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Knowledge Exchange in Innovation Networks and Innovation Policy for Networks – An Example of Policy Informatics

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Innovation Policy Evaluation

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- Policy makers almost desperately complain about the difficulties in promoting innovation.

- Innovation policymakers and business managers expect that investments in R&D will immediately produce a flow of products and processes with high commercial returns.

- Innovation managers mention a frustration with the messy and complicated features of the innovation process, which simply "does not seem to compute."

- Without a doubt socio-economic systems are confronted with a high degree of complexity when it comes to the development of new knowledge, its diffusion, and its commercial application in innovation.

- In the case of innovation, agents are confronted with true uncertainty that makes any forecasts and predictions impossible.

- Any analytical approach that tries to offer guidance and support for political decision makers has to acknowledge this intermingling of rich complexity and uncertainty.

- Policy consulting in the past has relied on the idea of a linear sequential innovation process with the invention and innovation phases strictly separated.

- Consequently, the complex interactions of heterogeneous actors were de-emphasised by assuming the actors to be endowed with an Olympic rationality that allowed them to apply an optimization calculus for their decisions.

- The major problem was identified in the existence of technological spillovers which distort the incentives to invest in R&D.

- Therefore, preventing technological spillover was frequently considered as the most important target.

- Since the 1990s in practical innovation policies innovation networks become prominent and challenge the idea of technological spillovers.

Structure

1. Innovation Policy Evaluation

2. Why are innovation networks the better alternative compared to technological spillovers when analyzing innovation processes?

3. How can learning and strategic choices in innovation networks be modelled?

4. How simulation models uncover hidden structures?

The Public Good Features of Knowledge

The renaissance of economic growth theory in the 1980s was heralded by a positive interpretation of technological spillovers.

With the help of these positive feedback effects (stemming from the public good nature of technological knowledge) the bottleneck of diminishing growth rates has been put away.

from **old** to **new** growth theory →

with technological spillovers

From technological spillovers to innovation networks

This positive interpretation, however, was at odds with the negative interpretation of technological spillovers prevailing in industrial economics (from the 1950s to the 1980s) where the public good features were also considered as distinguished feature of new technological knowledge.

There, the particularities of innovation processes were reduced to the standard set of modeling techniques:

- Agents optimize.
- The focus is on equilibrium.
- True uncertainty doesn‘t matter.
- Perfect competition as benchmark.

From technological spillovers to innovation networks

Technological spillovers - being the consequence of the public good nature - are considered as **incentive reducing:** Third parties can benefit from the new knowledge without contributing to its costs.

This kind of knowledge transfer happens involuntarily!

$$y_i = f(x_i, \ldots, x_n, r_i, Z_i) \qquad Z_i = \beta \cdot \sum_{\substack{j=1 \\ j \neq i}}^{m} r_j$$

y_i := Output of firm i

x_i := Inputs in the production of firm i

r_i := R&D-expenditures of firm i

Z_i := Spillover-Pool of firm i

β := Spillover-Parameter; β between 0 (private good) and 1 (public good)

r_j := R&D-expenditures of another firm j

From technological spillovers to innovation networks

$$\frac{\partial r_i}{\partial \beta} < 0; \quad r_i = 0 \; if \;\; \beta = 1$$

With public good features we have $\beta = 1 \rightarrow$ free-rider problems

This leads to a negative interpretation of technological spillovers: The private incentives to invest in R&D are smaller than the social optimal incentives.

Market-failure:

- State as knowledge producer (e.g. basic research)
- Implementation of intellectual property rights
- Subsidizing of industry research

From technological spillovers to innovation networks

Is new technological know-how a **pure** public good? Additional features of knowledge:

i) firm-specific (tacit)

ii) technology-specific (local)

iii) cumulative and complex (absorptive capacities)

From i) and ii) follows that β usually is smaller 1.

From iii) follows , that even if β = 1, it is not clear whether third parties may benefit from spillovers. They have to provide absorptive capacities μ to integrate the spillover.

$$y_i = f(x_i, \ldots, x_n, r_i, \mu_i \cdot Z_i)$$

$$Z_i = \beta \cdot \sum_{\substack{j=1 \\ j \neq i}}^{m} r_j$$

$$\mu_{\hat{\imath}} = g(r_i)$$

From technological spillovers to innovation networks

Besides appropriability conditions also **technological opportunities** play an important role.

In industries with rich opportunities we find stronger R&D activities compared to industries with low technological opportunities (e.g. compare biotechnology and textiles).

Technological opportunities of different technologies may influence each other. So called **cross-fertilization** effects (or technological complementarities) create rich new technological opportunities (e.g. bio-informatics, CNC-machine tools, optoelectronics …).

Technological advances in some technologies can have an impact on the overall technological development (e.g. computer technologies, dynamo, mass production …). For this deep effect the term **general purpose technologies** is used.

In the case of technological complementarities so-called idea-creating effects of technological spillovers are much more important than incentive-reducing effects.

(T_i := technological opportunities)

$$y_i = f(x_i, \ldots, x_n, r_i, T_i, \mu_i \cdot Z_i)$$

$$Z_i = \beta \cdot \sum_{\substack{j=1 \\ j \neq i}}^{m} r_j$$

$$T_i = T_i(r_i, Z_i)$$

$$\frac{\partial T_i}{\partial Z_i} \begin{cases} > 0 & \text{in the case of technological complementarities} \\ = 0 & \text{in the case of not related technologies} \\ < 0 & \text{in the case of technological substitutes} \end{cases}$$

From technological spillovers to innovation networks

The detailed view on technological knowledge and its features leads to a different interpretation of technological spillover effects:

Incentive-reducing effects change to **idea-creating** effects. Spillovers are now interpreted positively.

Conclusions for technology policy:

Create technological spillovers

e.g. technology transfer

e.g. collaborative R&D

From technological spillovers to innovation networks

Instead of R&D expenditures as an approximation of innovation the **knowledge base of companies** and firm learning moved into the center of interest:

„Firms cannot produce and use innovations by dipping freely into a general ‚stock' or ‚pool' of technological knowledge." (Dosi, 1988, S. 225)

„In particular, what often appears to be an involuntary flow of knowledge between firms may be nothing more than a pair of draws from a narrow but common pool shared by a group of agents within a common set of problems." (Geroski, 1995, S. 85)

From technological spillovers to innovation networks

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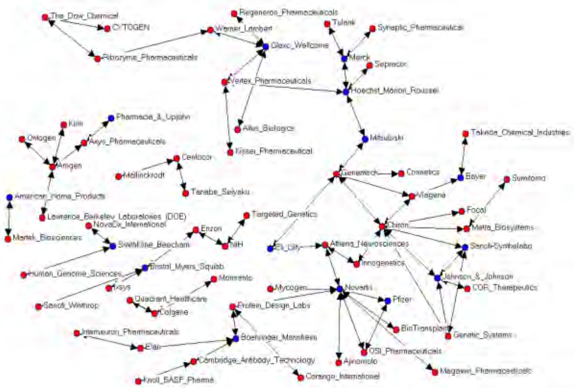
„The dominant mode of innovation is systemic. Systemic innovation is brought about through the fission and fusion of technologies; it triggers a series of chain reactions in a total system. … The interactive process of information creation and learning is crucial for systemic innovation … The characteristic trait of the new industrial society is that of **continuous interactive innovation** generated by the linkages across the borders of specific sectors and specific scientific disciplines.“ (Imai/Baba, 1991, S. 389)

In modern innovation research innovation networks are considered as an advantageous organizational device for complex innovation processes.



2. Modeling innovation networks in an agent-based framework

The recent literature focuses on knowledge creation and knowledge diffusion (instead of optimal R&D budgets).

