CENTRO RICERCHE
ENRICOFERMI

Economic Complexity and Artificial Intelligence

Presentation Day CREF Activities for the Scientific Council and the Internal Evaluation Committee

February 19, 2026
Aula Fermi, CREF

The Group

CENTRO RICERCHE ENRICOFERMI

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Resources and Collaborations

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External Financing (2022-2026) > 500k€

- European Commission - Various tenders: **€ 140k**
- PRIN PNRR 2022 TripleT (A. Sbardella): **€ 180k**
- PRIN 2022 WeCare (D. Mazzilli): **€ 90k€**
- PRIN PNRR 2022 CODE (F. Saracco): **€ 32k**
- Forward Partners RT3 (A. Sbardella, A. Tacchella): **€ 100k**

Proposals

- FIS + ERC Starting: **€1M** (D. Mazzilli)
- Horizon RIA DIS-CAPITAL: **€280k**
- Centre for Advanced Studies JRC-European Commission: **150k**

MoUs & collaboration network

Sapienza Università di Roma
IMT Scuola Alti Studi Lucca
CNEL Consiglio Nazionale Economia e Lavoro
Tor Vergata Università degli Studi di Roma
INAPP Istituto Nazionale per l'Analisi delle Politiche Pubbliche
ISI Foundation
Sant'Anna Scuola Universitaria Superiore Pisa
CNR-IAC Istituto per le Applicazioni del Calcolo
Università Cattolica del Sacro Cuore
Istituto dei Sistemi Complessi
Centro Studi delle Camere di Commercio Guglielmo Tagliacarne

cnrs
Institut des Systèmes Complexes
Universität Konstanz
UNU CRIS
University of Oxford
UNU MERIT
IFC International Finance Corporation World Bank Group
Northeastern University London
European Bank for Reconstruction and Development
KU LEUVEN
Complexity Science Hub
Peking University 北京大学
早稲田大学 WASEDA University
European Commission

Research pillars

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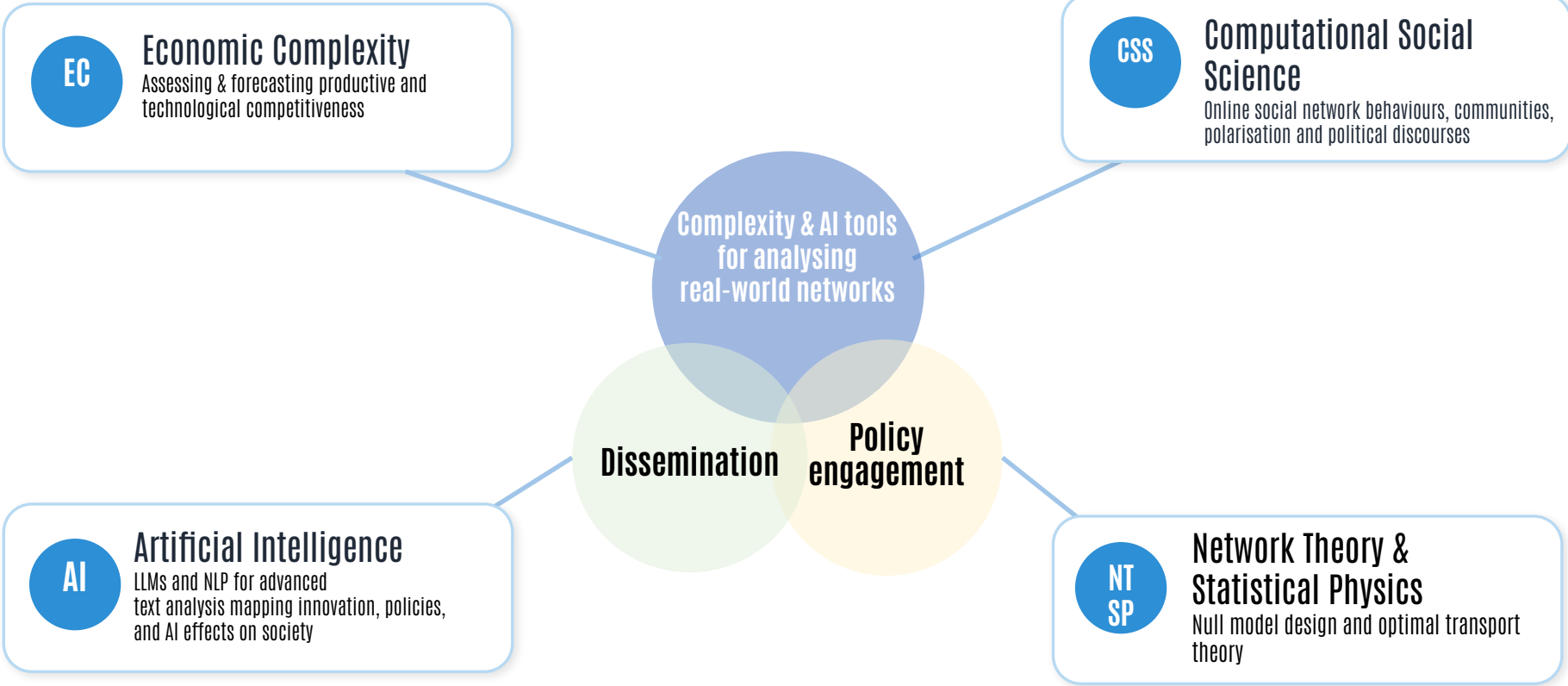
From methods to policy-relevant evidence relying on shared · datasets · methods · indicators



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1. Economic Complexity, computational social science, network theory

Economic Complexity: a data-driven & scientific approach to Economics

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"If it disagrees with experiments, it's wrong. In that simple statement is the key of science" - R. Feynman

Theoretical Tools (from Physics)
- *Dynamical systems*
- *Statistical mechanics of networks*
- *Optimal Transport theory*
- *Scaling laws*

Economic Complexity

Analytical Tools (from Computer Science)
- *Network science*
- *Machine Learning and AI*
- *Big data analysis*

Questions and models (from Economics)
- *Economic growth, inequality, development traps*
- *Innovation and sustainability*
- *Firms and startup development*

Novel empirical strategies to study the economy modelling economies as networks

connecting countries to the activities (products, technologies…) they specialise into and condensing the information into synthetic indicators

Economic Fitness and Complexity

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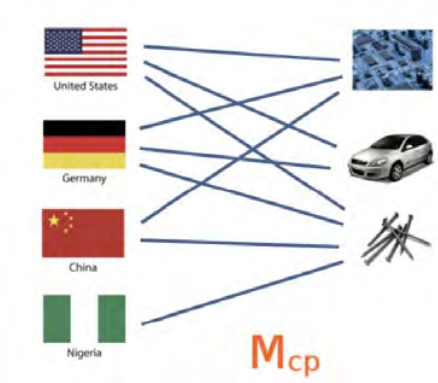
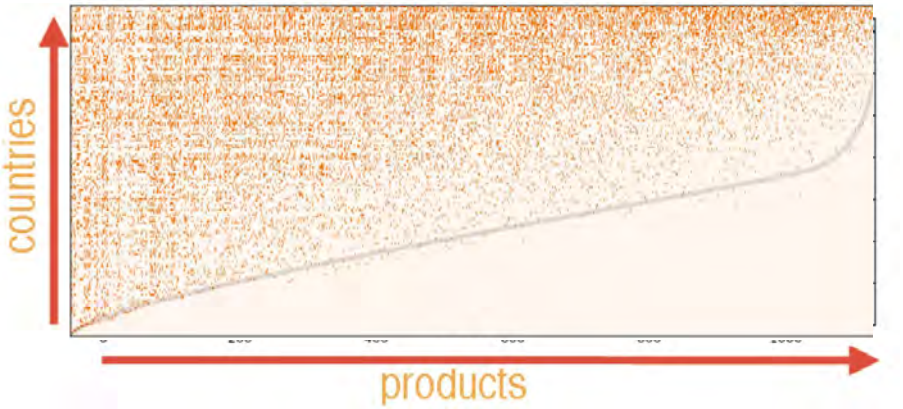




FITNESS

$$\tilde{F}_c^{(n)} = \sum_p M_{cp} Q_p^{(n-1)}$$

$$F_c^{(n)} = \frac{\tilde{F}_c^{(n)}}{\langle \tilde{F}_c^{(n)} \rangle_c}$$

COMPLEXITY

$$\tilde{Q}_p^{(n)} = \frac{1}{\sum_c M_{cp} \frac{1}{F_c^{(n-1)}}}$$

$$Q_p^{(n)} = \frac{\tilde{Q}_p^{(n)}}{\langle \tilde{Q}_p^{(n)} \rangle_p}$$

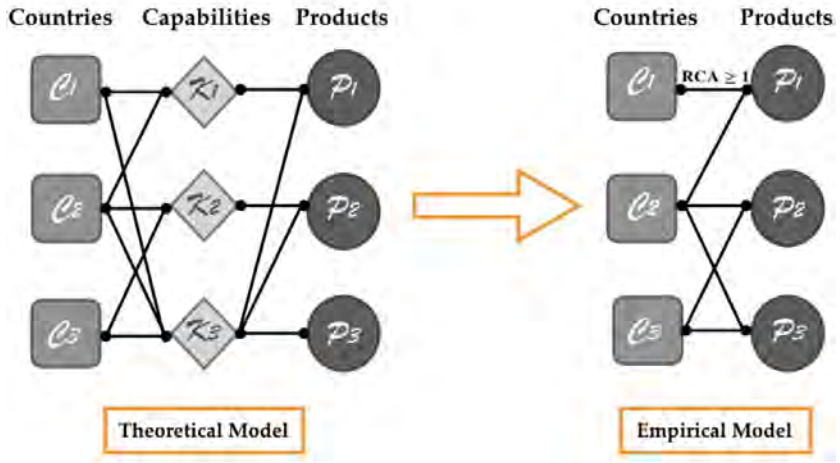
The less complex producer bounds the complexity of the product

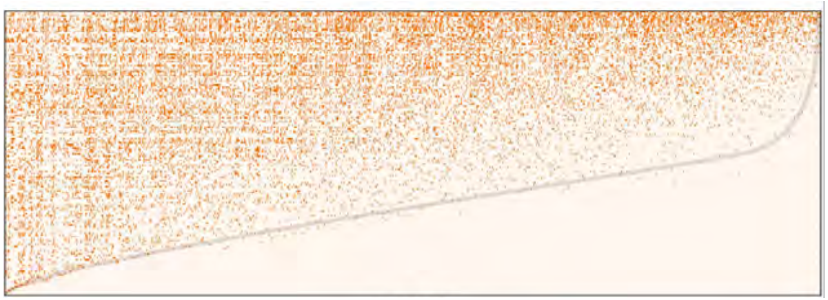
Nestedness (Mcp triangular shape): developed and competitive countries are more diversified and complex, most complex products difficult to export, least complex products prevalent in least complex export baskets

Fc = Fitness of country c diversification weighted by the complexity of the products in which c is competitive
Qp = Complexity of product p bounded by the Fitness of its least competitive exporter

AT, Cristelli, M., Caldarelli, G., Gabrielli, A., & Pietronero, L. (2012). A new metrics for countries' fitness and products' complexity. *Scientific reports*, 2(1), 723.

