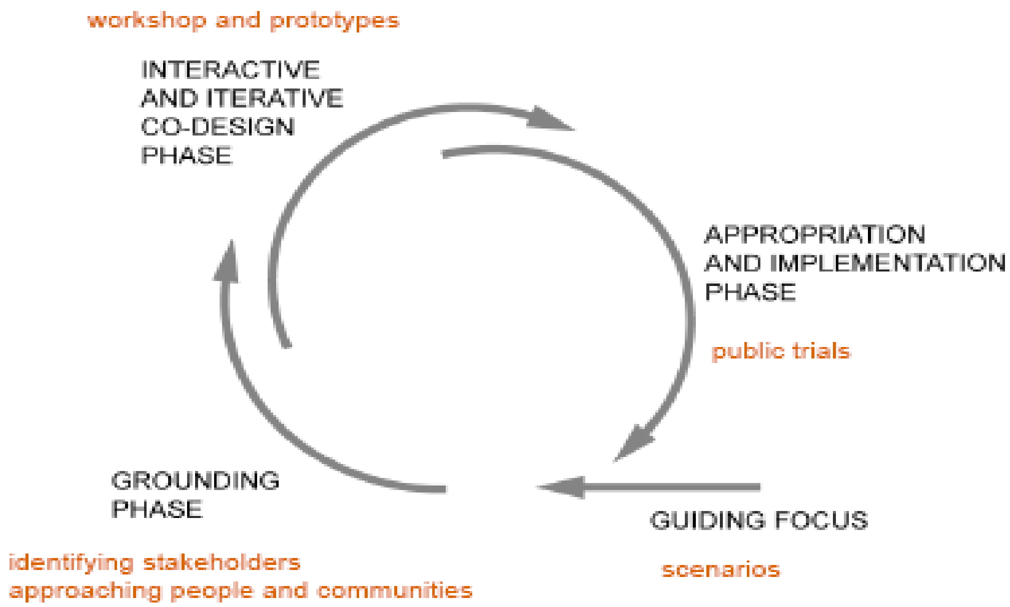


Figure 23. CKIR, Finnish Living Labs methodology

5.5 Catalan Living Labs

In Catalan Living Labs, even if there is not a formalized methodology, we can rely on documented cases (Bergvall-Kareborn, 2006) and presentations given in conferences and workshops.

Catalan Living Labs rely again in a three phase methodology conducted in a spiral, but with an important shift in focus towards implementations in real life environments that serve not only as a proof of concept but as a starting point for a public or commercial venture.

The first phase is devoted to group selection and here users are considered on equal basis with respect to the rest of the team (researchers, companies, etc.). However, the majority of projects are in B2B, where users are nurses in hospitals, patients, IT technicians, etc. Great care is taken in involving the relevant set of users, not only because their insights could contribute to develop a better product or service but because they could help in achieving a successful implementation in the market.

The second phase is devoted to the creation of an innovation arena where the project can develop free from hierarchical structures of the institutions participating. Also, many times, this involves the construction or the use of some kind of infrastructure such as high-speed networks.

The final phase corresponds to the actual experimentation in real life environments, paying special attention in experimenting and developing business models that could make the project sustainable.

Maybe the distinctive characteristic of this methodology is the development of an innovation arena with the objective to reduce the uncertainty and therefore the associated risk, while creating an initial demand by involving the relevant actors and showing its viability in real life environments.

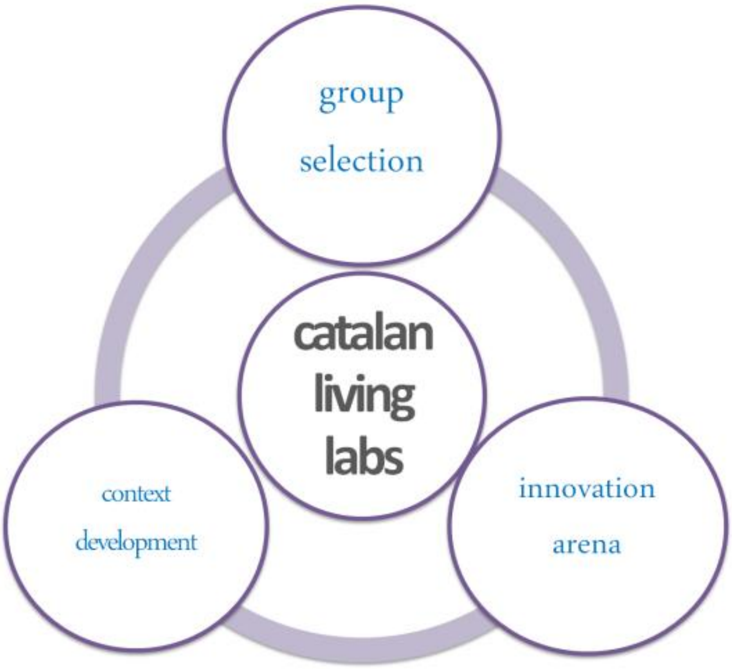


Figure 24. Catalan Living Labs

5.6 Mapping User Involvement in Innovation

Graphically mapping methodologies is a way not only of positioning them in relation to each other but also of relating them towards dimensions of interest.

If our aim is to map innovation practices that seek to involve users, the first dimension seems pretty obvious: the level of user involvement in the innovation process. Therefore at one end we will find methodologies led by experts, where users are seen as subjects of investigation while on the other we will have methodologies where users are the ones in charge of the innovation process.

The second dimension that seems relevant in terms of mapping user-centered innovation is the degree of openness. In fact, a user driven innovation process will benefit more from involving a larger and more diverse user base than a homogenous and small one. Examples of that are Open platforms and Open Source.

Besides selecting these two dimensions, we divided methodologies in five different categories,

1. Traditional. Considering innovation as a process similar to engineering, led by experts.
2. User-Centered. Where users are mostly passive subjects of study. This is the case of usability testing, Human factors and Applied Ethnography.
3. User-Driven. Where the user is the one who drives the innovation process. Such is the case of Open Source, Lead Users or Open Platforms.
4. Participatory. That seeks to involve users on equal grounds to the rest of partners in a co-creative process. Here we have Design Thinking, Participatory Design and Living Labs.
5. Collaborative. Where the collaboration, in terms of interchange, between different actors is stressed, ranging from closed networks to open marketplaces. There we find Joint Ventures, Collaborative Projects and MarketPlaces.

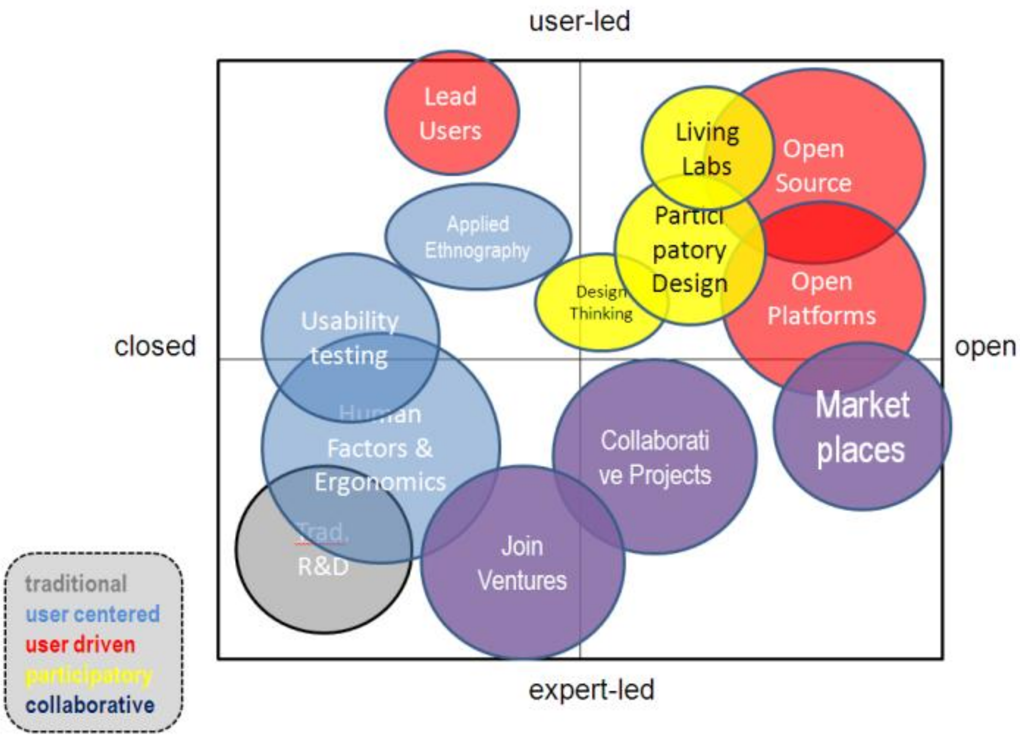


Figure 25. Mapping Innovation Methodologies

5.7 Analysis

Living Labs methodologies can be used in closed environments, but they probably make more sense when applied to open ones. Since they are instrumented as projects instead of platforms, once the project starts, the group of participants is defined and remains mostly stable. Therefore, Living Labs are positioned in the open side of the map, but not as open as open source or open platforms.

We find a similar situation when dealing with user involvement. Even if Living Labs aim to involve users as co-creators, their participation is mediated and they are not the ones leading the process. This contrasts with, for example, lead users who effectively drive the innovation process with an entrepreneurial spirit. Consequently we situated Living Labs again in the upper side but in the middle instead of in the edge.

Looking at the map we can observe how Living Labs methodologies contrast with user-centered ones in the way that they capture the insights of users. While in user-centered methodologies the insights of users are captured and interpreted by experts, in Living Labs the users themselves are the ones that shape the innovation in their own real life environments.