To model realistically processes in networks one cannot draw on R&D expenditures (e.g. large companies would always have an advantage over smaller companies).

For the analysis of innovation networks therefore the structure as well as the dynamics of firms‘ knowledge bases matters.

Naturally, the complexity involved in the analysis is almost exploding. An important question is: How can one approach the knowledge base of a company, knowledge emergence and diffusion?

A new modelling approach is moving into the center of interest: Agent Based Modelling.

Agent-based modelling

Agent-based Modelling is a computational methodology that allows the analyst to create, analyse, and experiment with artificial worlds populated by agents (computer programs) that interact in non-trivial ways.

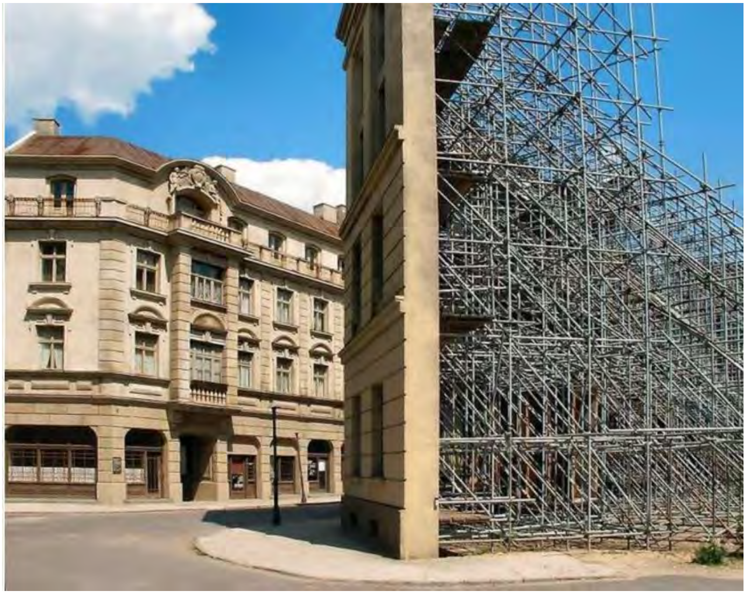
- Agents are units that have behaviour
- They act within a (simulated) environment
- Agents can
  - react to other agents,
  - pursue goals,
  - communicate with other agents,
  - move around within the environment
- Macro-level features can emerge from the interaction of agents

Agent-based modelling

► From understanding causalities to understanding system behaviour

► ABMs do not focus on the understanding of causal mechanisms but develop tools to understand system evolution and the impact of interventions into the systems.

► ABMs allow to investigate complex systems; however ABMs remain simplifying models.



2. Modeling innovation networks in an agent-based framework

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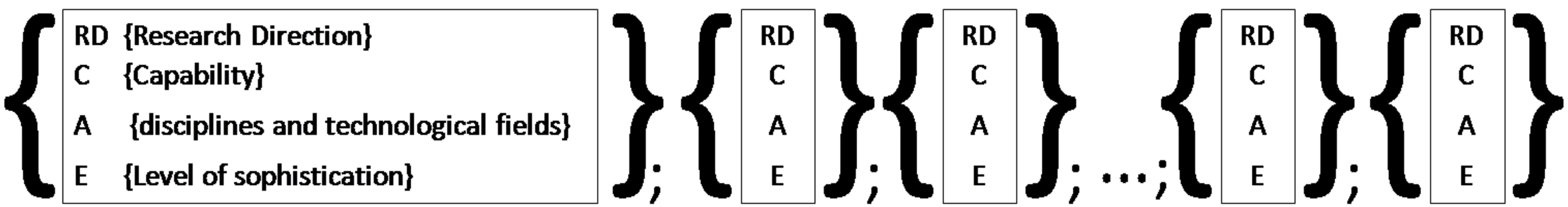
SKIN (Simulation of Knowledge and Innovation Networks) by Petra Ahrweiler, Nigel Gilbert und Andreas Pyka

The knowledge of a firm is modeled as a Kene: A Kene is a set of knowledge elements of variable size.

Each unit (quadrupel) is composed of a research direction RD, the competences C, the corresponding abilities A as well as the expertise E.



2. Modeling innovation networks in an agent-based framework

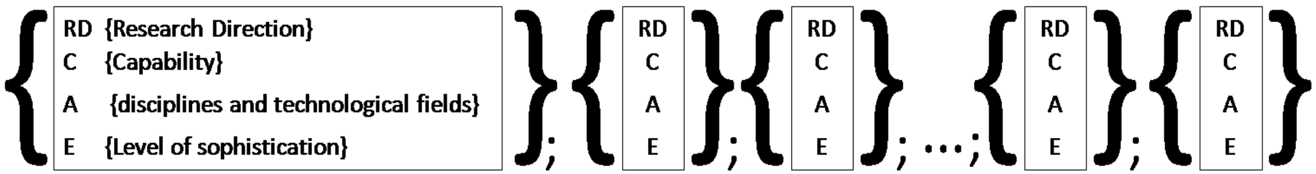
The Kene

RD (research direction) $\in$ {0, …, 9} 0:= pure basic research; 9 := pure applied research

C (capabilities) $\in$ {0, …, 1000} competence in a scientific domain e.g. organic chemistry ~ 3-digit IPC code C07 (organic chemistry)

A (ability) $\in$ {0, …,10 } specific ability e.g. preparation of peptides ~ 4-digit IPC code C07K (preparation of peptides)

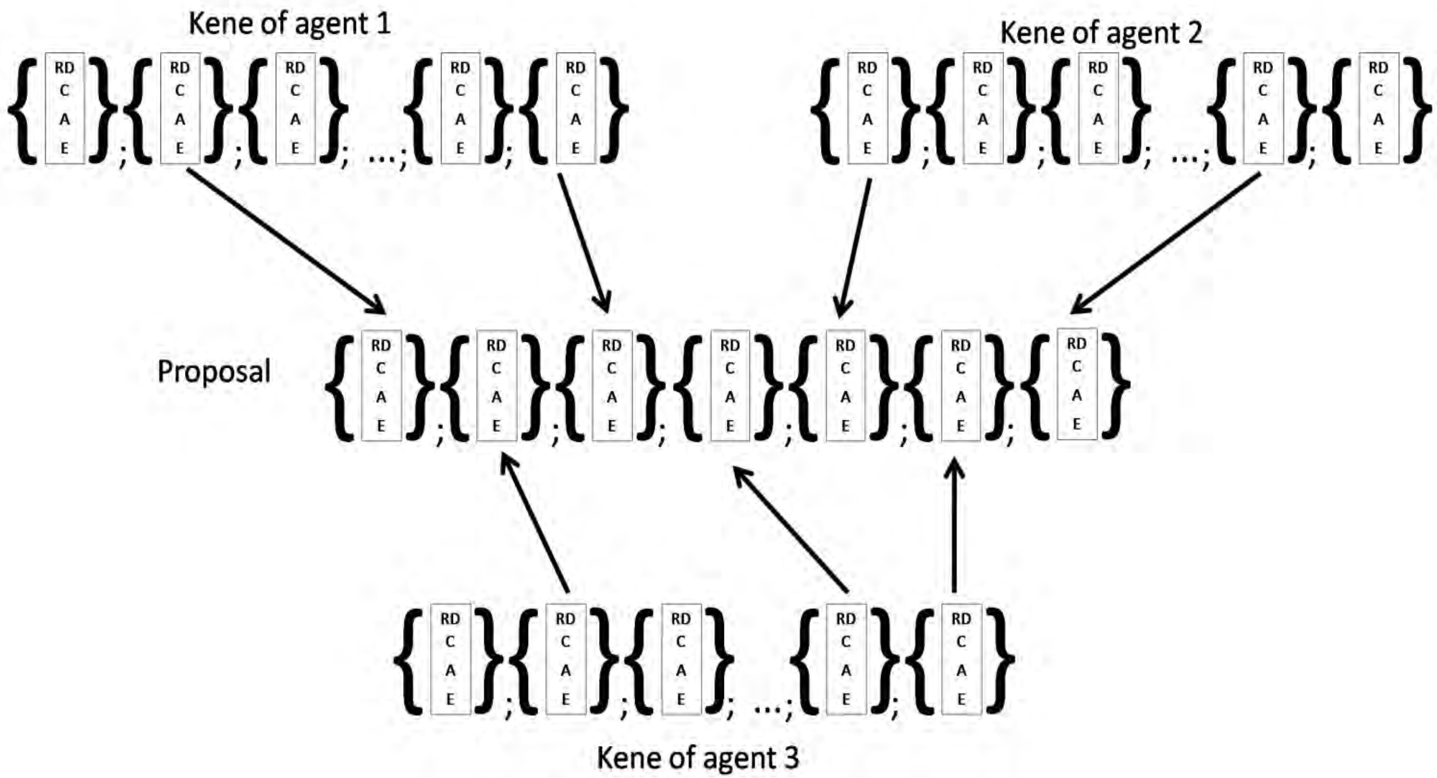
E (expertise) $\in$ {0, …, 40} 0:= not available