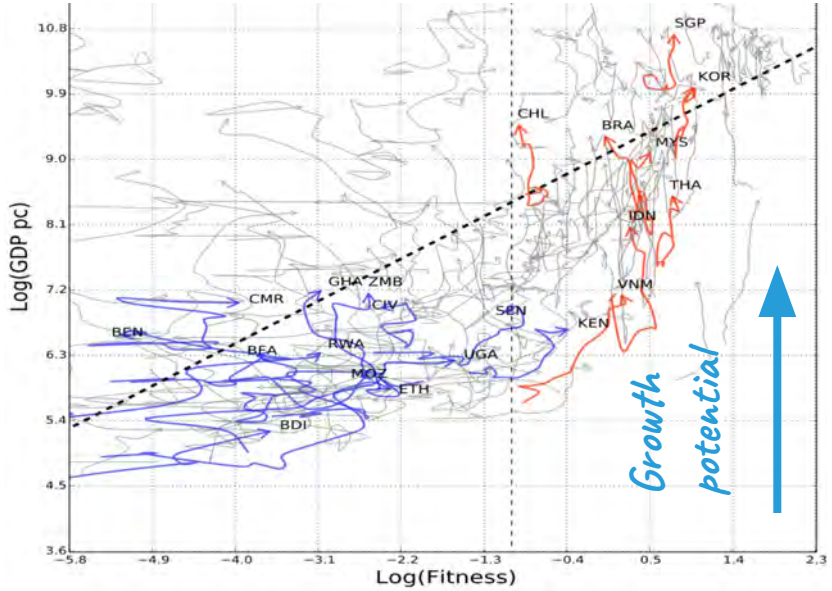
Economic Complexity as inference of unobservable capabilities





- **Capabilities: intangible factors that enable economies to transform resources into outputs**
- Conceptualised as an intermediate layer between countries and the products they export <u>but</u> not empirically observable… **we can infer info on capabilities through EC metrics**
- Each economy owns a set of capabilities: more capabilities lead to the ability to produce more complex products, some capabilities are essential for many products, others are rare
- Accumulating capabilities leads to more diversified and complex productive structures & higher competitiveness

Fitness and GDP as a dynamical system & state-of-the-art GDP forecasting



- *Fitness complementary to GDP*: uncovers hidden potential for growth and economic development
- *Strong predictive power for GDP growth* outperforming IMF forecasts (+ uncorrelated forecast error)

nature physics ARTICLES https://doi.org/10.1038/s41567-018-0204-y

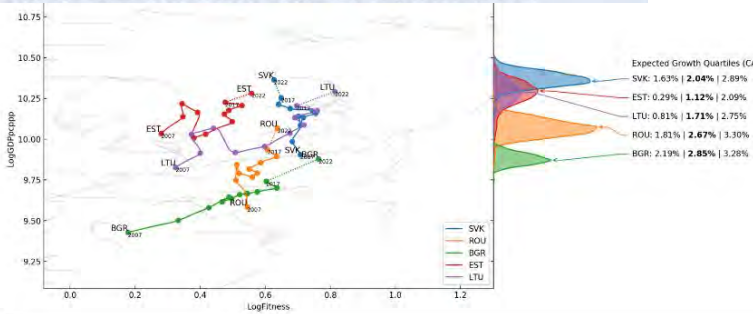
A dynamical systems approach to gross domestic product forecasting

A. Tacchella[1,2*], D. Mazzilli[3] and L. Pietronero[1,2,3]

Table 1 | Summary of the results

	All		Predictable		Unpredictable	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
IMF	2.09%	2.63%	1.95%	2.39%	2.40%	3.09%
SPSb	1.94%	2.46%	1.79%	2.31%	2.28%	2.76%
Velocity-SPS	1.65%	2.23%	1.65%	2.27%	1.62%	2.14%
SPSb+IMF	1.68%	2.22%	1.45%	1.90%	2.04%	2.72%
Velocity-SPS+IMF	1.51%	2.02%	1.37%	1.82%	1.80%	2.39%

A country c is classified as predictable if $\ln(F_c) > -1.5$ and unpredictable otherwise



Relatedness and feasibility predictive framework intuition

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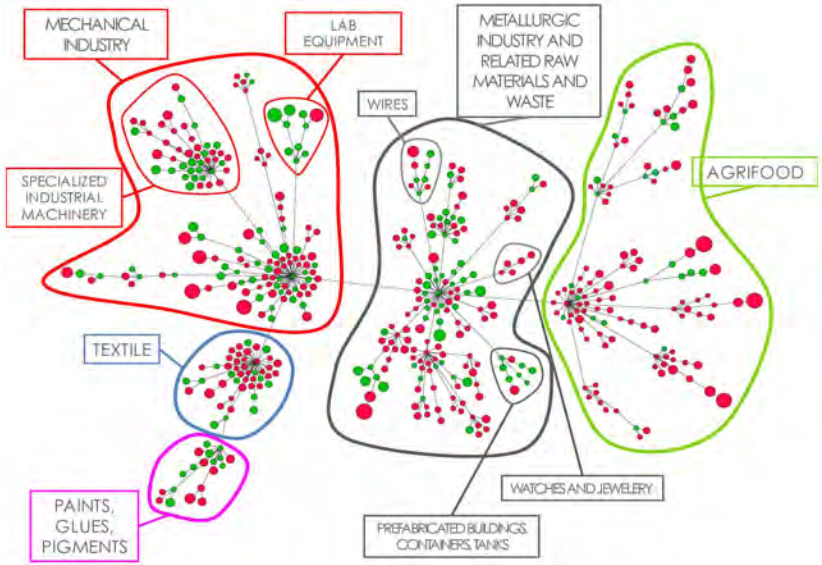
Relatedness

- statistical measure of the "distance" between two products, estimated from the number of countries that export both products competitively
- Two products are “close” if they are often found in the same export basket and thus share many capabilities
- If a country is competitive in many nearby products it signals the availability of related capabilities and the opportunity to diversify in related products

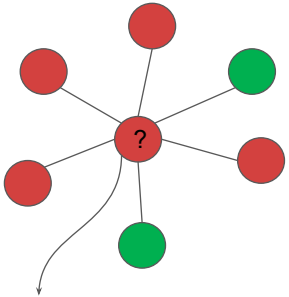
Product space – network that measures the relatedness of products through patterns of co-exporting

Zaccaria et al. (2014)



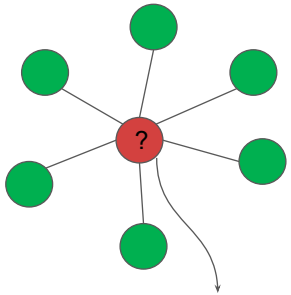
Feasibility: predicting future competitiveness in target products

Country A: competitive (RCA>1) in few products related to target product



Low probability of increasing RCA

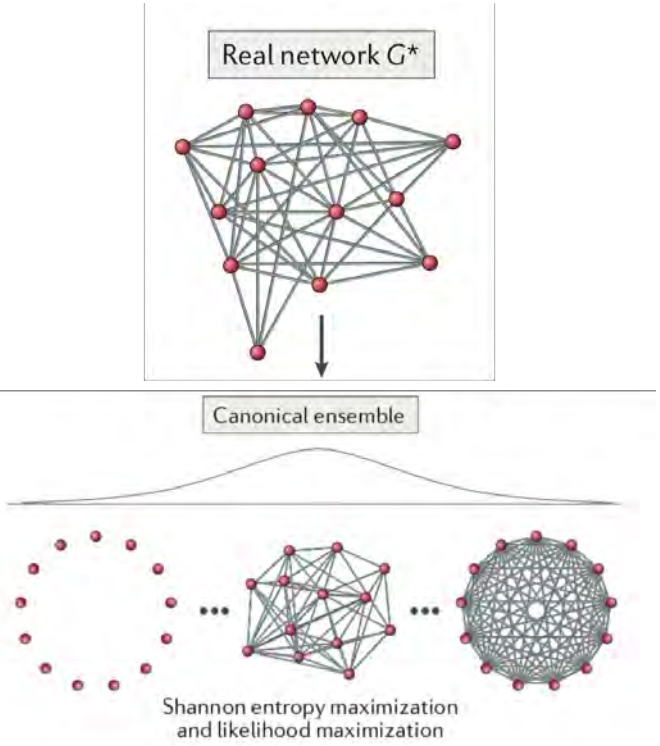
Country B: competitive (RCA>1) in many products related to target product



High probability of increasing RCA

Network Theory, Statistical Physics: null model development

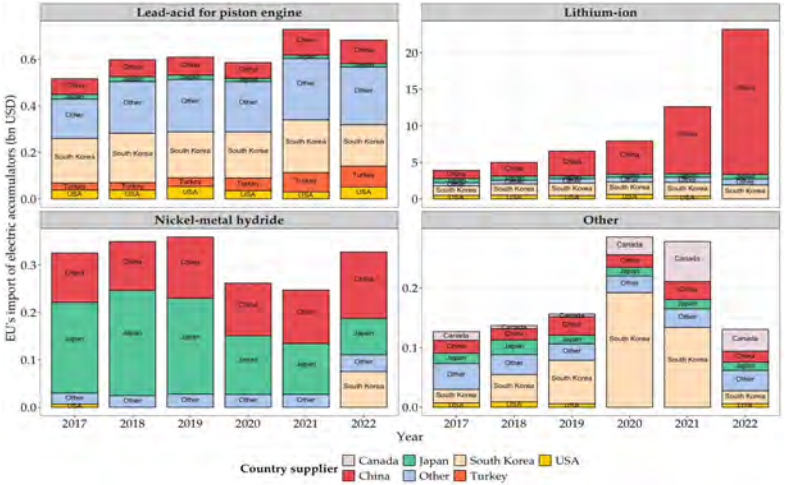
- **Real networks** often affected by **random noise**, we can filter this out using **null models: statistical models accounting just for part of the information of the real system:**
    1. Creation of a **randomised benchmark** network that preserves a chosen set of observed features (e.g., node degrees) but is otherwise **maximally random**
    2. **links in the real network are deemed statistically significant when they are more frequent than expected under this benchmark distribution**
- In this way, all **deviations** and **anomalous behaviours** can be effectively captured
- The strategy follows the **derivation of Gibbs ensembles in Statistical Physics** and ensures a **maximally random and unbiased benchmark** for evaluating the observed network
- Such a framework is flexible and can be adapted to different systems (e.g., **weighted, directed, signed networks**, **hypergraphs**) or to statistically validate through **relevant bipartite networks in Economic Complexity and Online Social Network analysis**

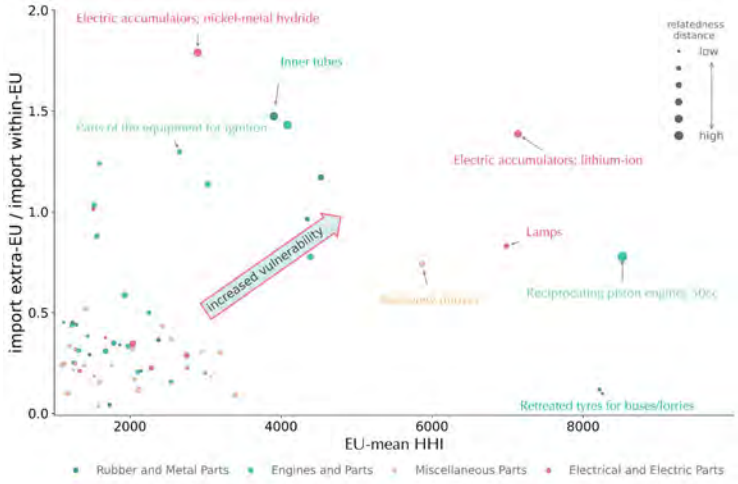


- **R. Piombo, L. Buffa, D. Mazzilli, A. Patelli,** arXiv:2602.04308v1
- **L. Buffa, D. Mazzilli, R. Piombo, F. Saracco,** G. Cimini, **A. Patelli,** Comm. Phys. (2026)
- **F. Saracco**, G. Petri, R. Lambiotte, T. Squartini, Comm. Phys. (2025)
- **A. Gallo, F. Saracco**, T. Squartini, npj Complex (2025)
- **A. Gallo, F. Saracco**, R. Lambiotte, D. Garlaschelli, T. Squartini, PRE (2025)

Vulnerability & competitiveness of the EU27 automotive industry

Automotive cornerstone of EU economy but losing prominence: novel empirical strategy to identify the auto supply chain using the EC framework & mixing data on international sectoral independence + export/import





- EU still competitive in export of cars (especially ICE and hybrid) and emergence of Eastern EU countries as manufacturer of components
- Growing dependency of the EU27 automotive industry on extra-EU critical inputs, emergence of China as main supplier
- Electric mobility transition vulnerability**:** forecasting yields no scope for future competitiveness in Lithium-Ion batteries currently imported especially from China
- *Italy* is shifting towards automotive components, no more finite vehicles

- **Cresti L, Mazzilli D, Patelli A, Tacchella, A., and Sbardella A** (2025). arXiv preprint & forthcoming in SCED.
- Caldarola B, **Cresti L**, **Mazzilli D**, Napolitano L, **Patelli A**, **Sbardella A, Tacchella A** (2025). Science for Policy Series. European Commission JRC.
- **Cresti L**, **Sbardella A**, and Virgillito M.E. (2025). L'Industria.