Still, revisiting Living Labs methodologies we can observe that even if each one stresses different aspects, all of them cover the innovation process at three levels:

1) Technological. Ensuring that the technological solution is viable and fills a space of opportunity.

2) Social. Assessing the social and user acceptance in terms of needs and interaction.

3) Economic. Assessing its viability in terms of business model.

Therefore, we can portray the process that takes place in Living Labs as a process of fitting high-level knowledge to mid-low level solutions in particular contexts at these three levels: technological, social and business model.

This is done with the help of two mechanisms. First by involving the constituency that possesses the tacit non-articulated knowledge about the context where the success of failure of the solution is going to be determined. And second by continuously assessing the validity of the hypothesis formulated with the introduction of this knowledge, in real life environments.

This process of fit is important and relevant because we know that most of the innovation occur in this mid-low knowledge level (Bhidé, 2008), and it is in this level where most of the value can be captured, because globalization made science both global an easily available, excluding it to a great extent from being a source of competitive advantage.

5.8 Conclusions

Our first and most obvious conclusion of portraying the process, carried out in Living Labs as a process of fit, is that they will be more relevant where the fit of a particular technology or set of technologies to a precise context is more significant. Therefore, products and services that depend more on their soft characteristics for user acceptance and economic viability seem to be more appropriate.

The second conclusion is that Living Labs will be more appropriate where the fit is less trivial. Indeed, if the fit is trivial, it can be possibly inferred from observing users without having to involve them. At any rate, in situations with multiple stakeholders, conflicting interests and a large space of solutions, the innovation problem may only be addressed by involving all constituencies and through its active participation, aiming to trap into their tacit knowledge that will be incorporated in solutions to be validated in real life environments.

Both conclusions can be easily translated into policy by portraying Living Labs as a resource that allows this exploration exercise in situations where the solution of the innovation problems is hidden behind a complex web of stakeholders and possible solutions.

Historically, this type of infrastructures have been portrayed as a public good and defended because of the competitive advantage that they could provide. This is probably even truer in the times of Open Innovation (Chesbrough, 2003) where the presence of three factors: large solutions spaces, global availability of knowledge and technical platforms which allow for the coordination of a large and distributed number of actors, seem to demand the creation and development of this type of infrastructures.

6 Living Labs: Arbiters of Mid and Ground Level Innovation

6.1 Introduction

Much has been written about the gap between Research and Innovation, many times raising notable interest in the business press as well as public policy (Moore 1991). The so-called "European Paradox" (E.C. 1995, Dosi et al. 2005), or the inability of European nations to transform their leadership in research into commercial successes in the marketplace is an example of this. The European Commission has identified pre-commercial public procurement as an instrument in helping to cover this gap (E.C. 2008, E.C. 2006). However, applied R&D and prototyping are characterized by a high degree of uncertainty in the potential commercial success of the proposed solution, driving potential entrepreneurs and investors away (E.C. 2006). This is where both the gap and the lack of financial support are located – a gap often covered by venture capital (Bos, 2008).

A number of initiatives in the E.U. (E.C. 2007), E.U. member states (Dekker 2008) and other countries like Canada (SDTC 2007), aim to address this gap by using pre-commercial procurement as an instrument to match products and consumer expectations and creating a test ground that can generate an initial demand (E.C. 2006).

Meanwhile, a new institution has been emerging in Europe, aiming to address the very same concerns- Living Labs. Living Labs are driven by two main ideas: a) involving users early on in the innovation process, and b) experimentation in real world settings, aiming to provide structure and governance to user participation in the innovation process (Almirall & Wareham, 2008). A typical Living Lab looks like a collaborative project engaging companies, academia, government and technological centers, where users are involved in nascent development stages and successive iterations are validated in real life environments. Living Labs have grown in the last two years to a network of institutions comprising 129 members, not only in Europe, but also in Brazil, South Africa, Mozambique, China and Taiwan.

An important concept in Open Innovation is the role and prominence of intermediaries (Chesbrough, 2006) which include well-known organizations such as Innocentive, Nine Sigma or InnovationXchange. Intermediaries have been classified so far, as agents, brokers or marketplaces (Chesbrough, 2006). We argue that Living Labs are also intermediaries and perform roles as facilitators of user involvement, and in some cases, orchestrators of the whole innovation process.

Given our limited experience with Living Labs, this research seeks to examine some of their best practices and methodologies, exploring to what extent they can contribute to close the gap between Research and Innovation. Thus, in our study, we address the following research questions:

1) How do Living Labs capture and incorporate the contribution of users in the innovation process?
2) How do Living Labs do support exploration and explotation?
3) In what kinds of innovation do Living Labs contribute? How?
4) Do Living Labs focus on incremental or radical innovations?
5) Do Living Labs focus on the evolution of products and services or the interpretation and negotiated meaning of the services?

6.2 Literature Review

There are numerous strands of theory that might be relevant when exploring the functions of a relatively nescient phenomenon such as Living Labs. We chose our theoretical focus based on the assumption that Living Labs represent a novel approach as innovation intermediaries in product development and validation, and relevant theories should embrace areas in which Living Labs are divergent from more traditional, deterministic R&D paradigms.

Users have been identified in a number of roles in crossing the gap between research and innovation. Maybe the most obvious of them is their role as a source of invention and ultimately innovation (von Hippel 1988, 2005). As semi-partitioned spaces that cultivate user-lead insights, Living Labs are fundamentally infrastructures that surface tacit, experiential and domain based knowledge to codified knowledge. Boisot and Li (2006) and Boisot et al. (2007) describe knowledge as either experiential, narrative, or abstract symbolic, representing categories on a continuum where knowledge is either uncodified and concrete (experiential), or codified and abstract (abstract symbolic). Narrative knowledge has some intermediate level of structure, but not to the degree to where it can be considered validated or objective.

According to the iSpace theory (Boisot et al. 2007), knowledge follows a social learning cycle where it begins from a state of experiential, undiffused and uncodified personal knowledge, and moves to a state as codified and abstract proprietary knowledge. This evolution is the domain of much traditional R&D and problem solving work. Under certain circumstances, knowledge can be further diffused into the public domain, losing its proprietary status or property right protection and becoming part of the public knowledge sphere. This transition can either be intentional by commercialization, or unintentional because of piracy, leakage or social diffusion. After time, public knowledge becomes adequately assimilated or absorbed into the general consciousness such that it is considered common sense. Diffused and absorbed common sense knowledge is re-employed in the scanning processes that underlie experiential knowledge, thereby completing the social learning cycle. Given the large emphasis on context based experimentation in Living Labs, this stream of thinking offers valuable insights into the processes that underlie their knowledge cultivation methods.

Another relevant, well-known stream of theory is the role of risk taking in entrepreneurial activities. Frank Knight (1921) established the paradigm of Knightian uncertainty versus risk. For Knight, it was important to differentiate between risk, where outcomes are unknown but quantifiable in known ex-ante probability distributions, and uncertainty (ie. Knightian uncertainty), which is, by definition, unquantifiable or immeasurable.

Knightian uncertainty has become an important concept in the literature on entrepreneurship and venture capital, as it is often argued that one of the important functions of VCs is to absorb Knightian uncertainty, where related institutions (e.g. traditional banks) would have a tendency to work with quantifiable risk. These early stages of product development and innovation characterized by Knightian uncertainty are frequently equated with March's (1991) seminal definition of exploration. March introduced two fundamental concepts of organizational operation and strategic renewal: "exploration includes things captured in terms such as search, variation, risk-taking, experimentation, flexibility, discovery and innovation. Exploitation includes things such as refinement, choice, production, efficiency, selection, implementation and execution," (March 1991, p. 71). To suggest that Living Labs only function at the level of exploration and not exploitation may confer unwarranted compression on the concepts. Although, as March argues, exploration is variation-seeking, risk-taking, and experimentation oriented, exploitation is variety reducing and efficiency oriented (March 1991), the fact of the matter is that almost two decades of research based on this thinking has lead to limited consensus on their exact definitions or theoretical utility (Li et al. 2008).

However, Bhidé (2009) extends concepts of explorations and Knightian uncertainty to develop a concept of "venturesome consumption", a process in which businesses and users experiment with and explore novel manners of integrating existing basic research into new products and services. Specifically, he refers to solving the technical challenges of commercialization; bringing the product to market through viable sales channels, platforms and supporting product ecosystems. He differentiates between high-, mid-, and ground-level innovation types. High-level innovation refers to the building blocks or raw material of common products or services (micro-processors, silicon or coffee beans). Mid-level innovations are the intermediate products or modules that are vital components of the product (motherboards, bean roasting expertise), where ground-level innovations are the knowledge or products that directly result in the consumption experience (laptop computer or cup of espresso). His general thesis is a response to the alarmist rhetoric that the wealthy western economies are losing their innovation edge to low cost but highly educated BRIC countries. He suggests that, while this may be true for many high-level innovations that do traverse national boarders quite easily, this is not the case for mid- or ground-level innovations, as they are often best conducted close to, and in tight collaboration with, potential consumers in their local markets or settings. Regional economics aside, the framework is of interest because it suggests that the consumer-lead innovation domain in which Living Labs function focuses on mid- and ground-level innovation. This has several implications. First it suggests that Living Labs are instances of "*venturesome consumption – the willingness and ability of intermediate producers and individual consumers to take a chance on and effectively use new know-how and products – (which) is as least as important as its capacity to take on high-level research"* (Bhide 2009 pg. 16). Here, resonance of Knightian uncertainty and Marchian exploration is clear. Secondly, that the innovation domains are highly defined by local contexts; their discoveries and insights are most relevant in regional markets, yet decreasingly valuable on an international scale. However, globalization greatly increases the potential for replicability of these insights.