R&D

- Radical Research -> new knowledge fields (C) are tested
- Incremental Research -> new ability (A) is tested
- Application of knowledge –> expertise (E) is growing

Learning in Networks → Combination of Kenes



Knowledge Metrics I

- The integration of external knowledge as well as the success probability of its application in joint research project depends on the „knowledge distance“.
- Very different knowledge (large distance) -> success probability is low; potential impact of the innovation is large.
- Very similar knowledge (small distance) -> success probability is high; potential impact of the innovation is low.

Knowledge Metrics II – Strategic decisions

To select partners in the networks, the agents use the similarities and dissimilarities of the knowledge bases.

Two strategies are considered (the real motivation of actors is hidden):

a) Conservative strategies: Partners with large overlapping knowledge bases are preferred.

b) Progressive strategies: Partners are preferred whose knowledge base is most distant.

Empirical innovation networks:

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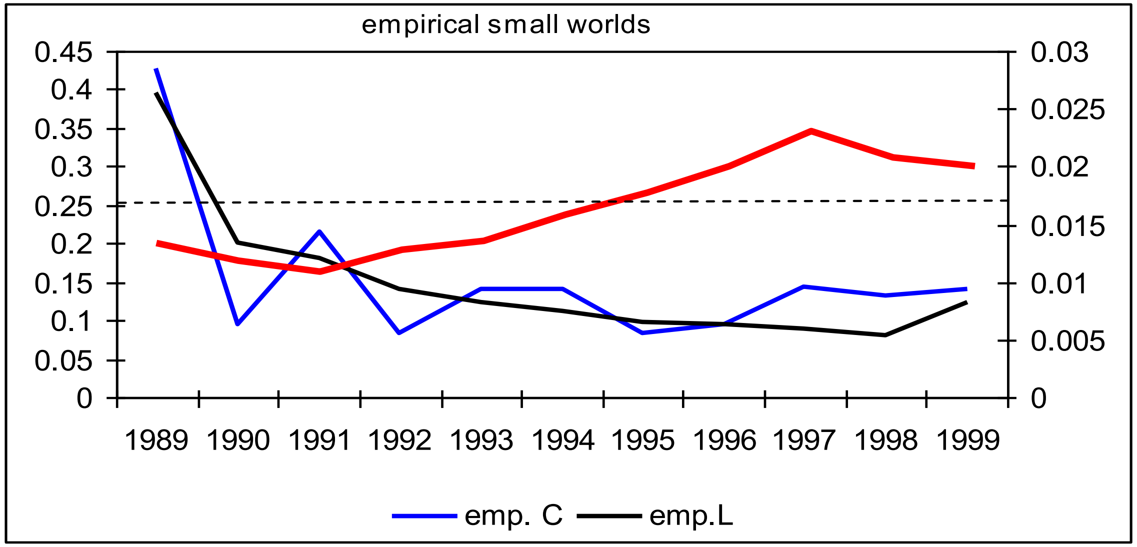
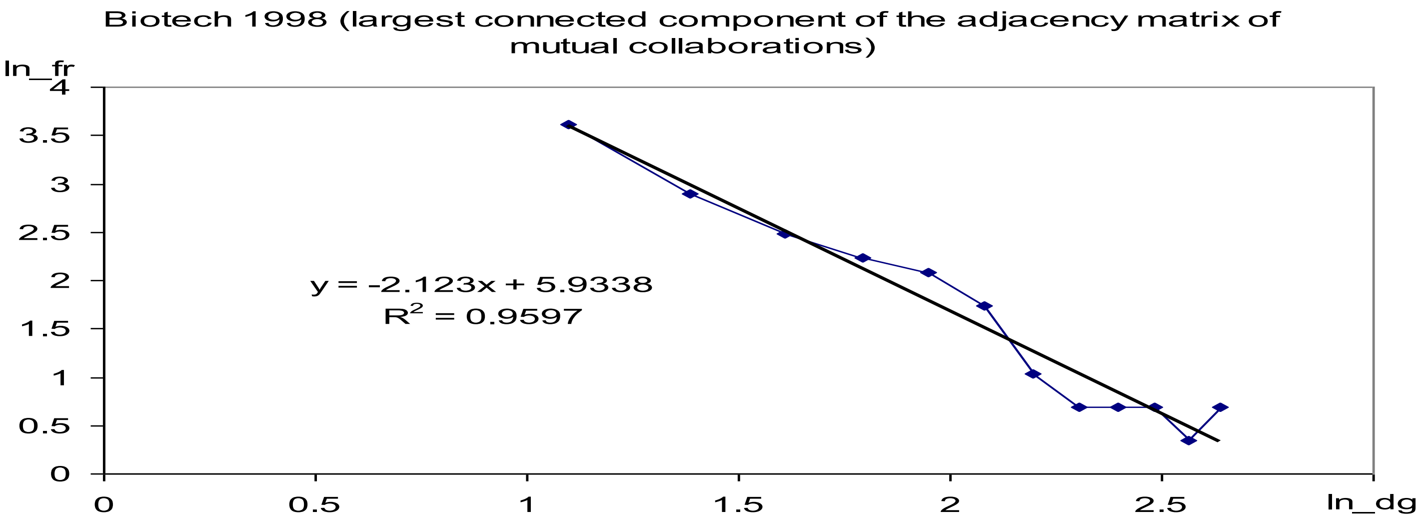


2

Small Worlds:

$$SW = \frac{C_{empirical} / C_{random}}{L_{empirical} / L_{random}} > 2$$

[Watts 1999]



Scale-free Networks: Degree-distribution is a Power-Law-distribution:

$P(k) \sim k^{-\gamma}$

[Seyed-Allaei, Bianconi, Marsili 2006]

Artificial innovation networks:

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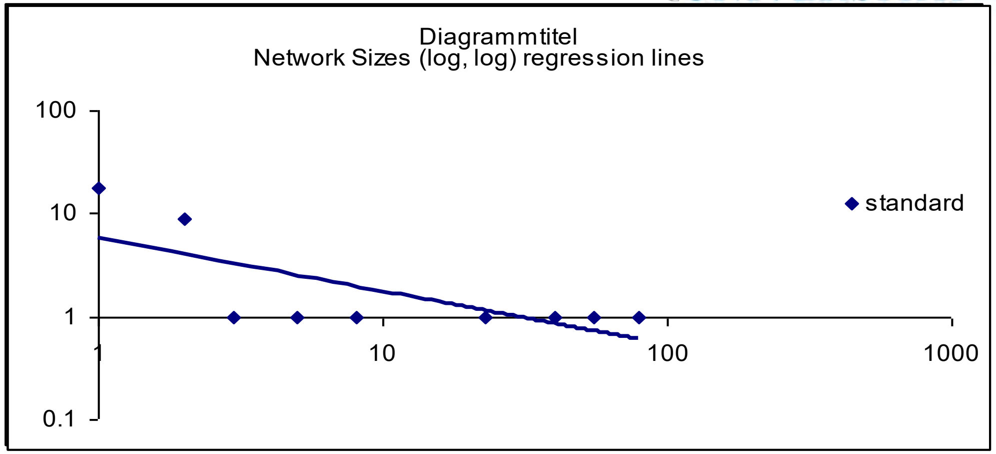
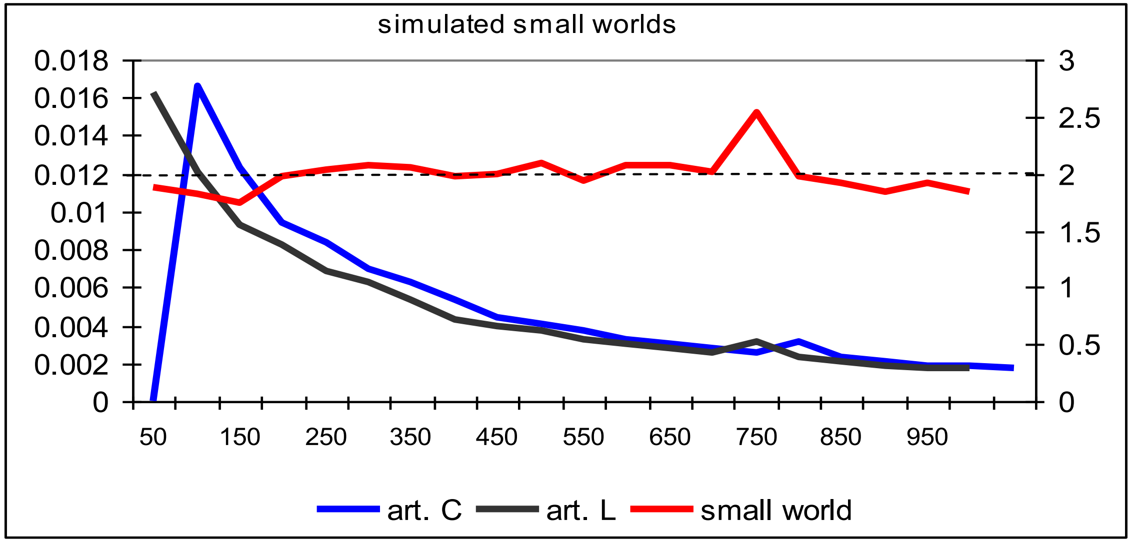


	standard
coefficient of power law distribution (R^2)	1.53 (0.822)



Testing policy options for Horizon 2020 ICT

JASSS

Petra Ahrweiler, Michel Schilperoord, Andreas Pyka and Nigel Gilbert (2015)

Modelling Research Policy: Ex-Ante Evaluation of Complex Policy Instruments

Journal of Artificial Societies and Social Simulation **18** (4) 5
<http://jasss.soc.surrey.ac.uk/18/4/5.html>
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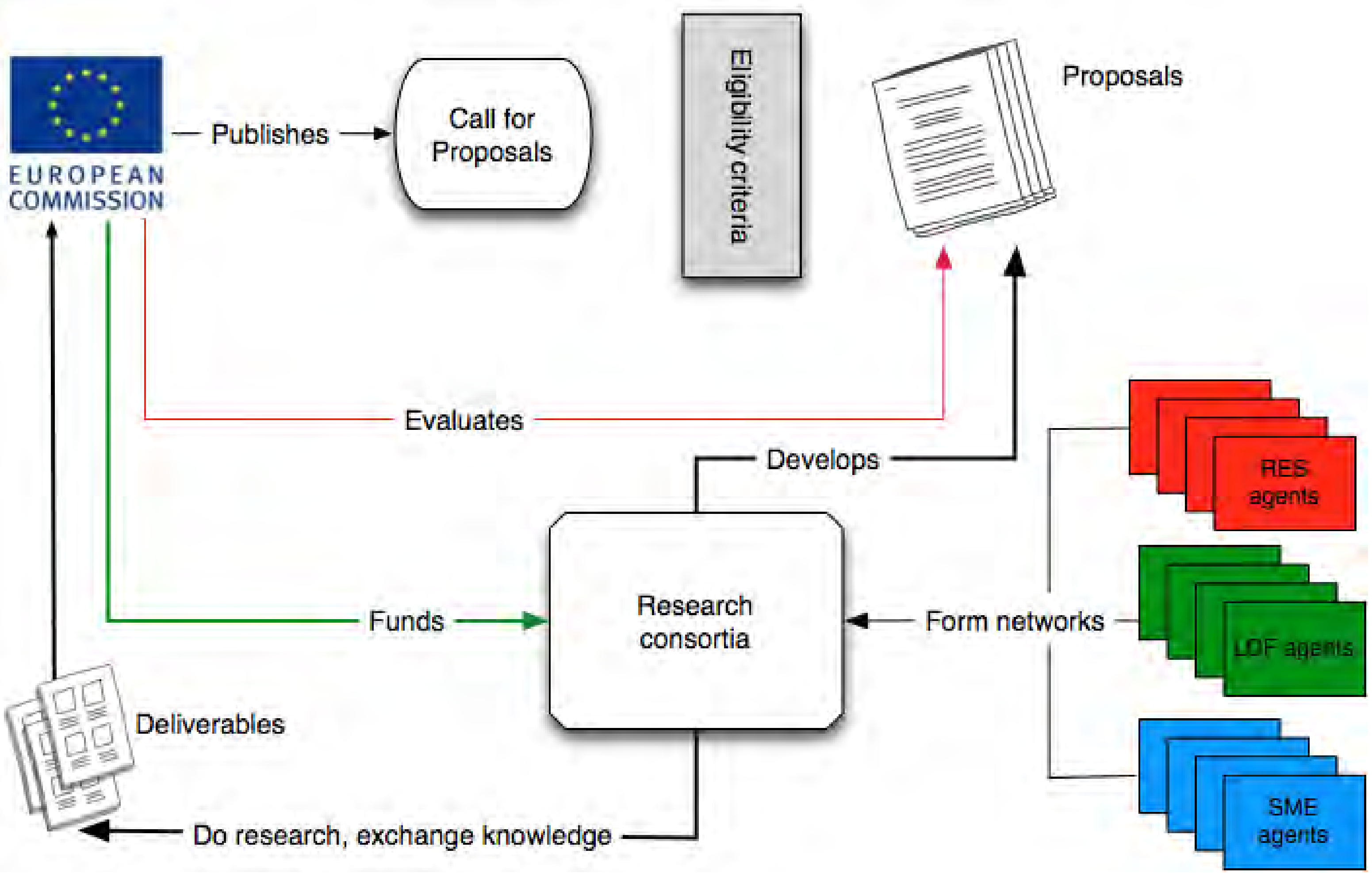
3. Analyzing innovation networks – Policy experiments in-silico

- How do the new instruments in Horizon 2020 shape the European research landscape (= networks created in previous framework programs)?
- Empirically calibrated simulation model of research networks created in FP6 and FP 7 in Information and Communication Technologies (DG InfSoc).
- Ex-ante evaluation of policy instruments.