Industrial districts in Italy

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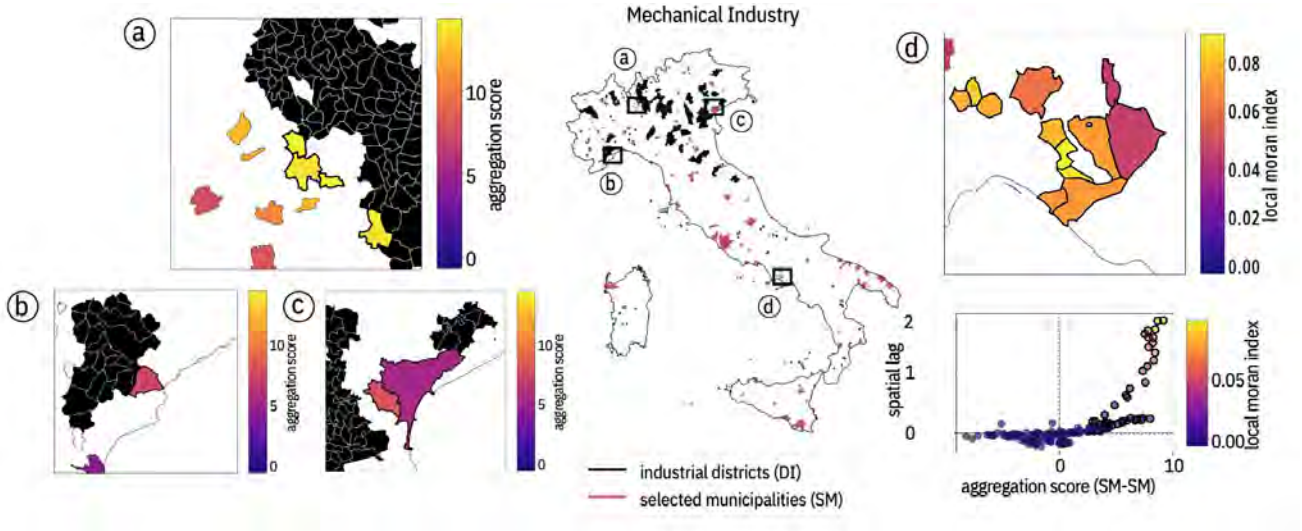

Emergent description of Italian economic structure through Economic Complexity lens: Analysis of Mechanical Industry industrial districts. In black currently tracked districts. In color newly discovered aggregations. Examples a-c show municipalities adjacent to existing district, example d shows a newly emerging district in the area of Naples

- EC framework to characterise the diversification profiles of industrial district tracked by the Italian Institute of Statistics
- We compare such profiles with all municipalities in Italy to retrieve those that express similar profiles
- Relatedness + ML classifier + spatial statistics approach to identify agglomerations of municipalities that constitute emerging and untracked industrial districts
- We find 18 potential new industrial districts and 70+ municipalities that could be added to current industrial clusters

Ongoing development: We are extending this methodology to provide a full characterization of the italian economic system with the lens of the EC Framework, ranging from exports, to local economic activities, to innovation systems. We plan to launch an open-data platform to share the results and insights of this analysis.

Straccamore M, Bellina A, Bumbea A, Mazzitelli A, and **Tacchella A (2026). Forthcoming in the It J of Regional Science**

Lessons for the Green Transition

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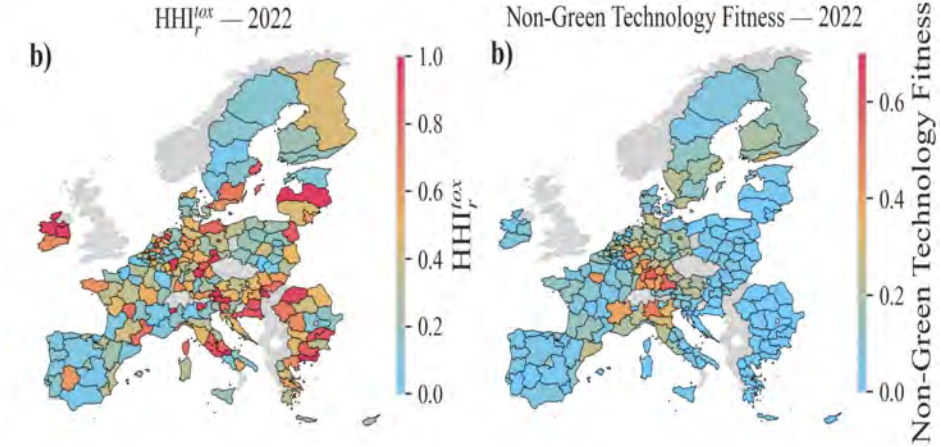


Toxic pollution and technological upgrading in EU left-behind regions (via ML tree based regression)

- Non green tech fitness is linked to more diversified pollution profiles while green tech fitness to less diversified pollution profiles
- Specialisation in complex non-green tech domains (Non green technology fitness) important driver for lower number of toxic pollutants in Eastern and Southern EU regions
- Specialisation in complex green tech domains (Green technology fitness) instead important in tech & industrial upgrading processes in Central EU regions

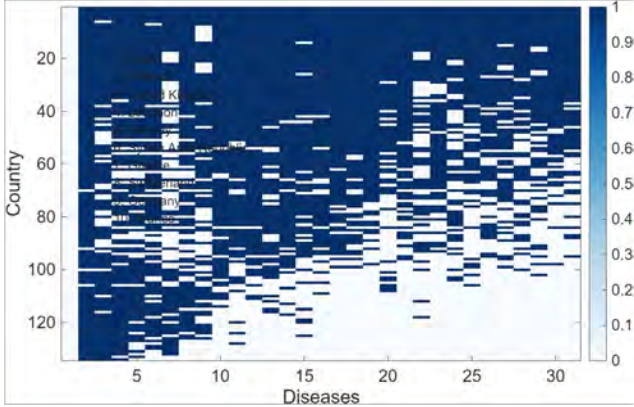
Specialisation and competitiveness in fossil fuel vs green technologies in Italy

- North-south divide with Northern regions more innovative in complex fossil fuel tech domains
- Green innovations are more disperse, low volumes but complex national specialisation with Southern regions developing new complex green capabilities

- **Tortora L., Bez, C, Patelli A, Sbardella A**, and Virgillito ME (2026). Forthcoming.
- Caldarola B., **Mazzilli D.**, Napolitano L., **Patelli A.**, and **Sbardella A.** (2024). Journal of Physics: Complexity.
- **Patelli A** and **Sbardella A** (2024). Il Mulino.
- **Patelli A.**,, Straccamore M, **Sbardella A** (2026). Forthcoming.

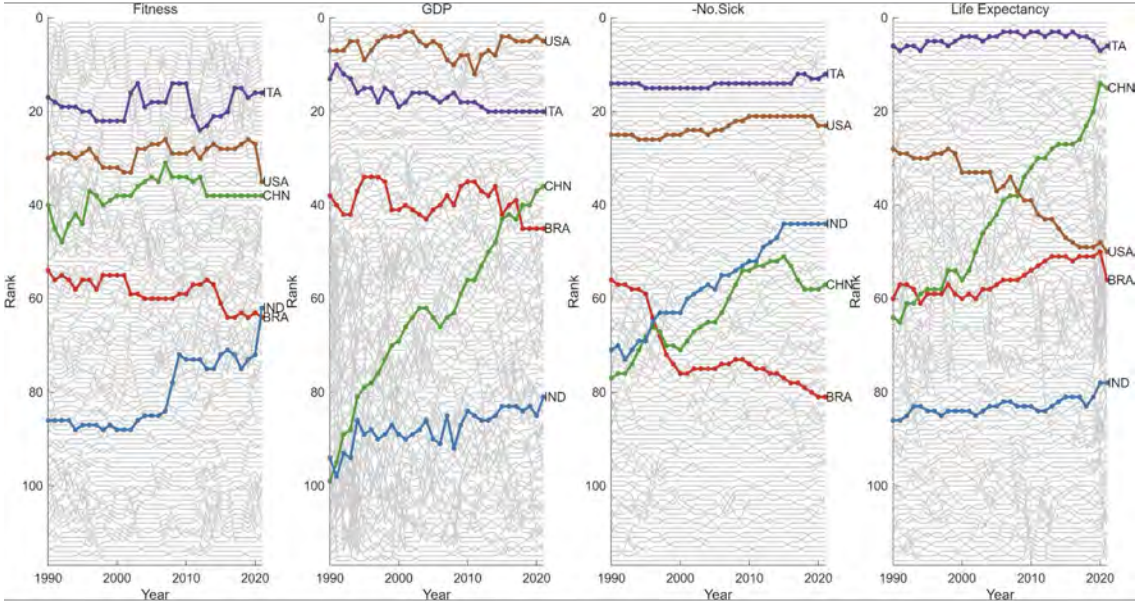
The Medical Fitness of countries

- **Medical Fitness** synthetic measure of a country's overall resilience and capability to treat major communicable diseases and public health risk
- **Nested structure of country-disease network** based on reporting of major communicable diseases across countries (Global Burden of Disease database)



- Non-trivial relationship with GDP and life expectancy illustrating different approaches to health system organization across countries

- Collaboration with medical expert to explore new criteria for analysis and planning of national medical systems



Dai B, Benzi R, Zaccaria A, and **Pietronero L** (2026). Forthcoming.

Optimal Transport (resource optimisation) in complex systems

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framework for the optimisation of resource allocation that formalises how a system should distribute limited resources across alternative choices to maximise payoff under constraints

Which products should a country produce?
How do insects decide which flower to visit or people spend their free time?

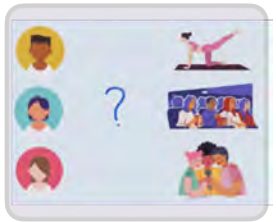
What to produce?

x y

Where to go?

x y

What to do?



x y

- Constraints in both layers
  - Money
  - Time
  - Availability
  - …
- Preferences in choice x-y, gain function
  - Profit
  - Nectar
  - Happiness
  - …

All these systems can be captured by a simple (sub)-optimisation framework as these diverse decisions can be described by a common rule: allocate limited resources to maximise payoff, possibly with frictions that make choices only sub-optimal

→ Study of Sub-Optimal models via Statistical Mechanics

Optimal transport tells us the best resources allocation plan, given their availability and the payoff of different choices

How sub-optimal are real systems?

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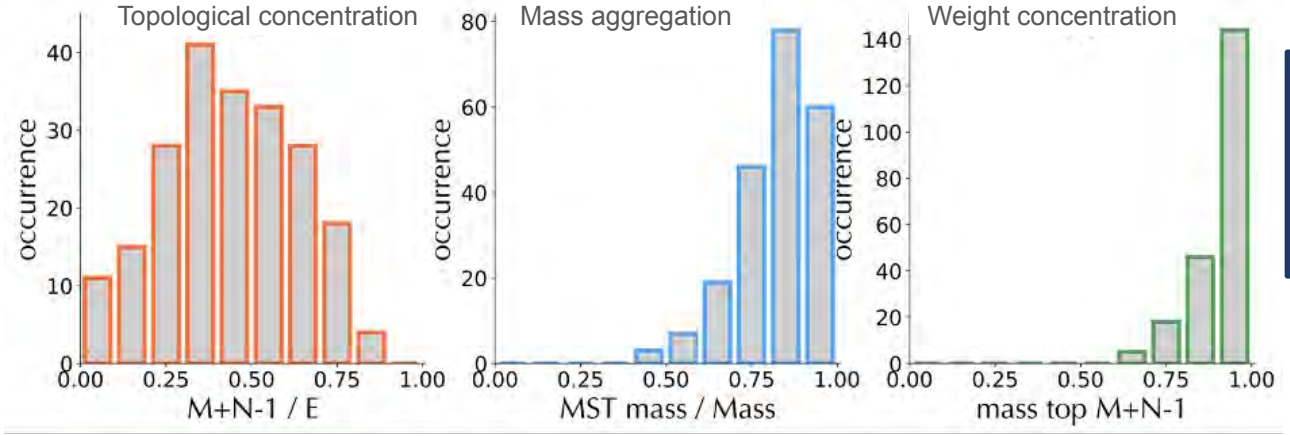

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Proposal: SORACS
Sub Optimal Transport
in Complex Systems

- Sub-Optimal Transport can be solved using **Statistical Mechanics** and **Information Theory**
- Important theoretical implication for Economic Complexity and Ecology (volume condensation and specialization/diversification patterns)
- It also presents a novel ***dense-to-sparse phase transition***

- Buffa, L, et al. "Maximum entropy modelling of sub-optimal transport." *Communications Physics* (2025).
- Piombo, R, Buffa, L, Mazzilli, D, and Patelli, A. "Statistical Mechanics of the Sub-Optimal Transport." *arXiv preprint arXiv:2602.04308* (2026).

Will be presented tomorrow in Auckland!