A final strand of research relevant to Living Labs is Design-Driven innovation. Design thinking attempts to cross the gap between a great idea and a great product by tapping into the users' needs, feelings and sensations by having a more exact understanding of what users explicitly feel or do when they use a particular product or service (Brown, 2008). At a primary level, design thinking places user experience and cognition at the forefront of study through well established tools such as usability testing, ergonomics, and both low- and high-tech ethnography. Fully focused on human psychology and perception, design thinking awards user emotions, rather than the product design, the highest status in the innovation hierarchy. It is most commonly associated with design firms such as IDEO or the recent D-School initiative at Stanford University (Brown 2008). An understanding of the user as a partner who is an "expert of his/her experience" and where the designer and the researcher supports him by providing tools for ideation and expression (Sleeswijk et al 2005; Sanders and Stappers, 2008) is at the core of the Living Labs approach (Mirijamdotter et al, 2006) which also shares tools and methods from design thinking.

However, at a deeper level, Verganti (2008) suggests that much design-driven innovation can also take an opposite trajectory. Through a deep understanding of the broader social trends and technology evolution, design-driven innovation can attempt to radically change the emotional and symbolic content of products by redefining the meanings and languages associated with them in a very deterministic manner. His proffered example is the Wii platform - how what was previously a gaming and entertainment platform has been renegotiated as a serious in-home exercise platform for an otherwise uncultivated market segment. In order to renegotiate the social meaning or vision of a product, designers must direct their attention toward the external interpreters of these meanings; that is, artists, schools, suppliers, distributors, other industries and the media. In other terms, design-driven innovation is less a function of understanding serendipitous user experimentation and experience, but rather about the purposeful interaction with the arbiters of product languages and socio-cultural meaning. Initially, the relation to Living Labs may appear less clear. As partitioned arenas for user experimentation and exploration, the relationship to design thinking and user experience is obvious. But it may also be plausible that Living Labs function as subtle yet powerful platforms that enable the renegotiation of social meanings; purposefully or accidentally. This idea connects with related work in economic geography that highlights social practice as providing locus and meaning to Innovation (Tuomi, 2002); as an enabler of innovation (Florida, 2005; Saxenian, 2006); and more recently as a source of competitive advantage through the willingness and ability of businesses and consumers to effectively use products and technologies derived from scientific research early on in its life cycle in venturesome consumption (Bhidé 2008).

6.3 Research Design

Despite the fact that the European Network of Living Labs (ENoLL), comprises close to 130 different organizations from around the world, their existence is fairly recent. In part because of its novelty and in part because of the lack of a precise definition of the term, under the Living Labs denomination we can find a diversity of practices, organizations and projects with varying levels of maturity. As a consequence, we choose to focus a recent set of practices carried out by one of the organizations through a sufficiently large time span, that could bring some insight on the roles of both users and the Living Lab involved in the process, making possible to assess its dynamics and the benefits captured by firms and public organizations involved.

6.3.1 Sample and Data Collection

We employ a multiple case-study methodology is the most appropriate for both the field and the research questions formulated in the present study. This exploratory method is best suited for investigating new and poorly understood processes, focusing on the “what” and “why” questions (Eisenhardt, 1989), being specially appropriate for research into new topics and new technologies (Shane, 2000; Stake, 2000; Mcdermott and O’Connor, 2002).

In this respect, the present research took advantage of the active participation and involvement of one of its authors in both the European Network of Living Labs (ENoLL) and the Foundation i2Cat.

For the selection of cases, we based our choice in two criteria:

a) Projects regarded as highly successful and perceived with a significant degree of innovation and high social value.
b) Cases where the involvement of users and the role of the Living Lab were highly salient.

Six cases were selected, from three different domains: health, media and industry: Opera Oberta and Cultural Ring in media, Teleictus, Eye Health in health and Industrial Ring and CatLab in industry. For each case, in-depth interviews using a semi-structured interview guideline were conducted with project leaders, Living Lab members, users and representatives of the firms involved. These industries were contrasted with secondary data such as project documentation, project websites and public presentations of the projects.

Case	Description	# of Interviews
Media		
Opera Oberta	High Definition IP broadcasting of live Opera	3
Opera Learning	Synchronous HD Opera courses	3
Health		
TeleiIctus	Remote diagnosis and treatment of Ictus	3
Eye Health	Remote diagnosis of eye related diseases	3
Industry		
Industrial Ring	Internet2 network connecting an industrial cluster primary in the automobile sector	4
CatLab	Catalonia Living Labs project	>2 years

Table 8. Selected Cases and number of Interviews per sector

In total, 19 interviews were conducted and recorded, lasting each one between 1 and 2 hours. Additionally, these cases were framed in the Catalan Living Labs project – CatLab, of which one of the authors was deeply involved for more than 2 years being its coordinator and representative in the ENoLL, European Network of Living Labs.

6.4 Research Findings

In presenting the findings we will first provide a short description of each case and the organization hosting them, allowing the reader to better frame and contextualize them.

The cases presented are organized in three main areas: health, media and industry, corresponding to some of the major areas of work of the i2Cat Foundation, the organization managing the projects.

Next, both the cases and the role of the organization in them, will be analyzed using the main research questions of this study.

6.4.1 Brief case stories

6.4.1.1 The hosting organization: i2Cat

i2Cat is a Foundation established as a public private partnership constituted by three universities, around ten private firms and the Secretary for the Information Society of the Catalan regional government. i2Cat began its operations in 1999 with the ambition to promote and develop the Internet Society in Catalonia, both from the point of view of research and through direct intervention in the society by means of setting up technological projects.

i2Cat organizes its work around clusters, which are focus areas of the foundation. Currently four clusters are active: media, infrastructure, health and learning. Parallel to this organization into clusters, a great amount of effort is devoted to the construction and maintenance of technological platforms such as high-speed Internet (Internet2), grid or optical networks. These platforms are the ones who support the projects carried on and organized inside the clusters.

The objectives of i2Cat are twofold. On one side traditional research has a prominent status, especially due to the participation of three major technological universities. On the other hand, a great deal of effort is devoted to more exploratory innovation. Not only because of the public and firm involvement in the i2Cat consortia, which clearly pushes the organization in that direction, but also because the i2Cat's response to the problem of the seemingly unlimited technological choice that IT has ushered in recent decades is experimentation; concretely, experimentation in context-rich social environments. i2Cat believes that the optimal way to discover the future uses of Internet2 and similar technologies is to tap into the users themselves by means of public, loosely controlled experimentation.

These practices found their match when the European Network of Living Labs started its activities. i2Cat was one of the founding members, and with the support of STSI (Catalan gov. funding agency for the Information Society) it started an initial program to coordinate Living Labs activities in Catalonia. This program crystallized in the launch on October 2007 of CatLab – the Catalan Network of Living Labs, comprising eight organizations performing Living Labs activities together with the Catalan government.

6.4.1.2 Cases in Media

Since the objectives of the i2Cat Foundation revolve around exploring the frontiers of internet by tapping into its next high-speed, high capacity iteration called Internet2, media has been an obvious area of work. Media, and more precisely, the use of high definition in media, with its almost unlimited appetite for bandwidth and speed, provides a natural, self-explanatory and highly compelling argument for the need of a bigger and faster Internet, a.k.a. Internet2.

Moreover, it was in media where i2Cat achieved its first successes that paved the ground not only for deepening its involvement in the area but for its development as an organization.

6.4.1.2.1 Opera Oberta – Opera Learning

Opera Oberta (Opera Oberta, 2001) explored the use of high definition video-conferencing and high-speed Internet in the context of live Opera. The driving force behind the project was Angel Fernandez, at the time Director of Technology of the Opera Theater Liceo in Barcelona. Angel was aware of the experimentation in high definition video conferencing that was taking place at the time and contacted i2Cat. Together with i2Cat support they were able to launch a team comprising technology providers like Thomson Multimedia (cameras and equipment), Barco (projection), Video Digital (MPEG2 coding), etc., telecom operators (Telefónica and Menta), public infrastructure networks (Cesca, i2Cat, Red Iris, Terrassa City Hall) together with commercial exhibitors (Cinesa Diagonal) and a network of universities where Opera performances were retransmitted.

On December 18, 2001, La Traviata was transmitted in HDTV using an HDSI link at 1.5Gb to a large movie theater in Barcelona (Cinesa Diagonal), while the same signal was broadcasted through SDI at 270Mb in multicast to a network of 4 universities around Catalonia.

Building on the success of this first experience and with the support of i2Cat, the project continued with additional retransmissions and evolved in three main directions. The first one was Opera Learning that extended this effort until 2004 with regular programming of elective Opera courses done through HD on-line video conferencing: first with a small network of Catalan universities but later on with the participation of Spanish, European and Latin American universities in the program. In order to carry on this effort, Opera experts and educators joined the project.

The second line of evolution was its transplant beyond Opera to other artistic manifestations beyond opera. Cultural Ring (Cultural Ring, 2003-2008), linked a dozen of Catalan centers and encompassed around twenty groups that regularly used the scientific high-speed Internet2 network deployed in Catalonia for art interaction.

Finally, the third line was its use for concrete Opera events that have become traditional in Catalonia, one of them is Opera on the beach, performed yearly.

Pre-commercial Gap

The next generation of high-speed Internet offers an important opportunity to content producers such as the Opera Theater Liceo. This opportunity materializes not only in terms of reaching a bigger audience but also from capturing additional value from their own productions.

The problem in 2001, and to some extend today, lies not in the technological readiness but in connecting the dots that make the implementation of this technology real. This involves steps that range from legal aspects like securing the digital rights of the performances (the fact that Liceo had these rights made the project feasible) to technological ones such as connecting cameras and broadcasting equipment to an IP network, or readiness in terms of infrastructure deployment by being able to use a high-speed network large enough for the project to finding viable services and business models able to sustain the project.