Agent types

	Contribution (length of kene)	Objectives	Research Direction	Capacity for Partnerships
RES	Variety of knowledge	Publications, patents	Basic or applied	Large (> 2)
LDFs	Variety of knowledge	Patents	Applied	Large (> 2)
SMEs	Specialised knowledge	Patents, publications	Applied	Small (1 or 2)

infso-skin flow diagram



3. Analyzing innovation networks – Policy experiments in-silico

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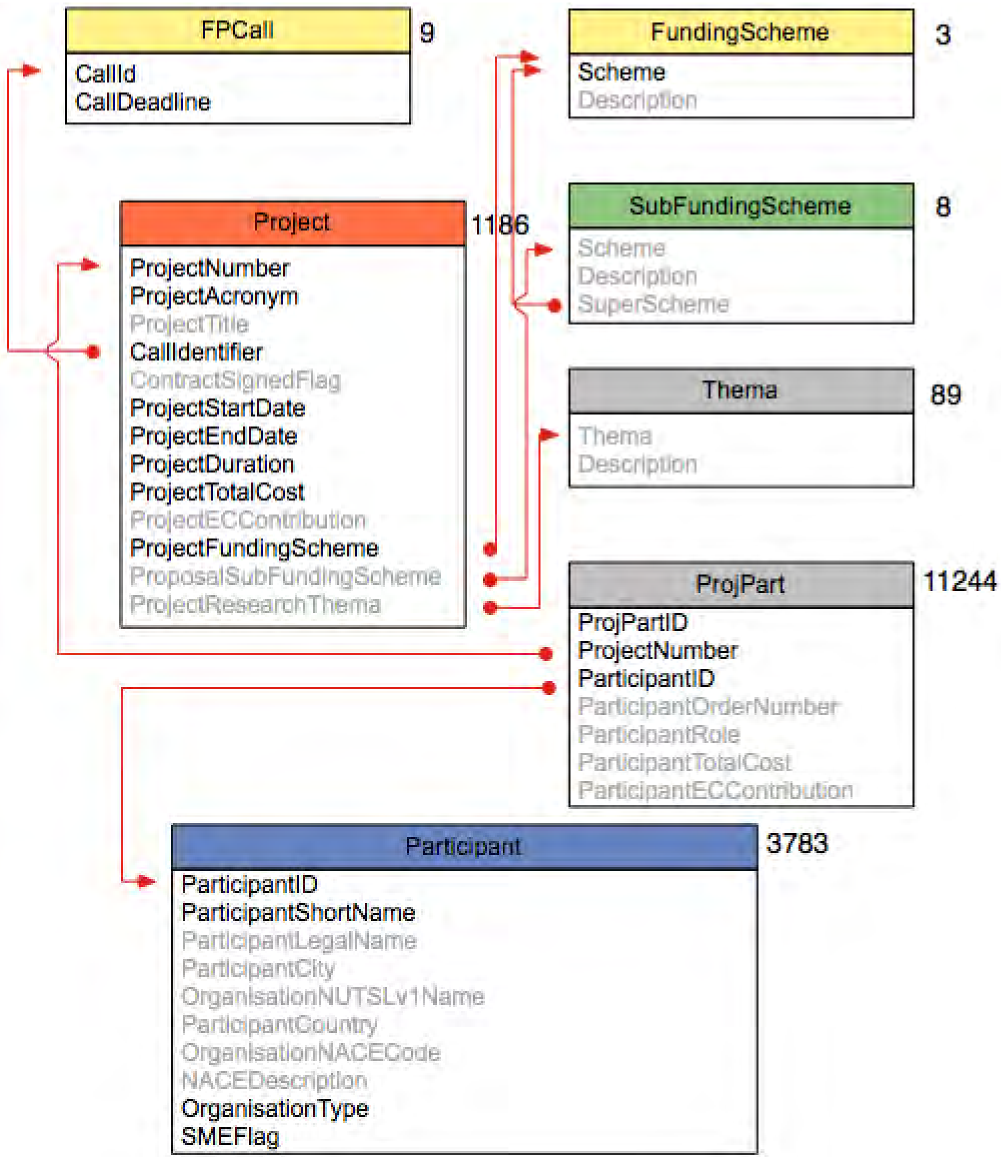
Data used in the model