Computational Social Science

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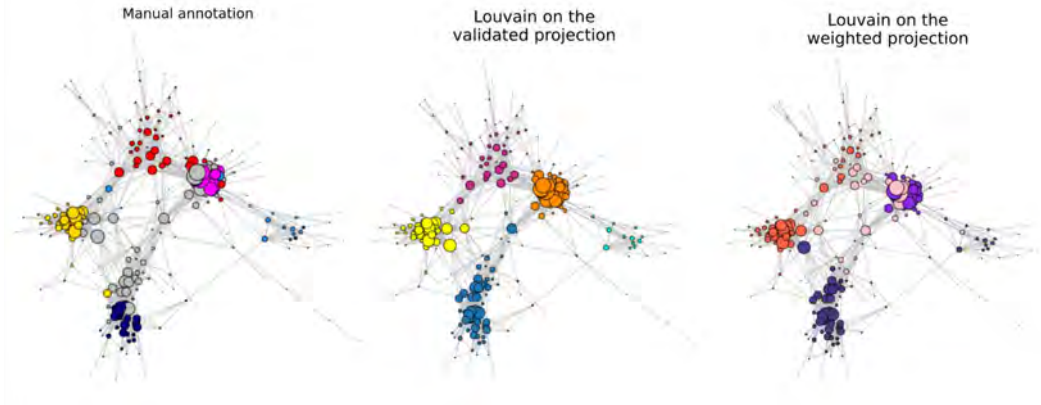
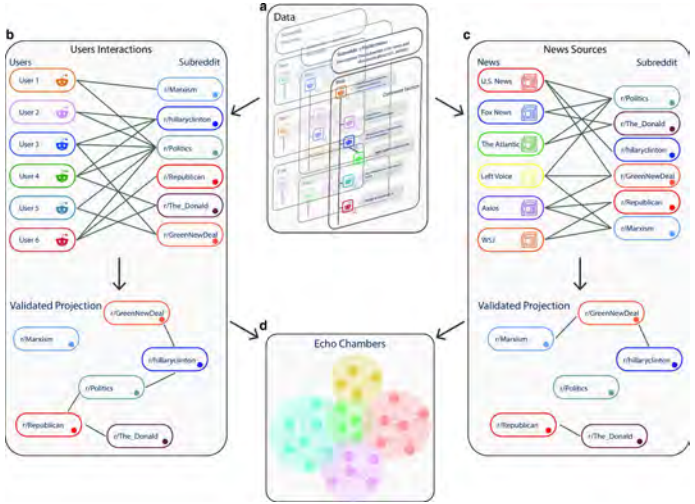
- In **Online Social Networks** multiple agents quickly interact in different ways → perfect example of a **complex system**!
- **Collective behaviours** can be studied and theories from **Social Science** are tested using tools from **Network Science**
- In fact, observations are rarely compared with **null-models**:
  it is not always clear if the observed behaviours are the mere effect of the **random noise** or if they carry some **relevant signal**
- Developing and using null-models allows detection of **non-trivial structure** in the online political debate that have an influence in the propagation of **(dis)information** (as **echo chambers**)

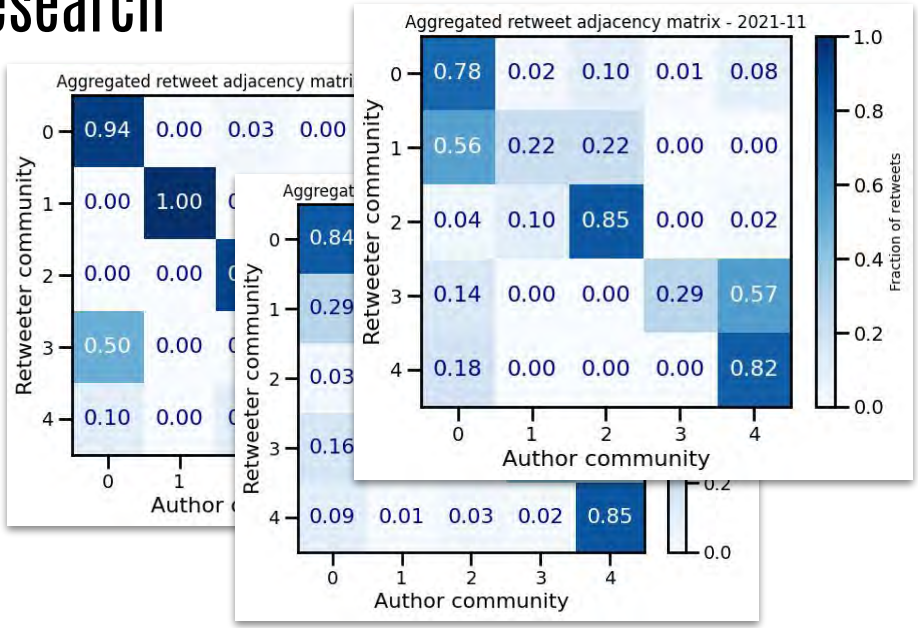


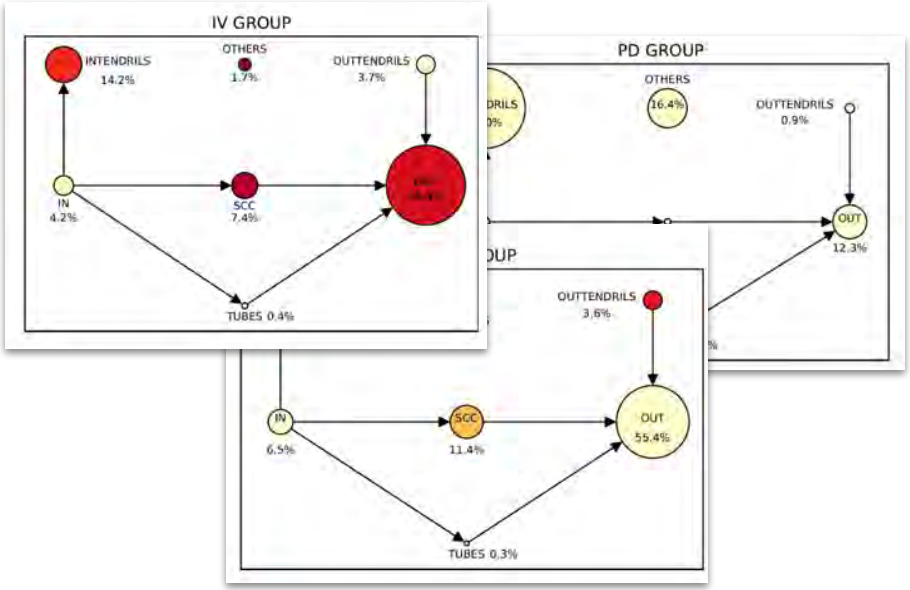


- **D. Cirulli**, A. Desiderio, G. Cimini, **F. Saracco**, arXiv:2510.27467
- G. Caldarelli, O. Artime, G. Fischetti, S. Guarino, A. Nowak, **F. Saracco**, P. Holme, M. de Domenico, arXiv:2510.15053
- A. Bellina, D. R. Lo Sardo, E. Brugnoli, **F. Saracco,** P. Gravino, V. Loreto, G. Di Bona, arXiv:2507.13068
- S. Guarino, A. Mounim, G. Caldarelli, F. **Saracco**, arXiv:2405.04896 (accepted by **Sci. Rep.**)

Computational Social Science: ongoing research

- The **evolution of online political** communities during the **COVID-19 pandemic**, and the different role of different communities. Source: **X/Twitter**
  In collaboration with **S. Guarino, S. Meloni (CNR-IAC, Rome), F. Colaiori (CNR-ISC, Rome)**



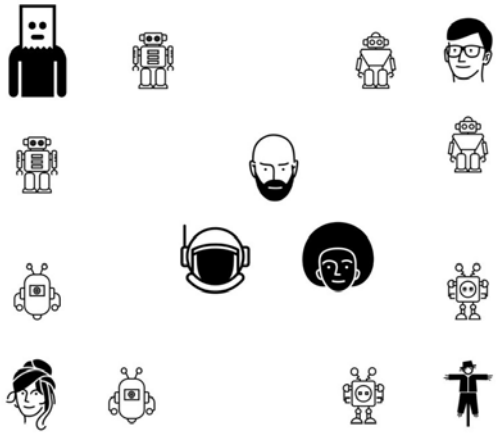


- The role of **opinion leaders** in Online Social Networks, as a network mesoscale (***bow-tie***) structure.
  Source: **X/Twitter**
  In collaboration with **S. Guarino (CNR-IAC, Rome), G. Caldarelli (CNR-ISC, Rome), A. Mounin (LUISS University, Rome)**

Computational Social Science: next steps

- **Online social networks** are dynamical systems by construction, but rarely their evolution is considered in the analysis. Including their dynamic in the analyses (and **statistically validating** it!) will uncover **non-trivial coordination activities**
- **Target: Reddit, Twitch, …**

- In collaboration with **G. Cimini (Università di Tor Vergata), A. Desiderio (ISI Foundation), R. Di Clemente, I. Iacopini (NorthEastern University, London)**



- Enriching the description of **Echo Chambers**, including the **negative** or **positive** reaction to the content posted by others.**Target: X/Twitter.**
  (EC: *digital communication environment in which users are disproportionately exposed to, and socially reinforced by, like-minded content and contacts, limiting cross-cutting information*)
  In collaboration with **SONY CSL Lab.**

2. Artificial Intelligence

AI: a vision for the role of CREF in Artificial Intelligence

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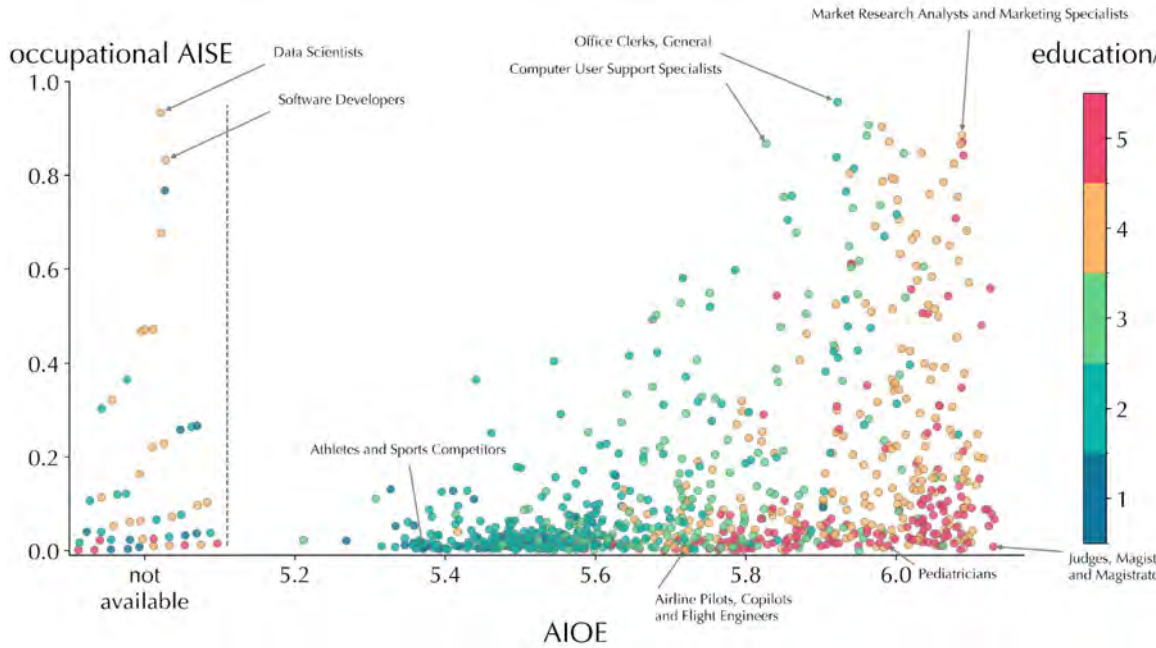
AI and Language Models are revolutionizing society and research: 2024 Physics + Chemistry nobel prizes related to AI and neural networks
but raining a Language Model like ChatGPT can cost > $500M: What role for “small science”?

- Development of ad-hoc language models
  - Fine-tuning of ad-hoc efficient models that can be used on massive tasks (e.g., millions of patents)
  - Development of novel analytical paradigms based on LLMs (e.g., technology embeddings, LM-Decision Trees)
- AI for policy and society
  - The future of work
  - Real-time mapping of AI innovation
  - AI-assisted policy analysis
- Cross-fertilization with other disciplines
  - Promote AI literacy to foster applications in other domains
  - Examples: AI to analyse innovation dynamics, raw material dependencies…

Which jobs will be more affected by AI?

AI advances raise fears of widespread labour substitution, including high-skill, white-collar jobs

- To assess AI impact on the labour market the literature relies on surveys and measures of technical feasibility (what AI can do in principle)
- **We estimate the AI exposure of jobs by following where the market is going, using AI applications developed by venture-backed startups** (Y Combinator), distinguishing feasibility from commercial targeting
- **AI Startup Exposure (AISE): LLM (Llama 3) to compare startup AI application descriptions with job descriptions and classify whether the AI tool can significantly affect the job's tasks**



- **High AISE**: routine organisational/information processing tasks (e.g., data analysis, office management)
- **Low AISE**: ethically sensitive/high-stakes judgment, managing uncertainty (e.g., judges, pediatric surgeons) despite automation technically feasible

- **Many high-skill occupations are highly "AI-feasible" but they are not all equally targeted by startups: high-skill catastrophe averted when incorporating both technical feasibility but also profitability and societal constraints?**

Fenoaltea E et al. Accepted in PNAS Nexus.

From Research to Policy: Engaging EU Policymakers on AI and Labour Markets

European Commission

SCIENCE FOR POLICY BRIEF

Industrial Innovation & Dynamics series

Challenges and opportunities for the EU labour market from AI development

HIGHLIGHTS

→ The European Commission adopted the **Digital Europe Programme** to equip the EU workforce with the necessary skills to cope with labour market changes induced from innovation in advanced digital technologies as AI.