Opera Oberta/Opera Learning created and validated some of these services, basically direct synchronous opera transmission and educational services based on HD videoconferencing. A collaborative approach in exploring this problem was indeed very appropriate because of the complexity of the solutions. Innovations did not materialize in any radical new technology but in the concretion of capabilities and technologies available in a pre-commercial stage into a novel service exploring its public acceptance and some of the possible business models.

It is important to remark that the problem and the resulting project were beyond the reach of any single actor or a small group. The need for the contribution of many actors and the unclearness of viable business models made it very unlikely that this project could emerge from traditional entrepreneurial - venture capital mechanisms or sponsored by large companies.

Possible alternatives were found and validated through a series of trial and error exercises coming from a collaborative exploration of the problems. This explorative process led to some imaginative alternatives such as tapping into the unused capacity of existing high-speed research networks linking several of them that were previously isolated.

Benefits captured by both companies and public institutions were diverse. For example, Technotrends acquired substantial expertise in HD video-conferencing, Telefónica and Red-Iris (the Spanish scientific network used as a backbone) gained expertise in handling high priority/high bandwidth traffic and in fine tuning networks, eliminating many bottlenecks and incidences (in Angel words: "Opera Oberta was a network cleaner"). The Opera Theater ended up with one of the largest HD Opera recordings and obtained public awareness, etc…

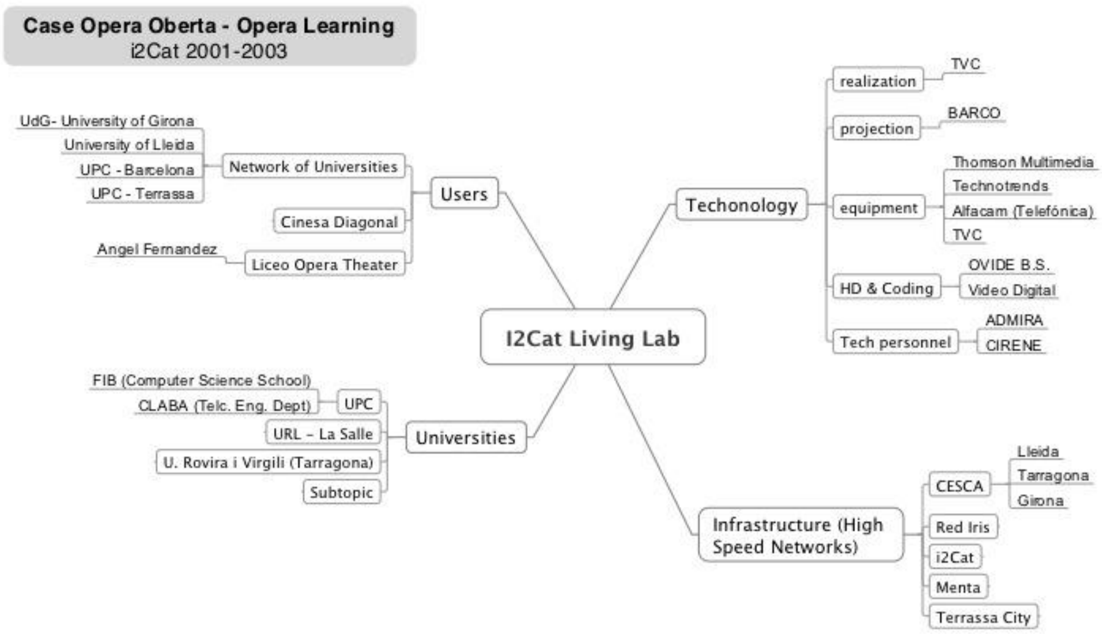


Figure 26. Participants in Opera Oberta – Opera Learning.

The Contribution of Users

In terms of taking advantage of the technology, we can distinguish two types of users in this project, one upstream and another one downstream.

On one side we can find Liceo Opera Theater and specially Angel Fernandez, technology director of Liceo. In the value chain it played the role of content providers. On the other side we can find the network of universities and the Movie Theater: Cinesa Diagonal who were the final recipients of the service.

The first role that we should emphasize was the one of Angel Fernandez who can be better described as a lead-user (von Hippel, 1986) and was, together with i2Cat, orchestrating and pushing the project forward.

The network of universities and the exhibition theaters did not play a passive role at all, but they contributed and shaped the innovation process in many ways behaving as co-creators. An example of this was raising the demands for bandwidth in order to achieve levels of quality in both image and sound that they considered appropriate (particularly in sound). Another example was their contribution in the definition and fitting of the elective course in the university program and their diffusion to other institutions.

Also, but to a lesser extent, the input from end-users – spectators or students – was captured and used to shape the service.

An important characteristic of this experience, also key in Living Labs experiments, was the fact that the project was done in real life. All performances were actual public performances and classes were open to all students who achieved valid university credits for their work. This allowed the gathering of a real experience, both in terms of user experience and in terms of the services and business models that had to comply, fit, compete, and add value to existing offers, users and organizations.

The role of the Living Lab organization

In contrast to other type of technologies like software, High-Speed Internet was not (and is not yet) readily available to users, nor can it be implemented by a single firm or a couple of firms like in lead-user driven innovation. Therefore, an organization, or a group of organizations like in this case, is needed to put these technologies into the hands of users.

The first role of the Living Lab consists in creating an innovation arena and involving the relevant actors and technologies enabling the exploration of a space of possibilities that were before beyond their reach due to the lack of a suitable platform (high-speed networks) and the need of multiple contributions to form a value chain. Both elements were beyond the reach of any single actor or even a group of them.

The second role that we can identify is the one of orchestrating and coordinating the experimentation while facilitating the identification of reachable targets (real products or services to validate) where to concentrate the efforts.

Besides, there is a third and probably the most distinctive role for Living Labs: mediating between users and the rest of actors. In this case this was materialized in two ways: first, involving the representatives of universities and exhibition theaters from the beginning on in the process, and secondly capturing the end user experience (mostly using qualitative methods) and introducing them as an input in the process.

Besides these three main roles of the Living Labs organization: mediator, technology facilitator and orchestrator we can point out two unintended ones.

One is the role as a connector, which is a necessary consequence of selecting and involving the parties in a common process. The other on is the role as a technology broker. Because of the central position of the Living Labs organization and its ability to understand the whole process, it is also able to see opportunities and technology complementarities between them. In the case of Opera Oberta/Opera Learning we can find both. Relationships previously inexistent were formed and participants did engage in a collective learning process acquiring technology and expertise from others.

6.4.1.3 Cases in Health

Health care relies in providing timely and adequate expertise and means to a precise target. Because expertise in health is so relevant, the use of high-speed Internet and its ability to provide the best available resource when needed seems valuable. However, a number of factors prevent its implementation and at the same time favor a collaborative approach to innovation.

6.4.1.3.1 Teleictus

Teleictus (Teleictus, 2007) is the brainchild of Dr. Ismael Cerdà working in Vic General Hospital and addresses the problem of having round the clock expertise in diagnosing and treating strokes. The project implements HD video conferencing system together with a tool for sending CT images (MIO from C2C – http://www.c2csis.com) and the MEDTING platform (http://medting.com) for sharing clinical stories , linking a reference hospital (Hospital Vall Hebron in the initial test) with a satellite hospital (Vic General Hospital in the initial test) together, using high-speed internet for the diagnosis and continuous monitoring of patients.

Even if stroke telemedicine is not new (Demaerchalk et al., 2009), Teleictus was developed independently, based on trials developed during 2005 and software components for visualizing CT images built between 2002 and 2004, and it presents some advantages in terms of integration and use of off-the-shelf state-of-the-art video-conferencing systems.

In a case similar to the previous one, an initial idea of a user, Med. Dr. Ismael Cerdà, who got supported by i2Cat and together assembled a team comprising telecom operators, equipment manufacturers, doctors and nurses, hospitals and funding agencies of both the Information Society and the Healthcare system. By experimentation, trial and error, this materialized as an initial experience that was rated as very successful.

The team managed to deploy a high-speed fiber connection (300Mb) between a central and a satellite hospital early on in the project and installed some off-the-shelf equipment beginning to discuss possible modifications and adaptation on it.

In addition to that, software allowing the sharing of CT images together with clinic stories was enlisted.

Surprisingly, one of the first discoveries was that the high-speed connection was not really a requirement, together with the high importance of the activation protocol and the mechanisms of coordination between partners due to the fast pace and the critical importance of time in the deployment environments (emergency rooms and emergency-like situations).

This example was not an isolated one but exemplifies a general trend in the project where technical aspects became less relevant as successive trials developed while the fit between technology and organizational procedures became a key element for its success. It was mid and low level knowledge in the hands of users what ensured this fit. Therefore, the initial plans for building sophisticated new equipment were discarded in favor of the integration of off-the-shelf commercial solutions.

Building on that success, more than 100 patients have been already treated with the system that is now expanding to a second phase comprising more than 20 satellite hospitals and some reference centers. A third phase covering all of Catalonia is already planned.

Teleictus has been awarded with the National Health Spanish Quality Award in 2007 (Premio Nacional de Calidad del Ministerio de Sanidad 2007) and with the BDigital Award to Digital Innovation in 2008 (Premi BDigital a la Innovació Digital 2008).

Pre-commercial Gap

Even if providing a solution for this problem may seem easy from a technical point of view, a number of factors prevent that companies embark in this endeavor. Among them we should cite:

- The perceived risk derived of dealing with a single client in a territory, in that case the Catalan Public Health System.
- The need for acceptance in a community where procedures are highly codified such as the medical sector.
- The lack of availability of an adequate infrastructure.

Therefore solving the pre-commercial gap in this case means solving a number of additional problems beyond the technical ones.

- The availability of a high-speed network.