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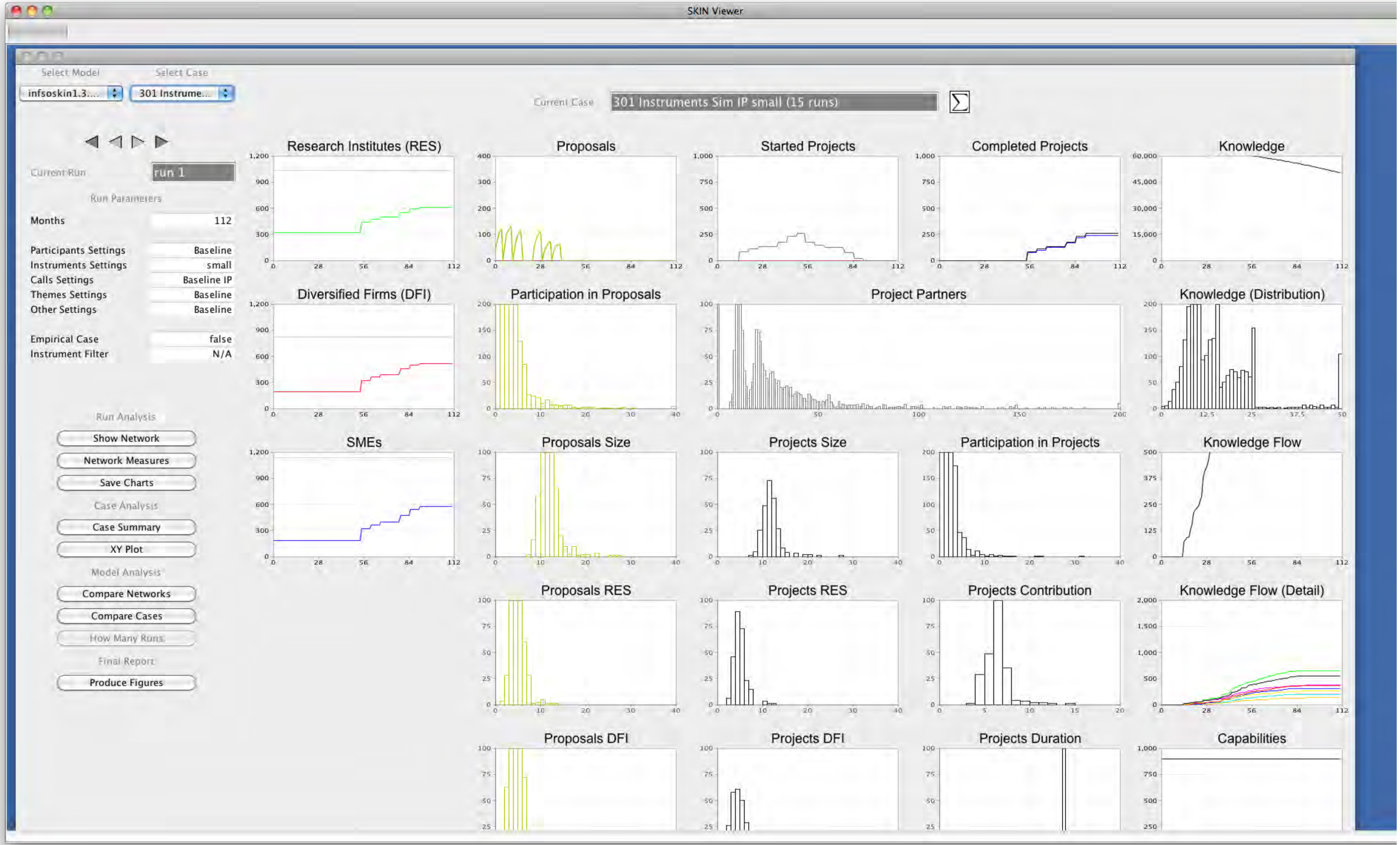
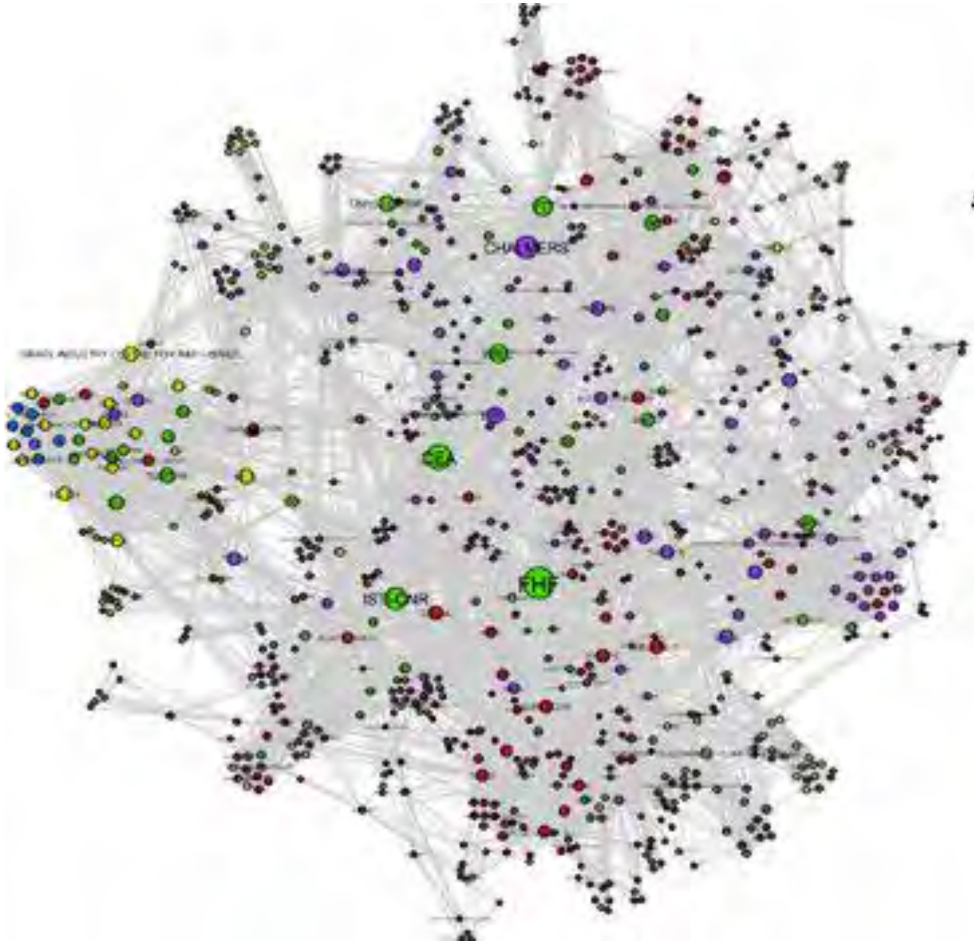
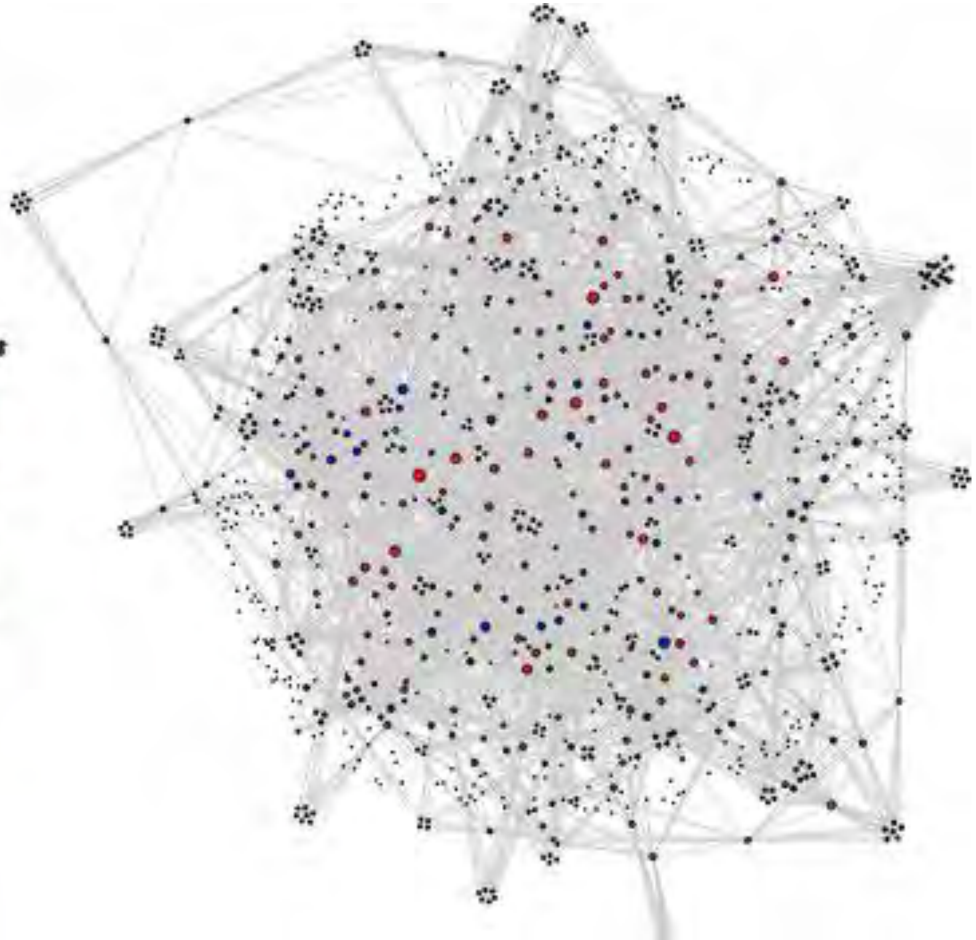
View on the simulation database