→ Clerical work and cognitive tasks are considered to be more exposed to AI substitution, whereas manual, operational, and technical tasks are comparatively less exposed.

→ AISE is a job-specific AI exposure metric based on data from financed start-ups whose output could potentially replace a job.

→ Results reveal the existence of a gap between potential and actual AI exposure, as start-ups are more likely to adopt AI development in niche tasks.

→ The AISE-based analysis reveals that **cognitive jobs are heterogeneously AI-exposed,** and exposure depends on advanced cognitive skills requirements.

→ Beyond technical feasibility and economic viability, **ethical and social considerations and trust in AI capabilities determine job exposure to AI.**

→ Considering EU countries' structure of the labour market, Germany and Belgium are the most actually AI-exposed. **The largest gap between potential and actual exposure is detected for Sweden and Italy, the former being more potentially AI-exposed than actually. The opposite is true for Italy.**

INTRODUCTION

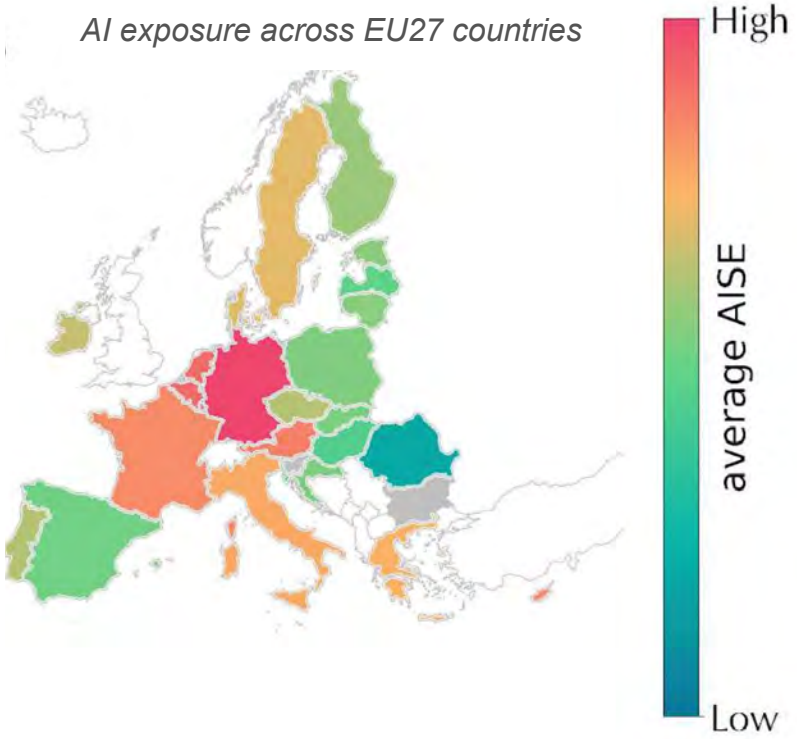
The debate regarding the implications of artificial intelligence (AI) on labour markets, particularly in light of advancements in generative AI, is highly polarized. Perspectives diverge sharply: while some predict widespread unemployment from AI-driven labour substitution, others anticipate opportunities for job creation and productivity enhancement. Empirical findings are mixed, with some studies highlighting complementarities between AI and human labour — particularly in high-skilled occupations — while others underscore the risks of workforce displacement and growing inequality.

Existing research indicates that AI is already transforming labour demand, though its overall impact on employment remains uncertain. Nonetheless, there is broad consensus that the current wave of AI, characterized by its ability to perform complex and creative tasks, represents an unprecedented technological shift with deep and heterogeneous implications across industries, occupations, and regions. Key concerns include the labour markets' flexibility, the quality of newly created jobs, and the absence of comprehensive regulatory frameworks.

AIOE AND AISE

A central challenge to defining possible changes in the labour market restructuring lies in accurately measuring occupational exposure to AI. Various methodologies have been used to estimate the extent to which AI capabilities overlap with occupational tasks, including tools such as the AI Occupational Exposure (AIOE) index. However, these approaches

Joint Research Centre

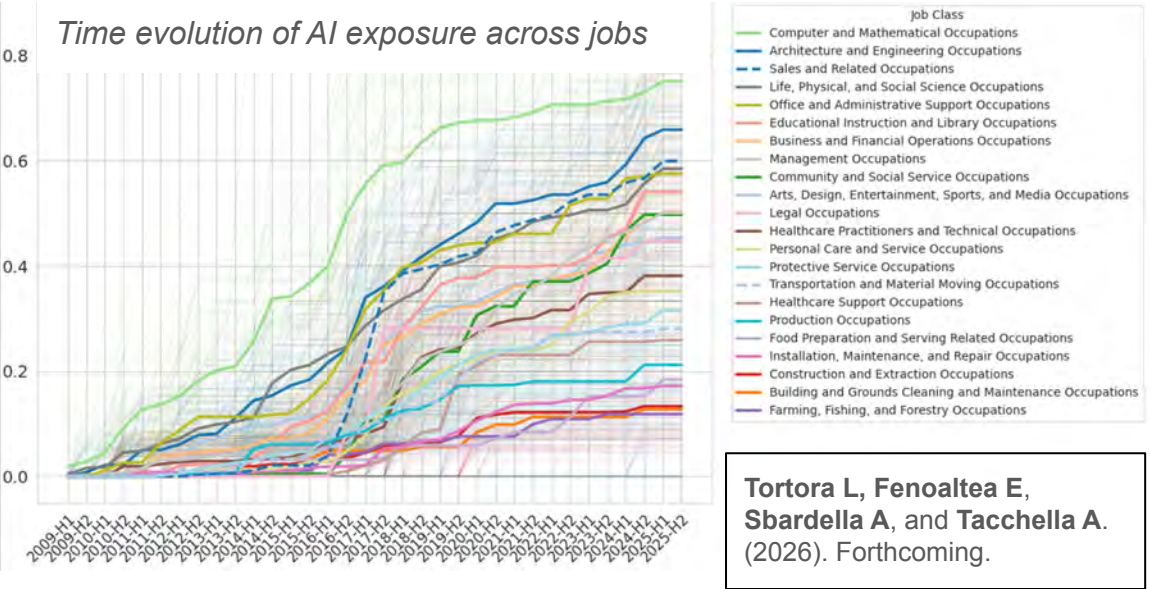


Albora, G., Diodato, D., **Fenoaltea, E.**, **Mazzilli, D., Patelli, A., Sbardella, A.**, Sciarra, C., **Tacchella, A.** and Zaccaria, A. (2025). Science for Policy Series, European Commission: Joint Research Centre, JRC141782.

Real-time mapping of AI innovation & labour market exposure via GitHub

- GitHub main online platform where programmers and firms publish software code: many new AI tools appear there first allowing us to track AI innovation in real time (150k+ AI-related projects, 2009–2025, using README texts)
- Using a **fine-tuned Llama 3** model, **we match each AI project to specific job tasks and assess whether AI is likely to help with or substitute for those tasks**
- → **AI exposure score for each task and each job**

Time evolution of AI exposure across jobs



Diffusion of AI exposure in the Job space

- **AI exposure diffusion dynamics** across the ***Job Space*** (job-to-job network where jobs linked if share similar skills): jobs not exposed at time t more likely to be exposed at t+Δt when neighbouring jobs exposed
- Highlights **reskilling pathways**: workers can move to “nearby” jobs requiring similar skills but facing lower AI exposure

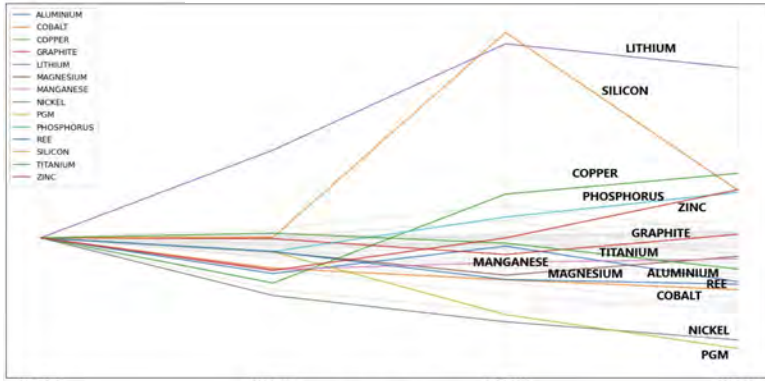
Tortora L, Fenoaltea E, **Sbardella A**, and **Tacchella A**. (2026). Forthcoming.

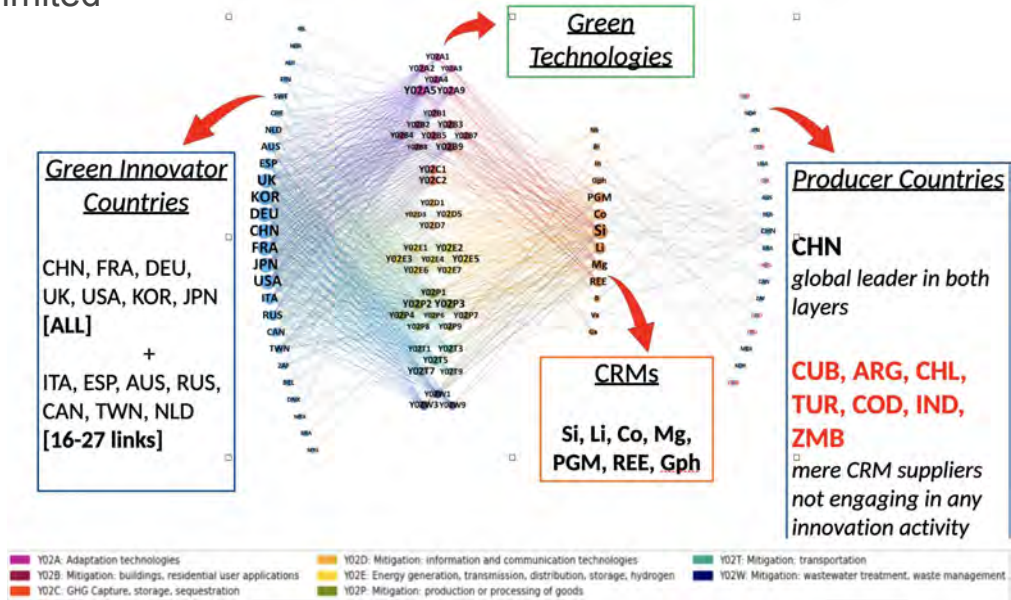
Mapping Critical Raw Materials (CRMs) into innovation

- CRMs (e.g., lithium, cobalt, nickel, rare earths, gallium…) essential inputs for green, digital, and defence/aerospace technologies
- Fast-rising demand in the green and digital transition
- Supply-disruption vulnerabilities driven by scarcity and geographic concentration in mining/processing + limited substitution options

- What we do: text analysis of patent abstracts combined with long-run CRM production data to track dependencies and emerging bottlenecks

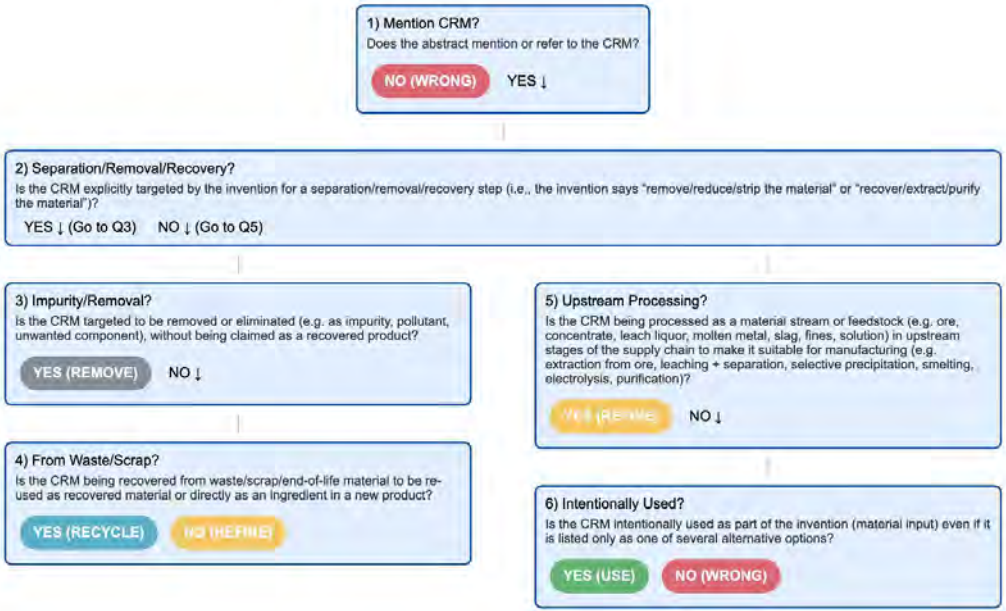
CRM mentions in patents over time

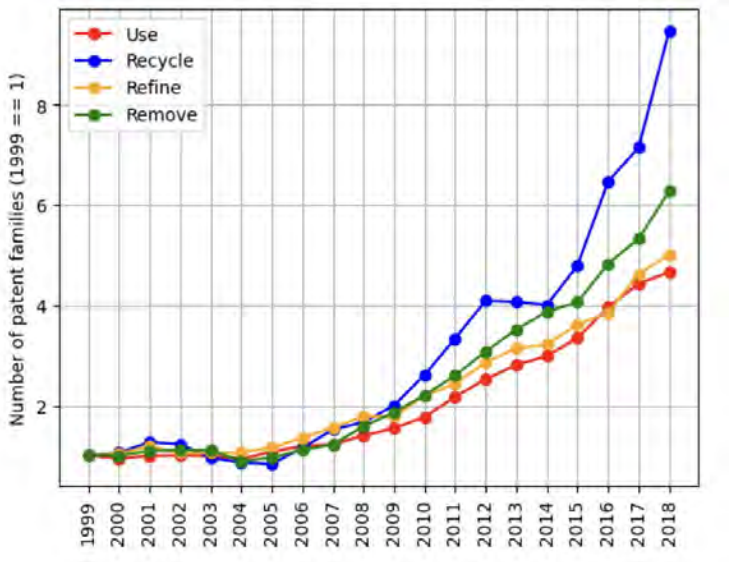




de Cunzo F, Consoli D, Perruchas F, and **Sbardella A** (2025). Industry & Innovation.