- The development or the plausible expectation of an initial demand able to cover for the development.
- Ensuring that the solutions fits into a medical protocol widely accepted and that it is in line with the standards and restrictions of the hospitals addressed.

Teleictus solved this problem forming a team that could be able to address all the issues together, meaning ensuring the participation of the Catalan Health Care Service (CatSalut), a telecommunications operator who agreed to install a high-speed connection (Al Pi) and a provider of HD videoconferencing equipment (Technotrends).

As a result, the team of companies and public institutions involved, have been able to capture value from the project, ranging from tailoring high-def video conferencing equipment to the health sector, to opening a new specialized commercial service for high-speed internet, a substantial reduction in cost simultaneously with a service quality increase for the hospital, a public award and recognition for both the Living Lab (i2Cat) and the entrepreneur and a gain in influence that will pay in the future, in the own words of Dr. Cerdà: "next time will be easier!".

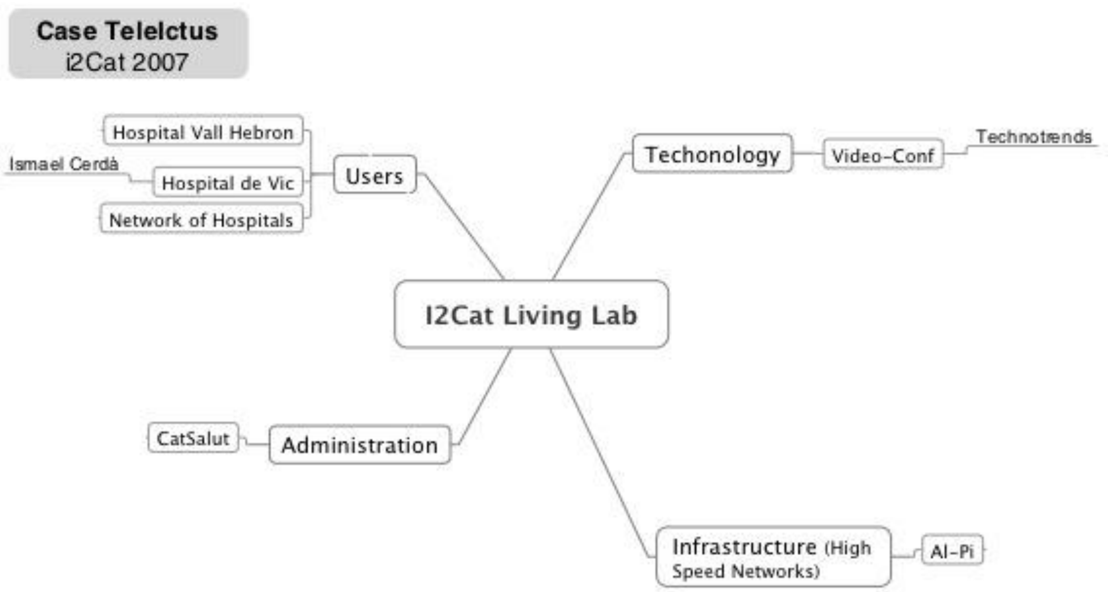


Figure 27. Participants in the first phase or Tele-Ictus.

The Contribution of Users

The contribution of users to the project was twofold. On the one hand we can find the role of a "lead user" in the person of Dr. Cerdà, who from his position in a public hospital greatly contributed to the project with an entrepreneurial attitude.

On the other hand, we can find that the solution was shaped not only with the collaboration of doctors from both hospitals but with the active participation of nurses and personnel from the computer departments of both institutions. Examples of their contribution in that second area can be found in the activation protocol, the physical placement of the instrumentation, the administrative circuit and in general the model of collaboration between hospitals and departments.

Once again, validation in real life conditions was a key element for success, not only for ensuring the validity of proposed solutions but for boosting the morale of the team involved.

The Role of the Living Lab organization

Again, lowering the risk associated with innovation by selecting participants and providing an arena where technological proposal could be operationalized was the key element for the success of the project.

Together with that, the division of the project in phases (first 2 hospitals, next 5 hospitals, etc …) and reachable milestones has revealed itself to be very important.

The existing habits in both hospitals of collectively creating protocols and the homogeneity of part of the groups involved greatly facilitated the integration of the rest of the members in the project, making the co-creation process easier.

6.4.1.3.2 EyeHealth

EyeHealth (2007-2008) aims to solve the problem of providing expert assistance in ophthalmology to rural family doctors located in remote areas.

In this case, the project was initiated by a private company: Ilo ophthalmology. Ilo provides expert diagnostic in ophthalmology not only to private users but also to doctors.

Ilo contacted i2Cat in search for expertise, who in its turn enlisted the cooperation of the Catalan Health Service (ICS). Because Ilo is located in Lleida (north of Catalonia – Spain) a group of medical doctors in the Pyrenees was selected for co-developing the project that has now become an active service.

The output of the project consisted in a system for acquiring, managing and processing ophthalmologic information, together with their images. The system is accessible by Internet. This is how it works: when a patient with a vision problem consults a family doctor enlisted in the project, the doctor can choose to take an image of the patient's retina, with a special easy-to-use instrument, and introduce it to the system. This image is later on evaluated by a specialist who, if needed, can enter into a dialogue with the doctor to further discuss the diagnostic.

Fast trials and the experience gained with them were also determinant in the evolution of the project. As an example of that we can appreciate the diminishing importance of the connectivity aspects through the process. If in the beginning the need for a high-speed connection was visualized as a requirement, as the project evolved, the evidence of the trials and the users present suggested that a completely disconnected service could also work, providing increasing benefits in effectiveness because of its asynchronous nature allowing grouping technical expertise and the equipment to serve different locations.

The system provides not only a better care to users who gain time and convenience by saving on travel and a much needed speed in the diagnosis and treatment of their conditions, but also enhances the expertise of less connected family doctors living in rural areas that engage in a continuous learning process with the specialists through real cases. Last but not least, the system represents a new business line for Ilo ophthalmology who can reach through it more patients and more doctors.

Pre-commercial Gap

In this particular case, two main factors prevented the entrance of a commercial company or the start of a public service in this territory. First, uncertainty about the technology, about the level of acceptance by the Catalan Public Health System and family doctors and about the validity of the operational and business model. And second, the need to ensure an initial demand.

The uncertainty about the technology was reduced by working with i2Cat. A finding of the trial and error experimentation was that the system worked acceptably well off-line (storing the images locally that were reviewed later on by the specialists), reducing the requirements for connectivity and thus enhancing the reach and implementation possibilities of the system.

Also, in that line, the continuous work with the administration and with family doctors could be characterized as a mutual learning of needs, constraints and expectations that greatly contribute to adjust the system to the target environment.

Moreover, the success of the system was progressively perceived by the administration, and this ensured first an initial demand and its acceptance and later on, its further expansion.

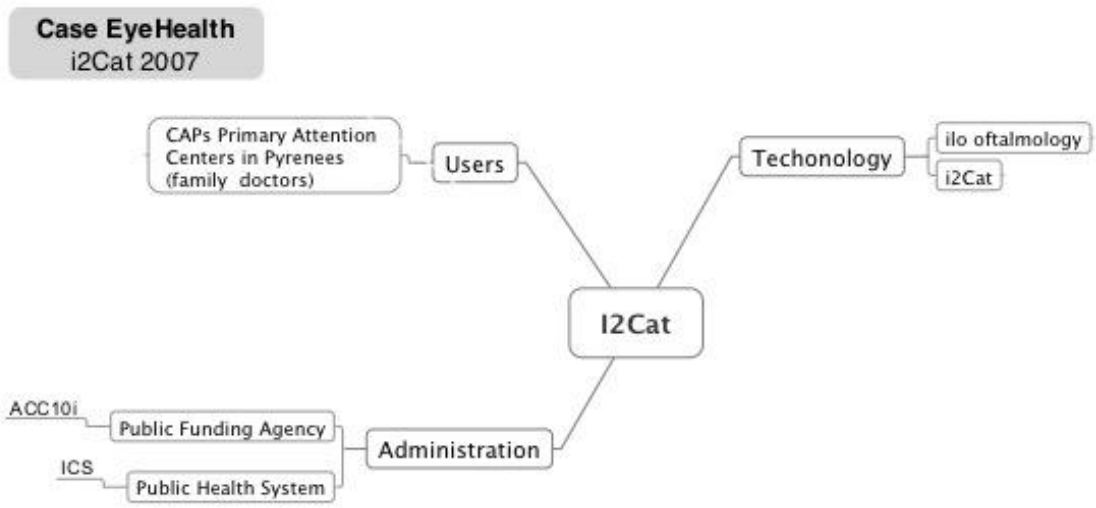


Figure 28. Participants in EyeHealth.

The Contribution of Users

The contribution of users in this project was significant, not only in supporting the project and allowing with their use of the system its further development and acceptance by the family doctors and the administration but also as co-developers.

One of the collective discoveries was the fact that on-line connections were not really needed in most of the cases. This finding allowed the use of flying equipment that worked off-line and moved from location to location in a fixed route, maximizing this way its use.

A nice characteristic of the project was also the diversity of users with whom the interaction occurred. Because of being in different villages and with different particularities they had similar though slightly different needs that enriched the final outcome.

The role of the Living Lab organization

The four main roles that we were discussing in previous cases: enlisting different actors, orchestrating the process, facilitating the technology and mediating with users are present here, too.

Compared to the cases discussed before, this one is more focused on a concrete solution and its implementation allowing more and faster interactions in its development.

6.4.1.4 Cases in Industry

Industry as a sector, presents many opportunities for an organization as i2Cat. Because the Internet has been fueled by mostly addressing end users, it is easy to find gaps and unfulfilled needs in industry, that a faster Internet can address.

Here we will describe a fairly recent but important effort: the Industrial Ring, aimed to explore these needs.