3. Analyzing innovation networks – Policy experiments in-silico



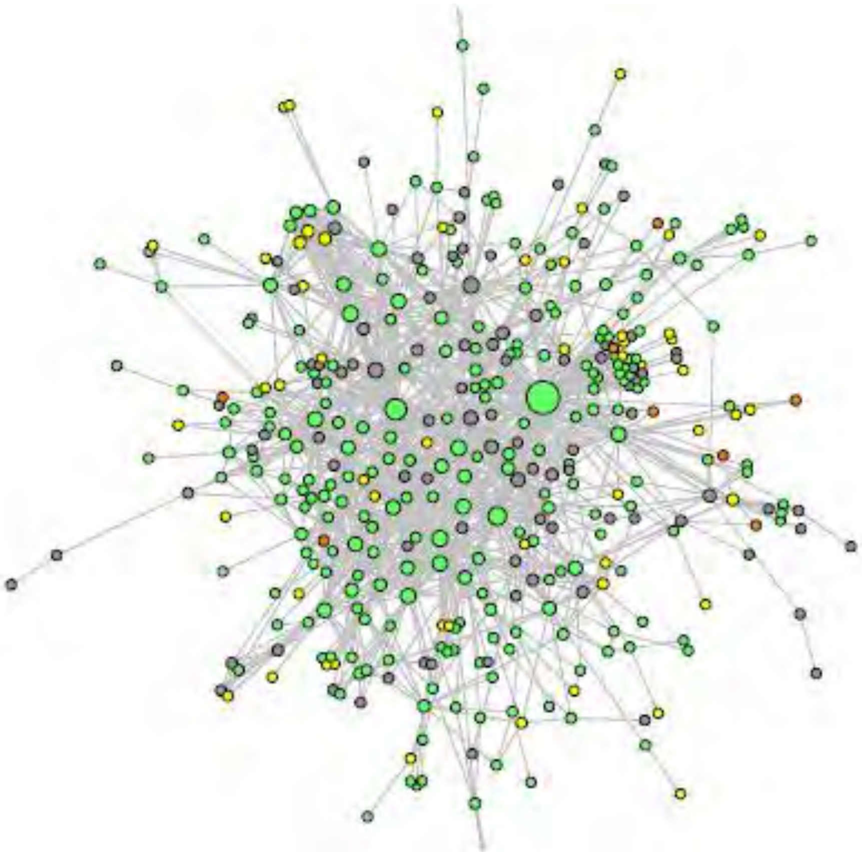
Empirical
Green: research institute
Purple: uni
Red: industry
Blue: public bodies
Yellow: SMEs



Simulated
Blue: RI
Red: industry
Green: SME

Baseline Scenario

STREPs only



		Emp STREP	Sim STREP (15 runs)	
			mean	*st dev*
Participants	RES in projects	786	809.9	12.738
	LDFs in projects	522	692.3	8.464
	SMEs in projects	747	804.6	11.005
	Participants in proposals (avg)	N/A	4.022	0.095
	Participants in projects (avg)	2.354	2.340	0.021
Proposals	Number of proposals	N/A	1292.1	35.789
	proposals-size-avg	N/A	8.231	0.056
	proposals-capability-match-avg	N/A	11.0	0.068
Projects	Number of projects	644.0	592.3	5.496
	Consortium size (avg)	8.025	8.208	0.072
	Project duration (avg)	34.2	34.0	0.000
	Project funding (avg)	2.8	3.0	0.028
Knowledge	Knowledge per participant	N/A	17.1	0.048
	Knowledge flow per project	N/A	6.8	0.145
Capabilities	Capability diffusion (Theme 1-8)	N/A	0.745	0.010
	Capability diffusion (Theme 9)	N/A	0.704	0.006
	Capability frequency (avg)	N/A	57.0	0.160
Network	Density	0.008	0.009	0.000
	Number of components	2	1.0	0.000
	Size of the largest component	2190.0	2349.7	18.495
	Diameter	6	5.000	0.000
	avg-path-length	2.846	2.846	0.015
	avg-degree	17.0	20.4	0.176
	avg-clustering	0.812	0.603	0.005

The "Business as Usual" Experiment

Extrapolation to 2020 (STREPs only)

		Sim STREP (15 runs)		Sim STREP 2020 (15 runs)	
		mean	*st dev*	*mean*	*st dev*
Participants	RES in projects	809.9	12.738	855.6	13.166
	LDFs in projects	692.3	8.464	734.3	8.834
	SMEs in projects	804.6	11.005	878.5	14.633
	Participants in proposals (avg)	4.022	0.095	6.560	0.139
	Participants in projects (avg)	2.340	0.021	2.907	0.031
Proposals	Number of proposals	1292.1	35.789	2286.3	51.279
	proposals-size-avg	8.231	0.056	8.304	0.032
	proposals-expertise-level-avg	5.1	0.028	4.8	0.034
	proposals-capability-match-avg	11.0	0.068	11.1	0.049
Projects	Number of projects	592.3	5.496	822.9	5.456
	projects-size-avg	8.208	0.072	8.199	0.054
	projects-duration-avg	34.0	0.000	34.0	0.000
	projects-contribution-avg	3.0	0.028	3.0	0.020
Knowledge	Knowledge per participant	17.1	0.048	15.2	0.050
	Knowledge-flow per project	6.8	0.145	7.8	0.151
Capabilities	Capability diffusion (Theme 1-8)	0.745	0.010	0.704	0.009
	Capability diffusion (Theme 9)	0.704	0.006	0.633	0.007
	Capability frequency (avg)	57.0	0.160	50.8	0.167
Network	Density	0.009	0.000	0.009	0.000
	Number of components	1.0	0.000	1.0	0.000
	Size of the largest component	2349.7	18.495	2511.4	23.353
	Diameter	5.000	0.000	5.000	0.000
	avg-path-length	2.846	0.015	2.768	0.013
	avg-degree	20.4	0.176	15.5	0.288
	avg-clustering	0.603	0.005	0.554	0.006

An example for experiments with policy changes: What happens, if there are changes to the instruments of funding?

Table 6: Possible ranges of the results of experiments

	Programme Scope Experiment		Hubs and Spoke Experiment				Elite and Selectivity Experiment		Specialisation Experiment	
	A Lower number of thematic areas	B Higher number of thematic areas	C Smaller consortia	D Larger consortia	E Higher funds per consortium	F Lower funds per consortium	G Higher funds per program	H Lower funds per program	I More SMEs	J More applied research
Participants	SMEs (-0+) LDF (-0+) RES (-0+)									
Proposals	More submitted proposals (+) Less submitted proposals (-)									
Projects	Size of consortia (+0-); participation of SMEs, RES, LDF (+0-)									
Knowledge	Increasing (+) or decreasing (-) knowledge exchange among agents									
Capabilities	Wide (+) or narrow (-) diffusion of capabilities									
Networks	Density (-0+), Average Path Length (-0+), Average Degree (-0+), Average Centrality (-0+), Average Clustering (-0+)									