Using LLMs to track Critical Raw Materials (CRMs) dependency



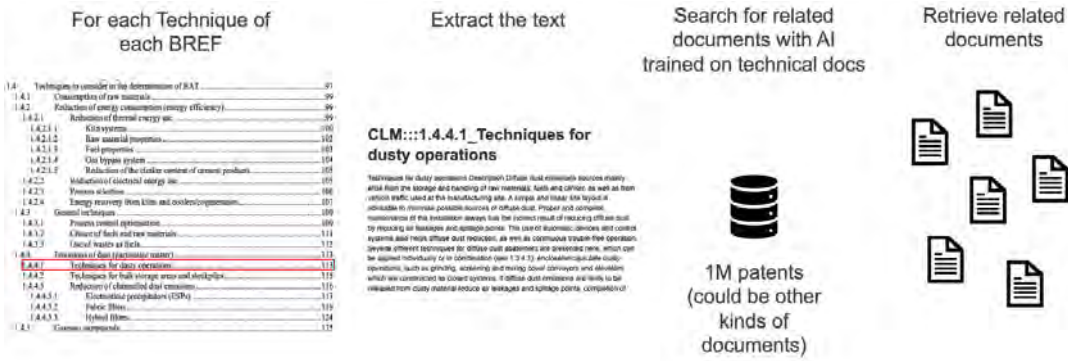


- Using LLMs we track the presence and function (use/recycle/refine) of CRMs across 6M patents worldwide
- We train the LLM to follow a decision tree, achieving 95% classification accuracy
- Recycle is the fastest growing function, increasing twice as fast as other categories

de Cunzo F, Patelli A, Sbardella A , and **Tacchella A** (2023). Papers in Evolutionary Ec Geography, Utrecth University Human Geography and Planning.

Using LLMs to match environmental legislation with patents

- LLMs can be used to create links between different domains and enrich our understanding of the interplay between policy and innovation
- We have collected the full corpus of EU legislation on Industrial Pollution Control and extracted 4200 technical descriptions of pollution abatement techniques
- With a specifically fine-tuned LLM (LLama 3.2 8B) we have matched 1M patents with the legislation, identifying capabilities and monitoring the dynamics of the related technological domains

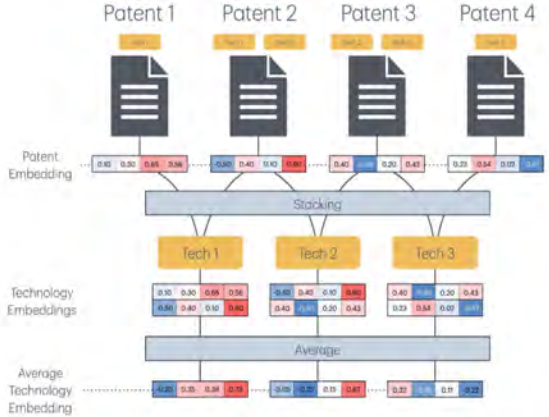


Tacchella, A., Marschinski, R. and Albora, G., LINKING GREEN INNOVATION AND ENVIRONMENTAL POLICY: MAPPING POLLUTION CONTROL TECHNOLOGIES WITH LARGE LANGUAGE MODELS. *Available at SSRN 5807662.*

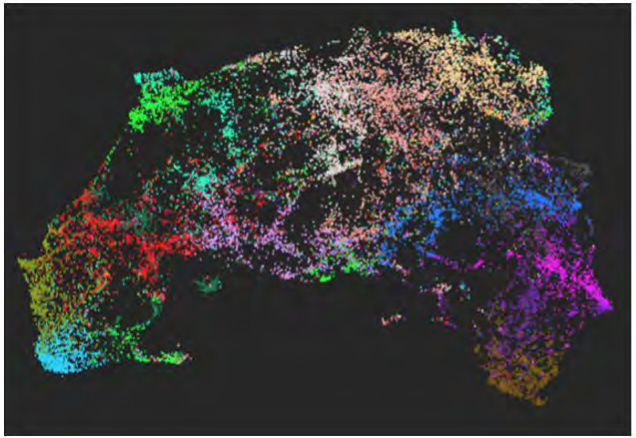
AI Models to uncover emergent innovation trends: ongoing work

CENTRO RICERCHE ENRICO FERMI

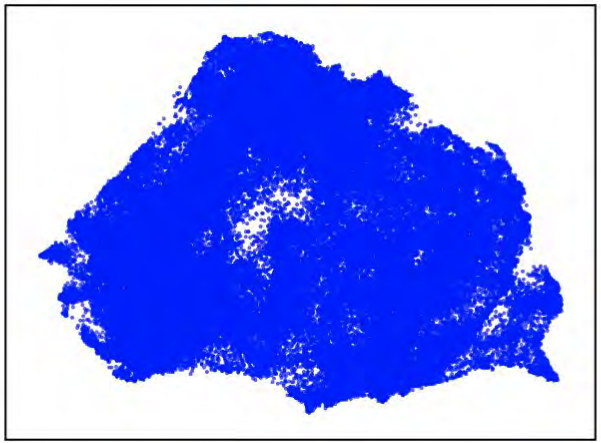
- Language models represent texts as high dimensional embedding vectors
- The metric properties of such high-dimensional spaces encode meaning and semantic similarities between patents, scientific papers or code
- We use these representations to forecast major innovation events (bursts of patenting/publishing, breakthroughs, or new trajectories) uncovering structure of knowledge recombination and emerging dynamical trends



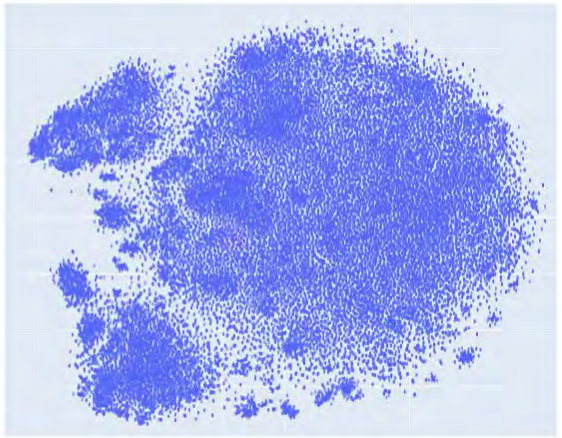
Patent Space



Paper Space (OpenAlex)



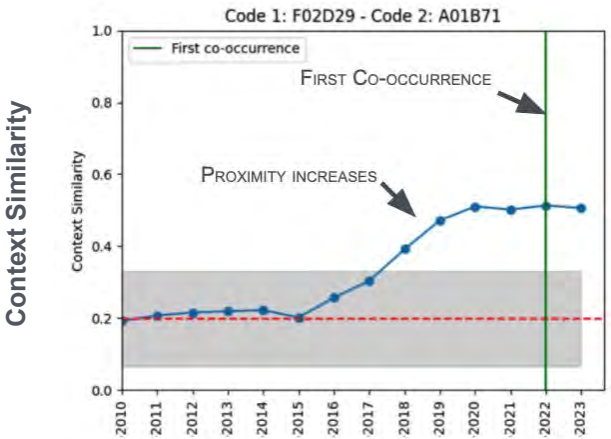
Code Space (GitHub)

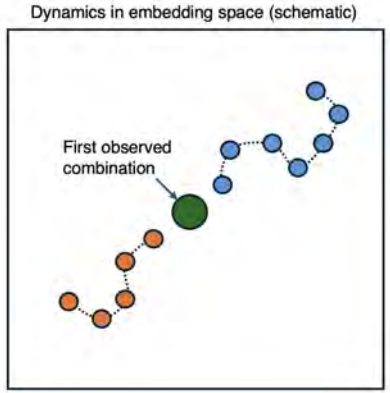


Innovation forecasting

- We use a fine-tuned language model to represent each technology code by the *contexts* in which it appears in patents (embedding)
- For pairs of tech codes that have **never been used together** in the same patent, we track over time whether their embeddings become **more similar** (their semantic contexts "converge") and thus more likely to be combined
- When the two codes **first co-occur** in a patent (green line), similarity typically has been increasing for years beforehand
- This "context convergence" signal predicts **novel technology combinations** with high accuracy **up to 15 years in advance**

Similarity between technology codes F02D29 (Systems for automatic control of engines) & **A01B71** (Adapting machine elements to or for agricultural purposes)





First co-occurrence in 2022: Application ID 3992535 - Work Vehicle: "[...] This patent introduces a safety mechanism for working machines that allows the operator to safely work outside the vehicle with the engine running. [...]"

Ongoing development: in a project funded by the EC we are applying this methodology to the discovery of emergent technologies on battery production and recycling, with a focus on European innovative capabilities

Tacchella A, Fenoaltea E, De Marzo G, Aroyehu S. Forthcoming.

Events, dissemination & open science

- ***Analyses, contradictions, and policy pathways for a just transition*, TRIPLE T project final workshop** [Feb 2026]
- ***Coupling Opinion Dynamics with Epidemics*, CODE project final workshop** [Feb 2026]
- ***Labour markets and AI* joint workshop with INAPP** [Feb 2026]
- ***Complexity in Economics and Finance*, StatPhys 29 Satellite** [July 2025]
- ***Behavioral and Social Aspects in Fighting Epidemics (BeSAFE)*, CCS 2025 Satellite** [Sept 2025]

- ***Notte Europea delle Ricercatrici e dei Ricercatori 2025* @CAE (Rome)** [Sept 2025]
- **Debate: *Left-behind places - reflections on a just green transition @Festival del pensare contemporaneo* (Piacenza)** [Sept 2025]
- **Newspaper article on "Domani": *Terre rare e riarmo: così l'Ue tradisce la sostenibilità*** [Oct 2025]
- ***Nuovi Equilibri* podcast: *Green Innovation and social justice*** [Jan 2025]
- **Special issue *Italian Journal of Regional Science*** [Apr 2025]
- **Data platform EFC Data (https://efcdata.cref.it/) + GitHub FERMI Repository (https://github.com/EFC-data/fermi)**

- ***Deep Dive into LLMs* course** [March 2025]
- ***Economic Fitness and Complexity Summer School*, 3rd ed** [June 2025]
- **Master's in *Economic Policy and Governance for Development and Resilience* UNU-CRIS -Universitas Mercatorum** [a.y. 2025-2026]

CENTRO RICERCHE
ENRICOFERMI

Thank you!