6.4.1.4.1 Industrial Ring

The Industrial Ring (Anella Industrial, 2008) is the youngest and probably the most ambitious project. Building on the success and the experience gained with the Cultural Ring, it aims to explore the benefits and services that high-speed Internet connectivity can bring to large manufacturing companies.

Its inception is similar to the rest of projects previously discussed. A lead user, in this case a professor of the Engineering School (Emili Hernández) in charge of students' projects and heavily involved with the automobile industry, enlisted i2Cat and both began to put the project into motion.

Its first incarnation is in the automobile sector, connecting auto companies (Seat-Volkswagen and Nissan), component suppliers (Gestamp, Ficosa), testing services (Applus-Idiada, Iteuve), engineering and integration companies (T-Systems, Sener, Ansys and Esi) with the two supercomputing centers of Catalonia (Cesca and BSC-CNS) through the participation of telecommunication providers (Albertis and Al-Pi).

Even if the project is still in its early stages we can already see how involving end users directly influences its outcome. In this case, building on the needs of the most advanced users, resulted on two services that again build more on Mid-Low knowledge than on High-level one.

These were the development of a service for large file transmission (typically CAD files are larger than 1GB) and remote car testing providing immediate results for telemetry and the integration for High Definition videoconferencing and monitoring.

Pre-commercial Gap

In a case similar to Opera Oberta, we can see how the lack of a widespread infrastructure prevents the birth of initiatives aimed at its use. And, in that case this factor goes together with the perception of a low and scattered demand because of the target group's focussing on companies and professionals rather than on the general public.

Finally there was also a perception of an undefined and unclear business model in an environment dominated by free services.

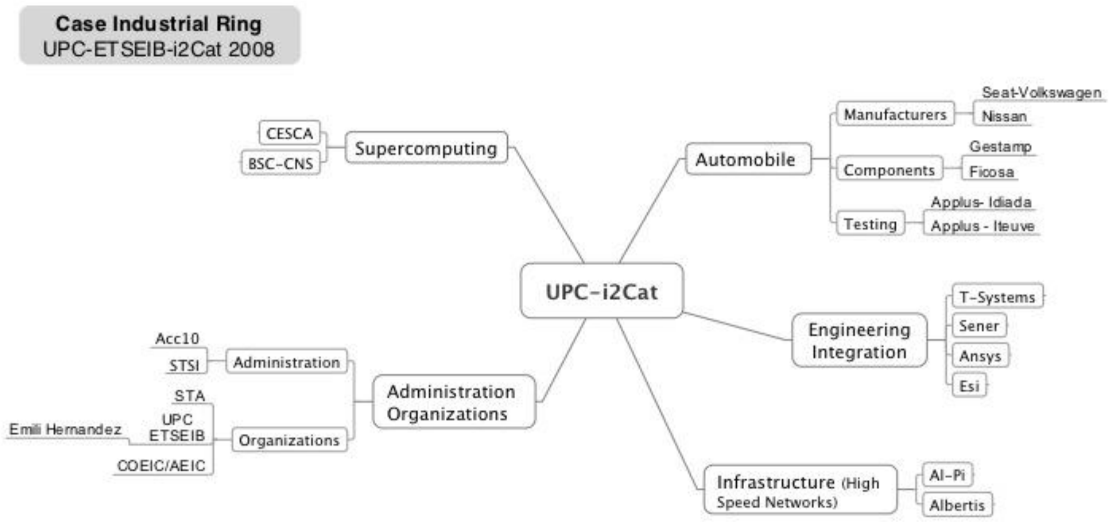


Figure 29. Participants in Industrial Ring.

6.5 Analysis

We summarized our findings in the cases in table 9, our findings are divided in four sections: methods used to close the per-commercial gap, role of users, role of the so-called living lab organizations and how value was captured by the different actors.

One of the means used to reduce the pre-commercial gap was enhancing technological availability, providing different options for solving the problem together with access to pre-commercial infrastructures when needed (high-speed Internet2 networks). Also collaboratively exploring user-acceptance and business feasibility greatly contributed to discard some solutions while accepting others. Finally, in almost all cases, we described how projects managed to mobilize some kind of public procurement creating an initial demand for the proposed service.

The role of users was threefold. First, in all cases they were involved in the validation of the product or service and the associated business model in real life trials. This was a key element for the projects to succeed. This venturesome (Bhidé, 2008) engagement of users provide an opportunity for exploration and allowed learning while sustaining the dynamics of the project itself.

In addition to that, in many cases we find users that could be very well described as quasi-lead-users. Indeed, the empowerment coming from the Living Lab allowed them to function as lead users.

Also, we discussed how the Living Lab organization played four main roles, acting as:

- Connectors. Selecting and enlisting the participants.
- Technology facilitators. Providing access to technologies and research infrastructures beyond the reach of users.
- Orchestrators. Orchestrating the process with milestones and project guidance.
- Mediators. Mediating between users and the rest of the actors, capturing their needs and wills with focus groups, interviews, active participation and ethnographic-like observation.

Value was captured in many cases by means of the new product or service developed, but we have also seen evidence of multiple spill-overs through the process.

	Opera Oberta	**Opera Learning**	**Teleictus**	**EyeHealth**	**Industrial Ring**
Pre-Commercial Gap					
Reducing technical uncertainty	X	X	X	X	X
Use of pre-commercial infrastructure	X	X			X
Exploration of user acceptance	X	X	X	X	X
Validation of Business Models		X	X	X	X
Creation of an initial demand		X	X	X	X
Role of users					
Existence of a “lead-users”	X	X	X		
Users involved in co-creation	X	X	X	X	X
Validation of user needs	X	X	X	X	X
Users involved in exploring business models		X	X	X	X
Role of Living Labs organization					
Enlists participants	X	X	X	X	X
Orchestrates the process	X	X	X	X	X
Facilitates access to technology	X	X	X	X	X
Mediates between users	X	X	X	X	X
Capture of value					
New products/services		X	X	X	X
New processes	X	X	X	X	X
Value captured by public organizations	X	X	X	X	X
Value captured by private companies			X	X	X
Spillovers administration			X	X	X
Spillovers public companies	X	X	X	X	

Spillovers private companies	X	X	X	X	X
Public awards			X		

Table 9. Summary of findings

In further discussing these findings we argue that three main dimensions are present and that is precisely the work in these three main dimensions, which allows closing the gap between pre-commercial knowledge and its implementation in innovative products and services.

Reducing Uncertainty

Assuming uncertainty and the risk associated with it, is the essence and "the reason d'être" of entrepreneurship. It is likewise the reason that prevents many endeavors to leave port and maintains them moored to safe harbor. European societies are in fact widely portrayed as being more risk adverse and this cultural factor has often being pointed out as one of the reasons for limiting entrepreneurship and therefore innovation.

A common characteristic of the cases described is that they manage to reduce the uncertainty, hence the risk, at both personal and team level.

At personal level, establishing a project as a framework for developing the initiative allowed that lead users obtained the permission to use time and resources for the project from the organization they were working for. Therefore, they have been able to pursue their endeavor without having to quit their jobs or making major sacrifices. The framework of a project created by the Living Lab organization allowed them that way to integrate their initiatives as actual duties in their respective organizations.

In *Democratizing Innovation* (von Hippel, 2005) von Hippel writes that "users are the first to develop many and perhaps most new industrial and consumer products". For that to become real, users must be proficient and understand the underlying technology. Open Source is an example of technology developed by users with high technological competences. This is, however, not always the case. Examining lead users, we often find that they are assisted by a company or organization that provides technological expertise. This is the exact same phenomena that we are witnessing here. The Living Lab organization assists and provides the user group with the necessary technology, allowing them to materialize their needs and, again, reducing uncertainty.

Beyond technology, there are two main types of uncertainty remaining: user acceptance and business model feasibility. Again, the living labs organization contributed to lower these risks by providing a group of users and a context where to experiment, almost risk free.

The Entrepreneurial Role of Living Labs

Besides, the Living Lab organization assumed more than a role as an enabler. They established and managed, many times in collaboration with a “lead user”, the innovation networks required to transform users’ needs into real products or services. It has been in all cases the Living Labs organization who was in charge of providing the necessary funds and who invested a significant amount of time and effort to convince partners, the administration or participate in competitive calls for projects in order to secure funding.

Furthermore, it was also the Living Labs organization who recruited experts from research institutes, companies and universities to provide the necessary know how and expertise.

It also convinced companies to invest in the projects, showing them the reduced amount of risk and the potential opportunity at their reach.

Finally, it were the Living Labs who coordinated the innovation network, either alone or in cooperation with lead users or companies.

These three characteristics of selection, formation and coordination of the innovation network are representative of an entrepreneurship attitude, in that case of the Living Labs organization.

Repeated interactions and a sequence of projects result in the formation of a network of companies around the Living Labs organization. Further characterizing this network we can observe a low degree of density in its interconnections and the central position of the Living Labs organization.

We can also notice how the Living Labs organization by involving users and the rest of actors and mediating between them, plays a crucial role in connecting medium and low level of knowledge (Bhidé, 2008) with user needs and economic viability and how this shapes the innovation process.

Innovation is therefore in these cases, not the solely result of technology transfer or mixing technologies but a case of fit. Given that in all cases there were a number of possible technological solutions available, the key aspect was how to find a solution that could fit at technological, business and user needs level.

This fitting is many times the case of high growth startup companies who deal mostly with mid level knowledge (Bhidé, 2008). And it is because knowledge about user needs, organizational structures, etc. is a key element for ensuring this fit, why the presence and the role of users is so important.

The characterization of entrepreneurs as using a trial and error mechanism with direct contact with key users and the market in order to find out functionalities, prices, new ideas, levels of user acceptance, etc. is widely known.