3. Analyzing innovation networks – Policy experiments in-silico

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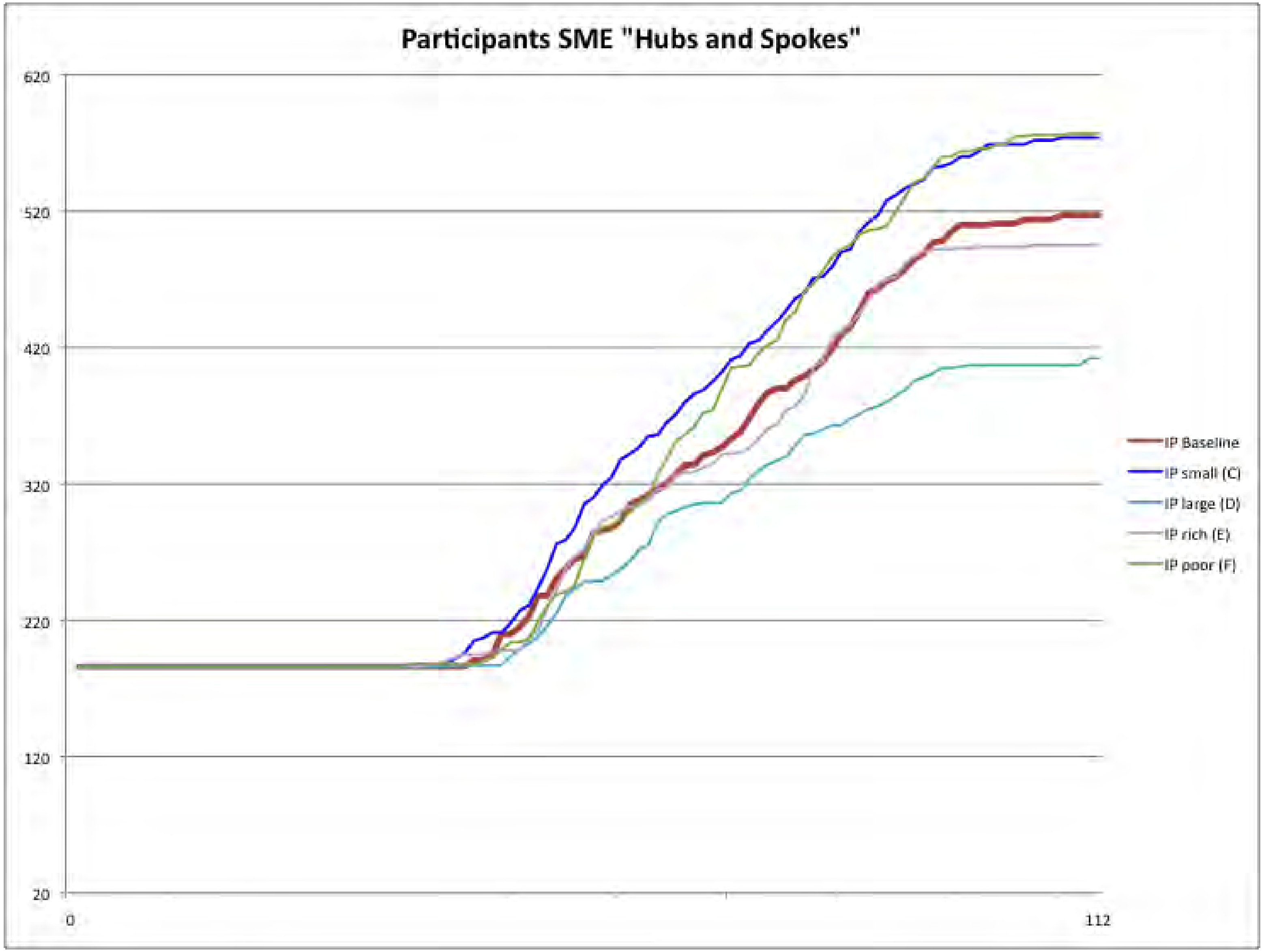
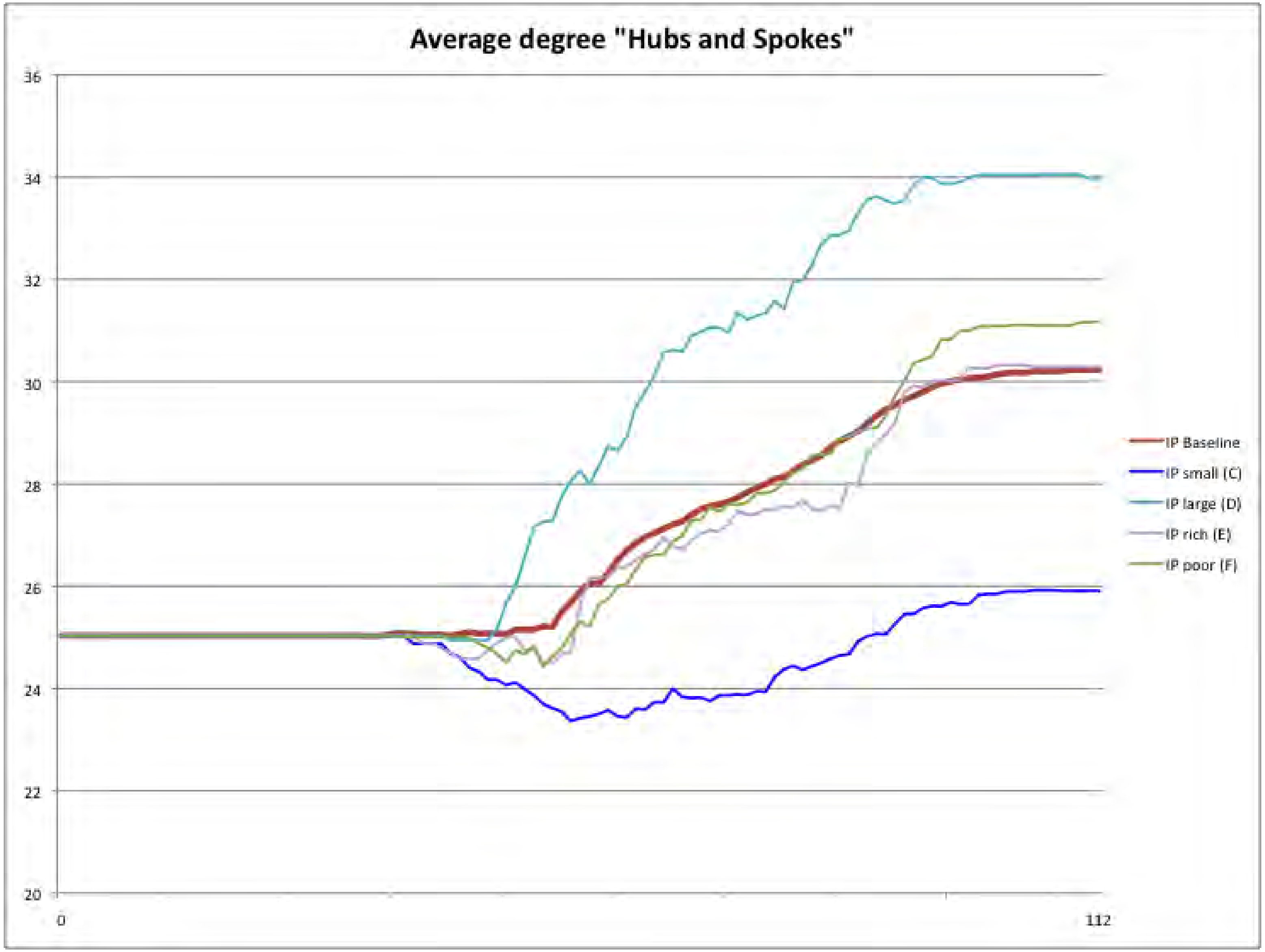


3. Analyzing innovation networks – Policy experiments in-silico



3. Analyzing innovation networks – Policy experiments in-silico

Table 8:. Results - Hubs and Spokes Scenario (all variable acronyms are listed and defined in Tables 1–5 of the Appendix). *Note*: The (•) means that the effect is intended

	Experiment C *Smaller consortia*	Experiment D *Larger consortia*	Experiment E *Larger monthly budget*	Experiment F *Smaller monthly budget*
Participants	+ participants	– participants	No effect	+ participants
Proposals	+ proposals – cap-match (•)	– proposals + cap-match (•)	No effect	No effect
Projects	+ projects – projects-size (•) – projects-contr	– projects + projects-size (•) + projects-contr	– projects + projects-contr (•)	+ projects – projects-contr (•)
Knowledge	+ knowledge + knowledge-flow	– knowledge – knowledge-flow	– knowledge – knowledge-flow	+ knowledge + knowledge-flow
Capabilities	+ diffusion	– diffusion	No effect	No effect
Network	– density + avg-path-length – avg-degree – avg-clustering	+ density – avg-path-length + avg-degree + avg-clustering	+ avg-clustering	+ avg-degree – avg-clustering

4. Conclusions

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- Innovation networks cannot be understood without understanding the knowledge dynamics which are generated by the agents which shape the network.

- Technological Spillovers are a simplification which is misleading. Learning, knowledge transfer and innovation takes place in network structures.

- Emerging network structures and knowledge dynamics can be analyzed in agent-based models.

- Agent-based models allows for conclusions of strategic considerations of actors which cannot be *measured* empirically.

- Insights are useful for designing policy instruments.

Thank you!

5. Literature

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