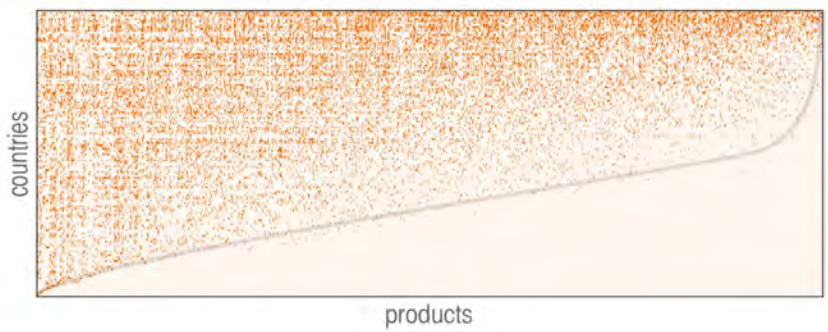
A SIX-DAY SUMMER SCHOOL ON ECONOMIC FITNESS AND COMPLEXITY FOR PHD STUDENTS, EARLY CAREER RESEARCHERS, AND PRACTITIONERS

Organised by Enrico Fermi Research Centre (CREF, Rome), UNU-MERIT (Maastricht), UNU-CRIS (Bruges) and the Young Scholar Initiative (YSI-INET)

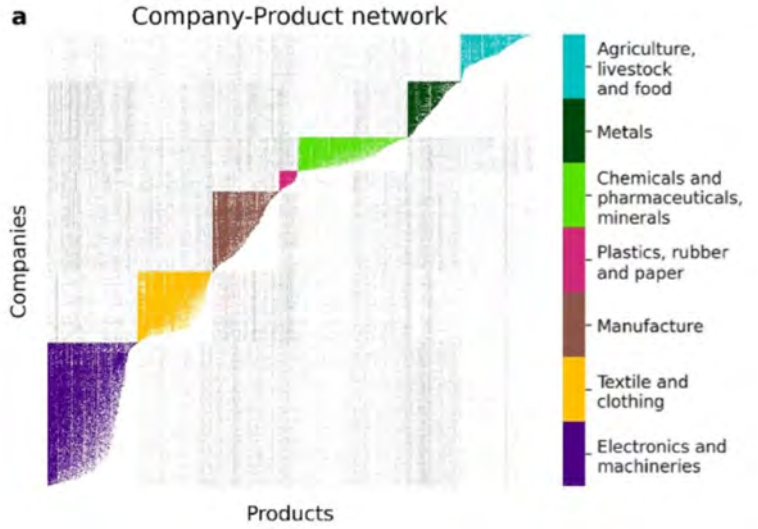
- An extensive introduction to the economic complexity framework, with:
  - theoretical and practical classes
  - presentations of state-of-art applications of economic complexity methods
  - policy debates
- More than 200 applications in the previous editions
- More than 30 international speakers
- Co-organised with the Young Scholar Initiative-INET (Oxford), United Nations University - MERIT (Maastricht), United Nations University - CRIS (Bruges)

Nestedness morphs with scale
Can we find scaling laws for nestedness?

Proposal: SECANT
Scaling Laws in
Economic Complexity
and Nestedness



Country Level



Firm Level

Multi-Scale Economic Complexity

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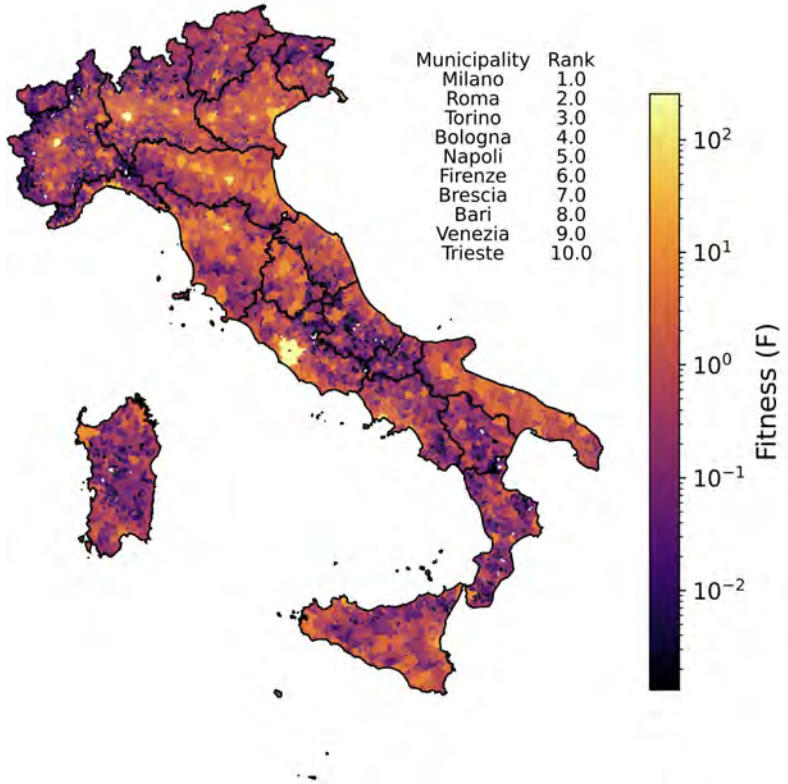
- Data about 4 million geolocated firms in Italy with corresponding ATECO code: 814 codes representing economic activities

Fitness and Complexity algorithm:

$$\begin{cases} F_e^{N+1} = \sum_t M_{et} Q_t^N \\ Q_t^{N+1} = \dfrac{1}{\sum_e M_{et} \dfrac{1}{F_e^N}} \end{cases}$$

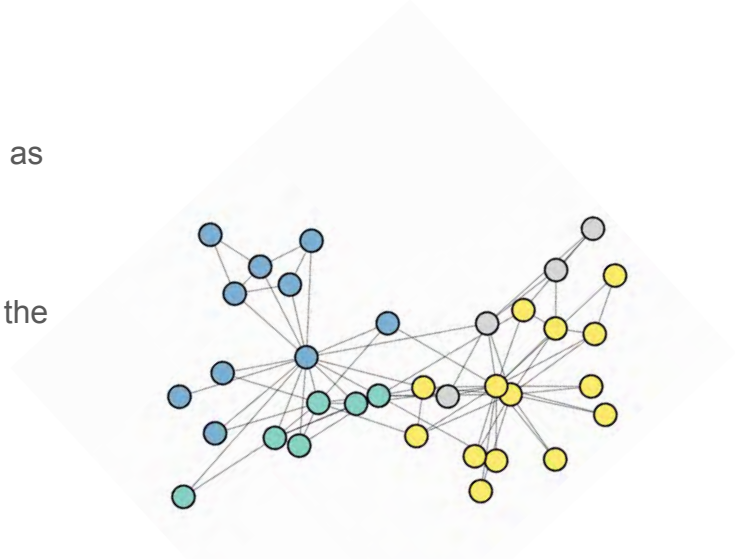


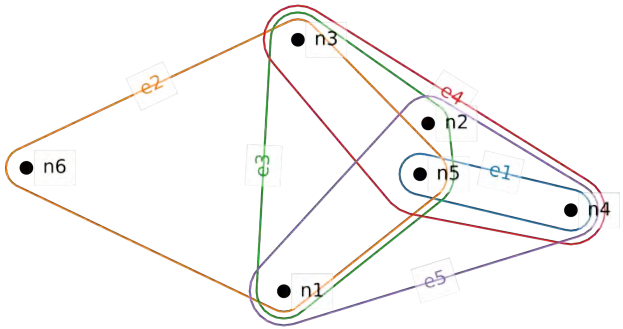
Network Theory & Statistical Physics: ongoing research and next steps

- **Sub-Optimal Transport:** the framework will be used for two distinct directions:

1. it will be implemented as a Null Model for networks with links associated to a cost, such as in the interbank network.
2. it will be used to characterize the costs on mutualistic systems such as plants-pollinators and economic complexity network

- **Temporal Networks**: the framework for **MaxEnt** null model will be enlarged to account for the evolution of the networks as required for the analysis of the dynamic of Online Social Networks



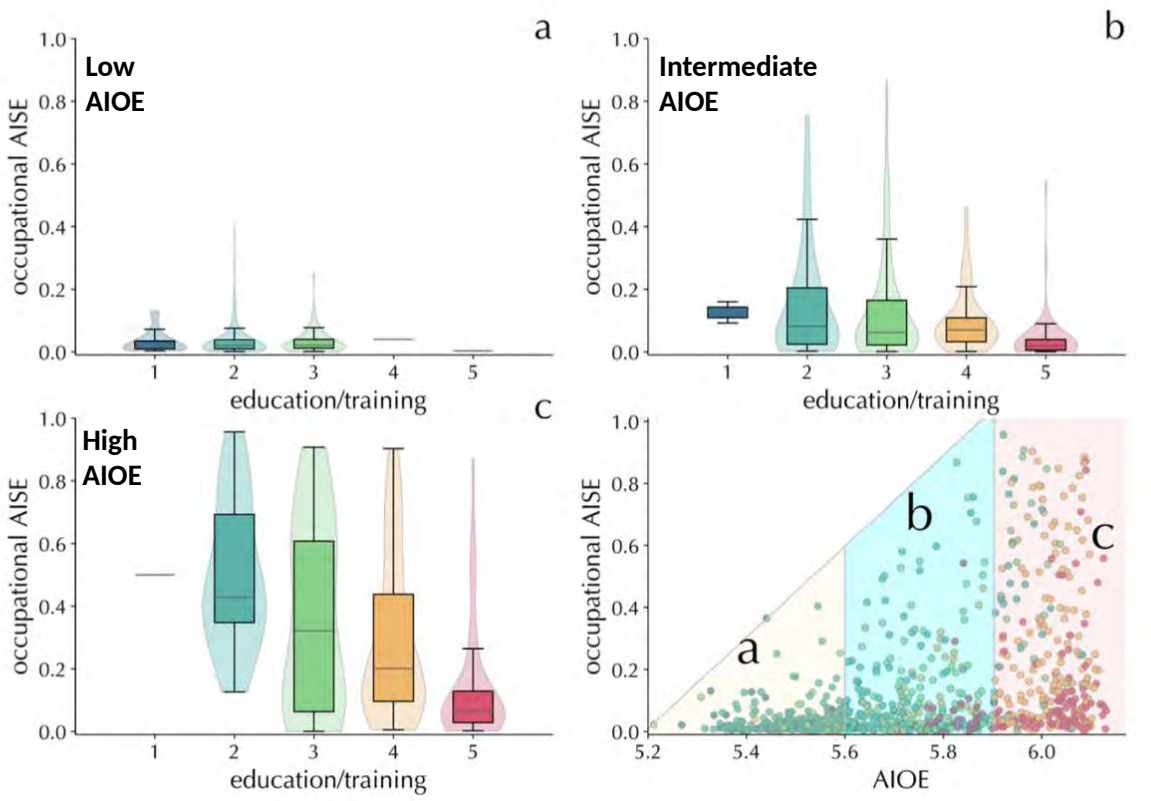


- **Signed networks, hypergraphs, etc:** investigations of further properties of null models for signed networks, hypergraphs, etc. developed in the last year will be target of the future research, as required by the various applications, especially in Online Social Networks and epidemics

AI exposure vs. education and training

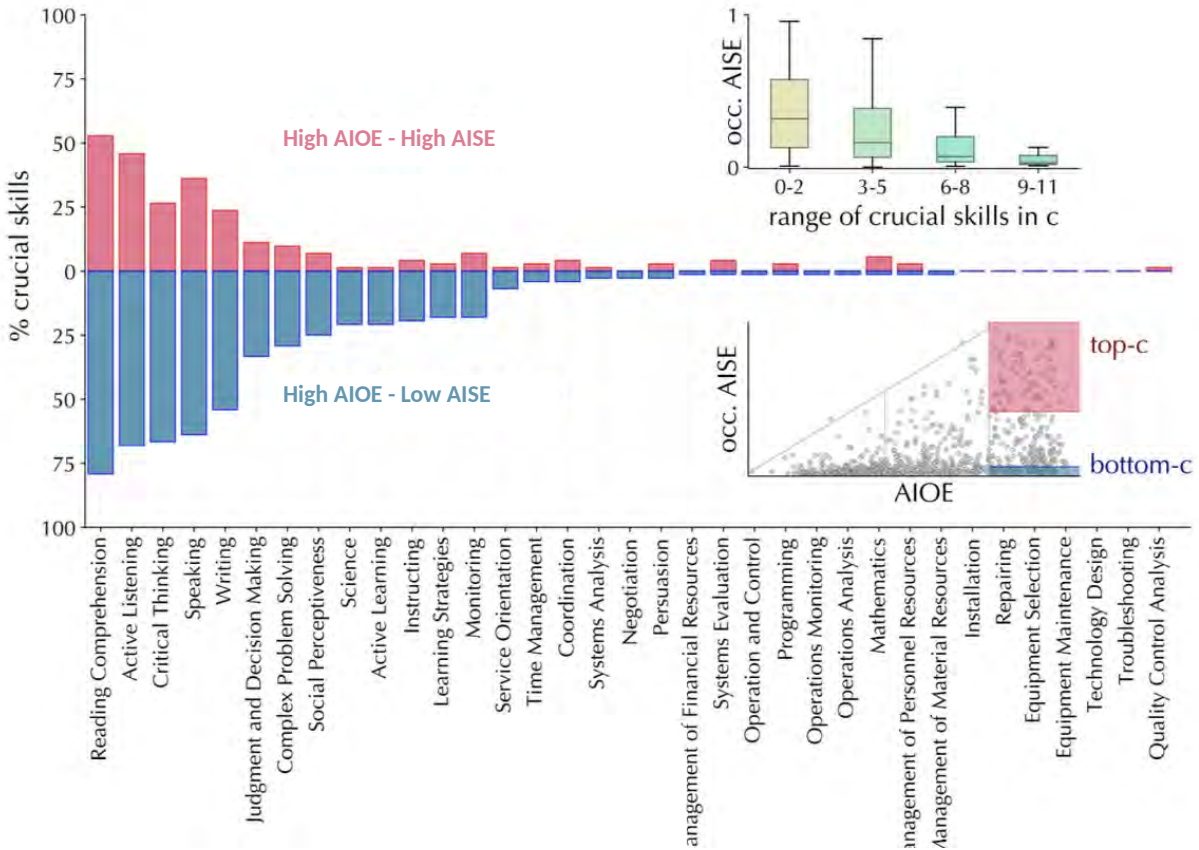
Colour = O*NET 5 **Job Zones** that classify occupations based on the typical level of preparation required (education, experience, and on-the-job training) ranging from **Job Zone 1** **(little or no preparation)** to **Job Zone 5** **(extensive preparation)**