We can therefore argue that Living Labs organizations reproduce, at least in part, not only the entrepreneurial functions but also their mechanisms.

Creating and experimentation arena

Both innovators and scientists highly rely in experimentation in order to accomplish their objectives. Yet, the nature of experimentation in both cases is absolutely different. While scientists seek to understand reality by uncovering casual relationships and use experimentation to falsify previous hypothesis, the innovator experiments are aimed to understand if the product or service works in a certain context, if customers deem it worth to pay and how much or to grab any idea that could help to improve the product.

Living Labs provide an innovation arena, a risk free area, for experimentation where innovation trials can develop. Its dynamics is succinctly captured by the common expression “try it, fix it”, meaning fail fast, try again and learn something in the process.

Developing an initial demand

New products cannot be successful without a user community eager to try and use this first version many times full of flaws, lacking important functionalities and with some or sometimes many technical glitches. The software industry has institutionalized this process with the “perpetual beta” concept. This user community provides the demand necessary to finance and sustain the development of a second or third version where many times this buggy product develops becoming a great one.

In this paper, all cases but one (Industrial Ring) rely on public procurement to ensure this demand. Industrial ring relies on the willingness of the big corporations involved in the project to go forward with it.

This initial demand is thus generated by involving either public organizations (health care and education are mostly public services in Spain) or corporations in the project. Therefore, they act as market creators.

It is important to note that this process can be of considerable size. In the case of Teleictus, for example, the service is, at the moment of the writing, being deployed to the whole network of Catalan hospitals.

6.5.1 RQ 1 User contributions

As we have documented, users contribute in Living Labs in a variety of ways. Using high speed Internet for transferring huge CAD files or providing remote telemetry services, such is the case of the Industrial ring, is a direct translation of lead-user needs. Another example EyeHealth were direct connections were replaced for temporary storage and batch processing.

However, the most common case of identification, codification and incorporation of knowledge in the hands of users can be found when dealing with tacit knowledge. Tacit knowledge is present and its codification is in fact present in all cases. A clear example of that is the incorporation of knowledge about placement of equipment in Teleictus or also in the search for a business model that could fit a complex project where a public health system with central and satellite hospitals is involved with private companies.

There is also a third type of knowledge in the hands of groups of users, especially lead users. This is domain specific knowledge. Again we can find many examples of the use of domain specific knowledge. Opera Oberta, because of its specificity probably provides the most clear cases. This is the case of the need of raising the quality of the music channel in spite of the one of the video or many specific issues about placement of the equipment and loudspeakers or insights about contents programming or diffusion.

Due to the iterative process inherent to Living Labs, we can find many similarities to iSpace theory described by Boisot (2007). In almost all cases we can find how users translate uncodified knowledge by validating it in experimental situations. From here, the results are codified and diffuse into the network of actors which, in our study, was the Living Lab networks. Accordingly, we formulate the following propositions.

> **Proposition 1a.** Living Labs observe user-lead practice in diffuse social contexts.
>
> **Proposition 1b.** Living Labs identify and codify tacit and practice based knowledge.
>
> **Proposition 1c.** Living Labs diffuse tacit and practice based knowledge into ad hoc innovation networks.

6.5.2 RQ2 Exploration and exploitation

The type of risk associated with exploration is probably the most evident because of its magnitude. This type of risk can be divided into technological, personal and market risk.

Technological risk relates to both technology availability and suitability for the intended task. Here we can find in all the cases how Living Labs reduce this risk. Almost all cases presented are based on the use of pre-commercial, research oriented platforms for experimentation. Such is the case of Opera Oberta, Opera Learning, Industrial Ring and Telecictus that use totally or partially the Catalan Internet2 network.

Personal risk is also a limiting factor, its assumption is a characteristic of the entrepreneur. Living Labs can mitigate of this risk by creating an innovation arena that mostly takes the form of a project financed by European, National, regional or directly by the funds of the Living Lab.

Finally, Living Labs also contribute to reduce the risk associated to user acceptance. They do this by creating an initial demand for products and services drawing on public procurement or on the capacity of the partners involved. This initial demand is a necessary condition for developing the product in real life environments and reverts once the project has finished in an steady flow of demand that covers the early stages of product development. Probably the most significant case, among the ones revisited in this paper, is the one of Teleictus, because this initial demand and the later support and adoption by the Catalan Health System is allowing its deployment through the whole Catalonia, but all projects equally enjoyed this benefit.

By contrast, exploitation is the process of selecting, implementing and validating successive refined prototypes in real life environments. If we examine with detail the cases presented we can observe that all of them relate to complex multi-stakeholder environments where coordination costs and business models are not so obvious. In the case of TeleIctus and EyeHealth we can find the mix of a highly complex public health system together with private companies, same case in Opera Oberta and Opera Learning and in the Industrial Ring we find the need of reliance in a public sponsored Internet2 platform made up with segments of dark fiber belonging to different administrations.

This consideration is important in terms of exploitation both for further developing the product or service and for finding a business model that could fit in this multi-constituency environment. Living Labs, because of their neutrality as organizations that come mostly from research or technological centers, are in a privileged situation to manage and provide governance to this type of projects. This is especially evident when contrasted with an start-up that will certainly be discouraged by the difficulties in capturing value and finding a model for governance. Hence, propositions 3 highlight the role of exploration and exploitation.

> **Proposition 2a.** Living Labs perform exploration by assuming Knightian risk, experimentation and discovery.

> **Proposition 2b.** Living Labs perform exploitation via refinement, selection, implementation and execution.

6.5.3 RQ3 Innovation types and levels

Bhidé (2009) argues that innovation levels can be high, mid, and low–level. High level innovation is basic research and easily transportable across national context, where mid- and low-level innovation constitute context defined adaptations that facilitating the adoption and use of new products and services.

This analysis fits well into our Living Lab cases. There we find exercises dealing mostly with low level innovation, where business models, customer adoption, interfaces, and other facets of the local social context were far more significant than the basic technologies.

For example, in the case of Opera Oberta & Opera Learning, the challenge was more in coordinating the experimental network of dark fiber, convincing the partners, find a suitable business model that could maintain the project first and the offering later and implementing existing technology (high - definition video-conferencing) into a novel context. A similar case was in TeleIctus, with the variation of the need for component integration between, high-definition video-conferencing, tele-monitoring and tele-diagnostic, together with the existing systems in the Catalan Public Health network. Similar cases can be presented for the Industrial Ring or EyeHealth. Accordingly, propositions 4 are presented.

> **Proposition 3a.** High Level innovation is highly portable across international contexts, where mid and low level innovation is localized, geographically and spatially bound.

> **Proposition 3b.** Living Labs operate and mid and low level innovation strata.

6.5.4 RQ4 Incremental or radical innovation

The evidence of the cases presented also show a mix of radical and incremental innovations. In Opera Oberta - Opera Learning high speed Internet is used for distributing live Opera contents to several theaters and potential home viewers. We can think of it as a radical departure from the established system of on-site performance. In the other extreme, the use of high speed networks to transport huge files and remote telemetry is probably better situated as an incremental innovation in practice, together with the cases of TeleIctus and EyeHealth.

Even if the size of the sample is limited, we can witness how its distribution is skewed towards incremental innovation. This may also be consistent with the real world, where incremental innovations are more prevalent overall.

A different way to characterize this process is portraying it as a process of fit, where innovations seek their fit in a precise context at social, interaction and manifestation of business value through an iterative process. We can probably all agree that this process of fit is neither exclusive of radical nor incremental innovations. In fact, both types of innovations can benefit from it.

> **Proposition 4**. Living Labs are agnostic as to whether innovation is technologically incremental or radical.

6.5.5 RQ5 Product evolution or interpretation of meaning

Boisot et al (2007) argues that experiential knowledge is codified and diffused through and social lifecycle of knowledge. This social validation process, resulting from testing hypothesis in real life environments and reusing them if successful is a key element of Living Labs. Tuomi (2002) highlights meanings from products and services as a social construction coming from social practice. Hence, social validation of knowledge can occur both in the accepted realm of a product's meaning, but also a new, renegotiated definition that emerges either accidentally or purposefully (Vernganti 2008).

Probably the most salient evidence of this process in the Living Labs sample occurs in novel uses that open the door of new practices. In the cases described, we can find some clear examples of this process, such as the reinterpretation of Opera Oberta as a learning tool involving a large network of Spanish and South American Universities or the use of EyeHealth as a platform for the advancement and education of rural doctors in ophthalmology. In both cases, meanings are completely redefined not only as a result of random events or serendipity, but also situated in purposeful interaction processes. Accordingly, our analysis suggests that that living Labs are equally aligned towards both accepted social meanings as well as the generation of new interpretations.

Proposition 5a. Living Labs perform context-based experimentation in order to generate local modifications within existing socially negotiated meanings.

Proposition 5b. Living Labs perform context-based experimentation in order to generate new socially negotiated meanings for products and services.

6.6 Discussion and Conclusion

A cross case analysis of Living Labs has found that the function in closing the pre-commercial gap by manifesting initial demand for products and services as well as orchestrating the actions of disparate actors in order to gain critical mass for the creation of a product or service. They observe, codify and diffuse tacit knowledge based in specific social settings. They also facilitate both exploration and exploitation at mid- and low- innovation strata. Finally Living Labs are agnostic to whether their innovation are incremental or radical, and work both within existing social meanings, as well as to renegotiate them.

As a novel, emergent concept, delineating Living Labs against other forms of innovation intermediaries remains challenging. Clearly, future empirical work can add to the theoretical precision, as well as greater understanding of their predominant methods and relative advantages.

7 Conclusions and Outlook

In the last decades we have been witnessing to an important transformation in both the relative importance of innovation as an economic drive for growth and change and how the innovation process unfolds.