- **Low AIOE:** AISE is consistently low across job zones, with limited dispersion
- **Intermediate AIOE:** AISE increases & more differentiated by job zone, higher-skill occupations higher median exposure and greater variability
- **High AIOE:** AISE higher on average but heterogeneous, indicating uneven startup targeting among occupations with similar high theoretical exposure
- **High-education job zones highest median AISE but also wide dispersion —> Not all highly educated occupations equally targeted by AI!**
- **Not only high-skill catastrophe: some mid- and low–job-zone occupations relatively high AISE**



Crucial skills and exposure

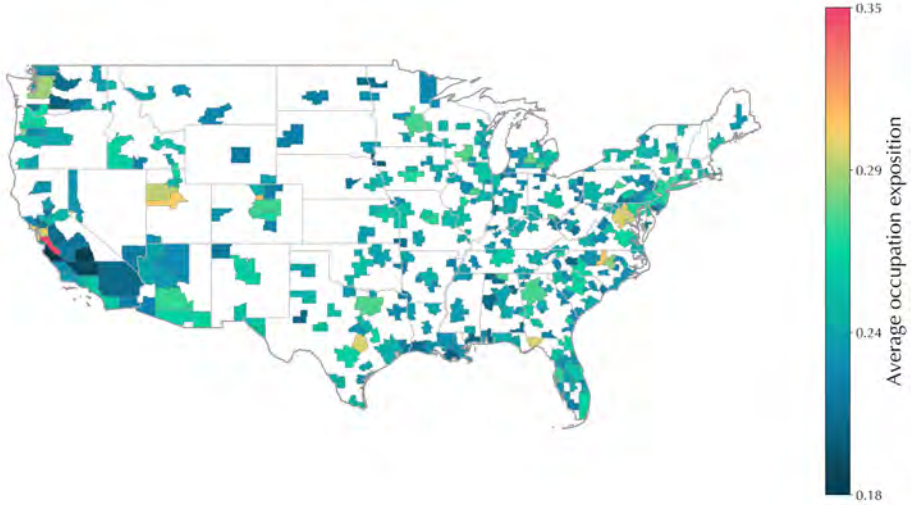
- At a given AIOE, larger crucial skill sets associated with lower AISE, suggesting that **skill breadth moderates exposure, for high AIOE when:**
- **Low AISE** more crucial skills (judgment, managing uncertainty, social interaction, high-stakes, accountability) & harder to standardise/automate
- **High AISE** easier to codify and scale tasks (information processing, coordination, routine cognitive work)
- **Combining AISE and AIOE informative on complementarity vs. substitution**, differentiating between what AI could do and what startups are actually building products for:
  - high AIOE-high AISE (pink) into more direct task substitution
  - high AIOE-low AISE (blue) potentially mapping into augmentation



Geographical AI exposure in US metro areas

Geo AISE obtained by averaging occupational AISE using occupation employment shares within US Metropolitan Statistical Areas

- Exposure highly uneven across US MSAs reflecting differences in local economic structure and innovation systems



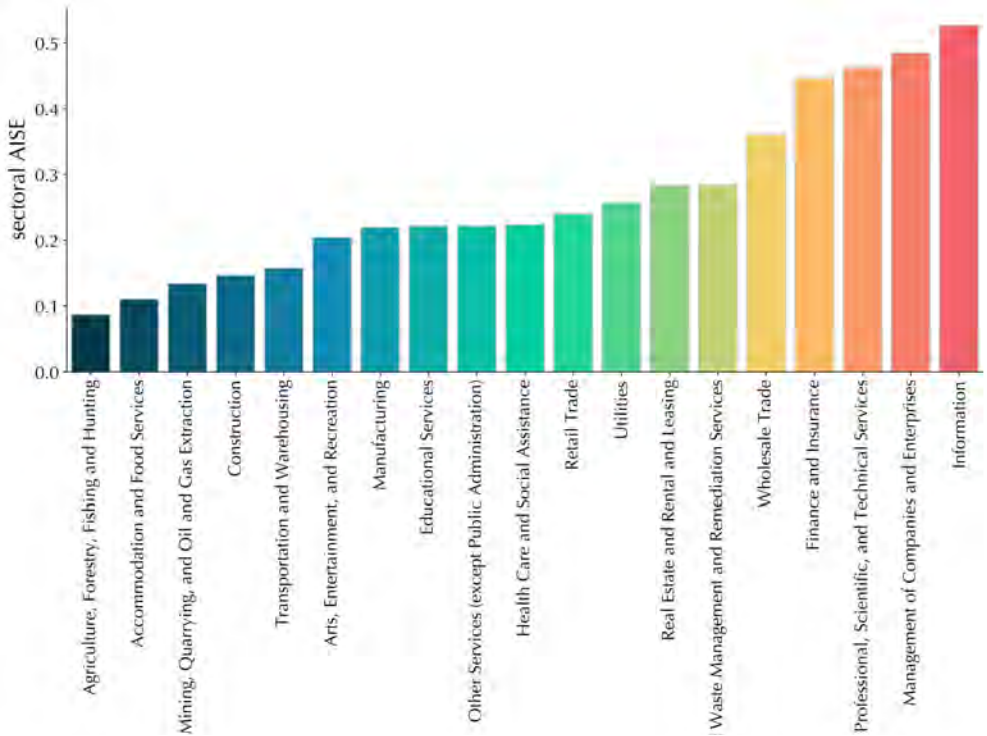
- **Lowest exposure** in manufacturing- and agriculture--oriented MSAs, especially in the Midwest

- **Highest exposure** in knowledge-intensive MSAs with strong innovation ecosystems: Silicon Valley (San Jose/Santa Clara), Bay Area, San Diego + Boston, Washington DC, Austin, Denver/Boulder, Salt Lake City, Miami

Sectoral AI exposure

Sectoral AISE computed as an employment-weighted average of Occupational AISE within each 2-digit NAICS industry

- **Low exposure**: manual and context-dependent sectors (construction, agriculture, food preparation, transportation)
- **Intermediate exposure**: sectors mixing routine office/process tasks with on-site or high-stakes activities (manufacturing, retail, real estate, education, arts & entertainment)
- **High exposure**: information- and data-intensive services (information, finance and insurance, professional/scientific/technical services, lower management, wholesale trade, administrative and support



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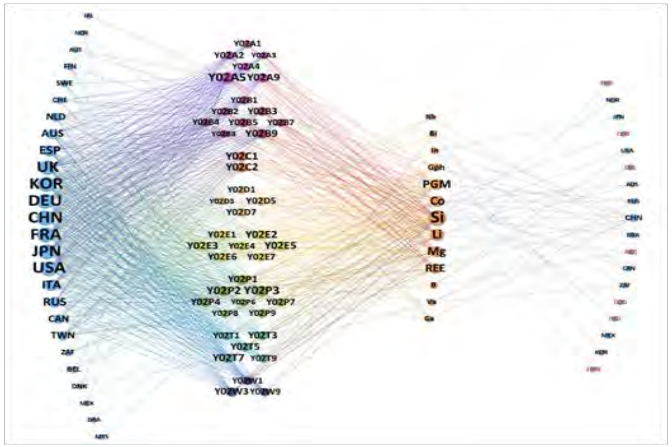
Embracing socio-economic complexity in the sustainability transition

A complexity view of the transition able to incorporate heterogeneous effects in competitiveness, knowledge generation, labour markets, and inequalities

- **Which countries/regions will benefit the most from the transition and which risk falling behind?**
- **How do countries' pre-existing capabilities shape new green development trajectories that offer the greatest opportunities for growth and job creation?**
- **Which domains of non-green know-how are more conducive to green?**
- **What is the new material base of green technologies and can we shape equitable and stable supply chains for critical raw materials?**
- **Which place-based industrial policies can ensure a just transition?**



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European Patent Office CodeFest challenge

CENTRO RICERCHE ENRICOFERMI

Challenge on AI applications on patents from the European Patent Office

50+ international teams competing

Joint team CREF-Univ. Konstanz developed the technology forecasting model (2024) and extended it to match innovation with sustainable development goals and environmental legislation (2025)

2024 Edition: Second Prize 🏆

2025 Edition: Finalists 🏅

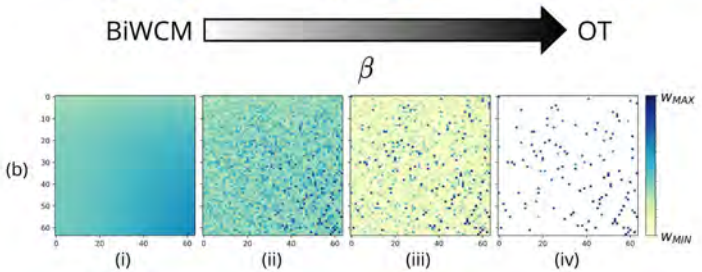
CREF TEAM ACHIEVES SECOND PLACE AT CODEFEST 2024 FOR GENERATIVE AI PROJECT

2024 Edition: CREF Second Prize 🏆

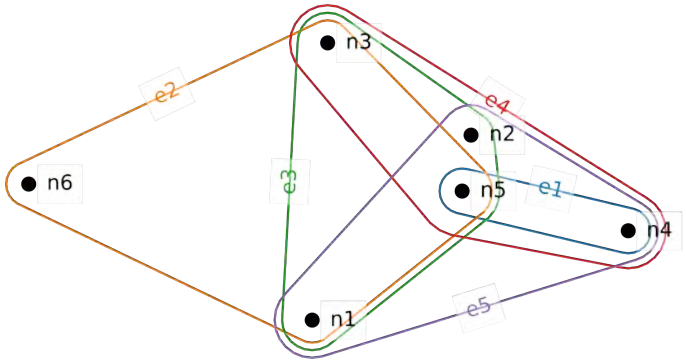
2025 Edition: CREF Finalists 🏅

A research team comprised of researchers from CREF (**Andrea Tacchella, Enrico Fenoaltea, and Filippo Santoro**), along with collaborators from the University of Konstanz (**Giordano De Marzo and Segun Aroyehu**), achieved an impressive second-place finish at CodeFest 2024 in the Generative AI category. The top winners were announced on December 4th at the EPO's Patent Knowledge Forum, a major event for the patent information community.

Network Theory & Statistical Physics: ongoing research and next steps



- **Temporal Networks**: evolution of networks over time for the analysis of the dynamics of **Online Social Networks.**
  In collaboration with **G. Cimini (Università di Tor Vergata), A. Desiderio (ISI Foundation), R. Di Clemente, I. Iacopini (NorthEastern University, London)**



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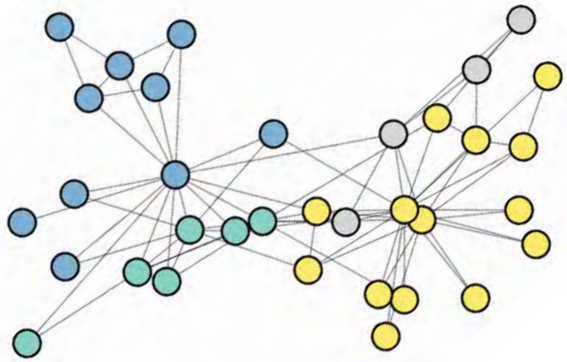
  1. as a **Null Model** (for networks with links associated to a cost, such as in the interbank network)
  2. to **characterize the costs on mutualistic systems** (e.g., plant-pollinator networks



- **Signed networks, hypergraphs, etc:** further investigations and applications in **Online Social Networks** and **epidemics**. Based on:

- **F. Saracco**, G. Petri, R. Lambiotte, T. Squartini, Comm. Phys. (2025)
- **A. Gallo, F. Saracco**, T. Squartini, npj Complex (2025)
- **A. Gallo, F. Saracco**, R. Lambiotte, D. Garlaschelli, T. Squartini, PRE (2025)