Advances in technology and changes in consumer behavior together with the entrance of Asian low-cost, high-skilled producers moved the focus from production and effectiveness to innovation and added value. And by doing it, they increased the number of technological possibilities available, enlarging the space of potential solutions exponentially.

At the same time, the Internet has changed many of the rules of the game. By making information and knowledge easily available to almost everybody,. as well as by greatly enlarging the capacity to connect, both people and ideas, and therefore the way and the speed at which innovations diffuse and evolve.

This increased communication capacity obviously affected the velocity at which recombination takes place, but also the social validation and construction of theories and proposals and thus the formation of meanings.

These three elements: technological advances, broad availability of knowledge and increasing capacity of "*being connected*" were the main culprits of the changes in the locus and in the way innovation takes place. Companies and society in general cannot rely anymore on selected and small R&D groups as the sole source of innovation. Best minds are everywhere and so are the best ideas. Therefore the focus is changing from a high-end unique R&D capacity to being able to "*connect & develop*" through collaboration.

Advancing the understanding of this collaboration in environments of varying complexity and discussing how insights can be captured from a broad range of actors in real life experimentation environments, has been the objective of this thesis.

We have delved into how collaboration can increase the explorative capacity of agents who relinquish control of part of their strategic components to their partners and how this apparent loss of capacity results in a better performance than the ones with full control.

There, our main contribution has been around explaining when Open Innovation is superior than Close Innovation and vice-versa. We found that three main parameters should govern this decision. First the level of complexity at which we are operating. Secondly the openness of the partnership set that a certain type of business can sustain because of coordination costs. And finally, the number of agents available in a certain industry. This last factor is many times a substitute for the previous one, because in activities with a low number of participants the partnership set tends to close.

We have also contributed by understanding how the process of collective discovery arises from restricting rather than fully exercising strategic freedom and learning by choices made by others.

Next, we discussed the increasing importance of institutions that aggregate and process information from agents' "*Best Cases*" and with it construct hypotheses, elaborate new theories and uncover "*Best Practices*".

Here our main contribution lies on presenting a model for collective learning mediated by an institution. And using this model to explain how critical is the selection of cases, because better results are achieved by sampling a small set of the best ones.

The revealing of the critical role that adoption plays in the process of validating or falsifying theories coming from patterns or statistical inferences is also a key contribution of this section.

Both, result in clear insights in very practical aspects, like how many best cases to sample, how comprehensive they should be or how is better to use cases and how statistical inferences such as regression analysis could provide more interesting insights together with when agents can safely rely on the insights of Business Schools and when they should actively pursue innovation.

Again complexity reveals itself as a key explanatory variable, but not only complexity but also the role of the agents who by adopting and validating or falsifying the insights of business schools play a crucial role on exploration. This social aspect of theory building, where business schools propose hypothesis and the community of agents perform the experimentation. A key element of this process is, of course, an entrepreneurial society and here the set of incentives and cultural values play a major role.

However, our models, even if they are able to provide new insights and with them contribute to our understanding of innovation, lack relevant aspects of the real world.

Among them, competition. Innovation is certainly a societal quest, but it is also a key element in strategic competition and even if knowledge is a non-rival good, the consequences derived of its use can provide significant advantages to first-movers or to agents enjoying an incumbent position in the market. Modeling competition is therefore necessary if we want to understand collaboration.

There is also a second important aspect, this time at societal rather than individual level. Agents are not equal in embracing innovation, nor is it possible for any society to foster innovation by uniformly raising the levels of technology adoption or entrepreneurship. There is indeed a large history of policies designed to promote start-up creation, to enhance entrepreneurship, or to help SMEs in the adoption of new technologies. Introducing these differences in our models will surely help in understanding not only innovation dynamics but finding out tipping points and size effects.

When dealing with concrete implementations of the collaborative aspects of innovation, such as Living Labs, the insights from the theoretical models appear to be more relevant than ever. Certainly, Living Labs attempt to capture the insights of seemly large groups of users and incorporate them into the innovation process. They are not alone in this attempt, many other exercises such as crowdsourcing aim a similar purpose.

In this area we aimed to understand the contribution of this new form of mediated user involvement in innovation. We did that by understanding their contribution in codifying tacit and practice-based knowledge and conveying domain knowledge into ad-hoc experimentation environments. Because of the type of contribution, they operate mostly at mid-low level innovation seeking the "fit" of products and services at three levels: technological, social by creating and changing meanings and business model.

However, Living Labs are as much about experimentation in real life environments as they are about user involvement. In this area our findings reveal that reproduce many aspects of start-ups, such as supporting entrepreneurship, creating an innovation arena and fostering an initial demand that allows further product development. They do that by involving partners from multiple sectors such as academia, government, companies and users. This multiple involvement makes Living Labs particularly apt in complex multi-contextual environments where start-ups could not have the necessary capacity for coordination.

This is however still an area of exploration. We still know little about who, when, how and why users should be involved in the innovation process and we probably know even less on the most adequate mechanisms for the governance of this involvement.

Two main vectors guide user involvement. On one side we have a continuous between expert-lead and user-lead innovation. On the other we have the two opposite forms of governance: open and closed models. Between them we can find many variations such as Marketplaces, crowd-sourcing, Open Source or Living Labs are among others, that attempt to structure and provide governance to this involvement. When ones are more appropriate than others, how incentives should be managed and how users should be approached and selected are still questions open to discussion.

Maybe one of the most interesting aspects is how to capture value from this involvement. In all cases we try to build on the diversity of insights of a large number of participants for creating a larger offer, such as in marketplaces, contributing with domain knowledge to a collective endeavor, such as in Open Source and crowd-sourcing projects or using this diversity for providing fit, such as in Living Labs.

There is in all cases, a process of collective construction and aggregation that is probably not adequately mapped in current practices. This process relies on the construction of shared meanings and understandings. And, as we have discussed in our simulations, this is an iterative process that relies on the aggregation of information and the adoption and posterior validation or falsification of hypothesis. This is a process mostly driven by greedy agents constantly looking for improvement, eager to sacrifice and walk this extra mile that could make them succeed in the market. Both, the motivation that drives adoption and the mechanism for aggregation are not yet well understood and represented not only in Living Lab exercises but in general in Open Platforms.

And it is precisely in these open real world scenarios where many interesting things are happening around collaboration. Among them, we are witnessing the confluence of competitive mechanisms like markets with collaborative ones. We are also witnessing how interaction labs are leaving the corporate walls for facing real life environments in the wild. Platforms are becoming the new scenario for experimentation and innovation. Platforms have indeed some mechanisms for capturing value and develop competition. And yet, user participation, collective creation through a process of aggregation and diffusion that fosters recombination, are aspects still underdeveloped. These aspects are the ones who hold the seeds of future innovation and where this thesis aimed to provided a modest contribution.

Appendix A

Lemma: Absent epistatic interactions between α and β, "Complete Product" and "Sale to OEM" specifications are equivalent.

Proof: We only need to show that given locations of firms on the landscape, any player will want to make the same choice regardless of whether the model is one of "Complete Product" or "Sale to OEM." (We present the argument for the "Fixed Partnerships" specification but it applies unaltered to the case of "Flexible Partnerships.")

Let us look first at the case of "Complete Product." Given the locations of all firms, think of a Firm α that is considering what product feature to reconfigure. It will reconfigure that feature s_i, i=1,…,8 such that the contribution to fitness is maximal. Fitness in this case is computed as:

$$(c_1+c_2+c_3+c_4+c_5+c_6+c_7+c_8+c_9+c_{10}+c_{11}+c_{12}+c_{13}+c_{14}+c_{15}+c_{16})/16$$

where c_i is s_i's contribution.

Suppose that the feature that raises fitness the most is s_7. Without loss of generality, we may assume that s_7 interacts epistatically with s_1 and s_4. The crucial assumption here is that s_7 does not interact epistatically with s_i, i=9,…,16.

The new payoff is then:

$$(c'_1+c_2+c_3+c'_4+c_5+c_6+c'_7+c_8+c_9+c_{10}+c_{11}+c_{12}+c_{13}+c_{14}+c_{15}+c_{16})/16$$

where c'_1, c'_4, and c'_7 are the contributions associated to choices s_1, s_4, and s_7. Notice that only s_7 has changed (from 0 to 1 (if it was 0 before) or from 1 to 0 (if it was 1 before)) but the epistatic interactions also change the contributions of s_1 and s_4.

We may obviously rewrite this as

$$(c'_1+c_2+c_3+c'_4+c_5+c_6+c'_7+c_8)/16 + (c_9+c_{10}+c_{11}+c_{12}+c_{13}+c_{14}+c_{15}+c_{16})/16.$$

Notice that the second component of the sum is a <u>constant</u> from the point of view of Firm α (this is so because we are assuming that there are no epistatic interactions between α and β).

Consider now the "Sale to OEM" model. Suppose that the situation is exactly as before (same landscape and same locations of all firms on the landscape). Firm α is considering what product feature to reconfigure. It will reconfigure feature s_i, i=1,…,8 such that the contribution to fitness is maximal. Fitness in this case is computed as:

$$(c_1+c_2+c_3+c_4+c_5+c_6+c_7+c_8)/16.$$

Clearly, the feature that raises fitness the most should be s_7. The increase in fitness in the case of "Complete Product" came only from contributions associated to features that enter the fitness function of Firm α in the case of "Sale to OEM," therefore, if s_7 was the feature that raised fitness the most before, it must be the one that raises fitness the most now also.

Therefore, the two models are equivalent.

Note that when epistatic interactions occur across subsystems (α and β), then the two models are not equivalent because in this case

$$(c_9+c_{10}+c_{11}+c_{12}+c_{13}+c_{14}+c_{15}+c_{16})/16$$

does not remain constant when Firm α reconfigures some of the product features under its control.

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