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Working Paper

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CREMA Working Paper, No. 2021-28

Provided in Cooperation with:
CREMA - Center for Research in Economics, Management and the Arts, Zürich

Suggested Citation: Bickley, Steve J.; Chan, Ho Fai; Torgler, Benno (2021) : Artificial intelligence in the field of economics, CREMA Working Paper, No. 2021-28, Center for Research in Economics, Management and the Arts (CREMA), Zürich

This Version is available at:
https://hdl.handle.net/10419/246011

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Center for Research in Economics, Management and the Arts

Artificial Intelligence in the Field of Economics

Working Paper No. 2021-28

CREMA Südstrasse 11 CH - 8008 Zürich www.crema-research.ch

Artificial Intelligence in the Field of Economics

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Abstract: *The history of AI in economics is long and winding, much the same as the evolving field of AI itself. Economists have engaged with AI since its beginnings, albeit in varying degrees and with changing focus across time and places. In this study, we have explored the diffusion of AI and different AI methods (e.g., machine learning, deep learning, neural networks, expert systems, knowledge-based systems) through and within economic subfields, taking a scientometrics approach. In particular, we centre our accompanying discussion of AI in economics around the problems of economic calculation and social planning as proposed by Hayek. To map the history of AI within and between economic sub-fields, we construct two datasets containing bibliometrics information of economics papers based on search query results from the Scopus database and the EconPapers (and IDEAs/RePEc) repository. We present descriptive results that map the use and discussion of AI in economics over time, place, and subfield. In doing so, we also characterise the authors and affiliations of those engaging with AI in economics. Additionally, we find positive correlations between quality of institutional affiliation and engagement with or focus on AI in economics and negative correlations between the Human Development Index and share of learning-based AI papers.*

Keywords: Artificial Intelligence, Machine Learning, Economics, Scientometrics, Science of Science, Bibliometrics

JEL: B40, N01, A14

* Corresponding author: Ho Fai Chan (hofai@qut.edu.au). Thanks to Alison Macintyre for reading through and providing useful feedback during our preparation of the initial manuscript. Thanks also to Iván Aranzales for inputs to the earlier stages of project brainstorming. This research has been supported by an Australian Research Training Program (RTP) Scholarship and the Australian Research Council (ARC), DP180101169.

1 Introduction

The quest for artificial intelligence[1] (AI) has affected many fields and disciplines; economics is no exception. It began with the dream of creating human- or animal-like machines and automata such as Leonardo da Vinci's robot knight, walking lion, or Vaucanson's duck[2]. Thomas Hobbes starts his famous *Leviathan* with:

> Nature (the art whereby God hath made and governs the world) is by the art of man, as in many other things, so in this also imitated, that it can make an artificial animal. For seeing life is but a motion of limbs, the beginning whereof is in some principal part within, why may we not say that all automata (engines that move themselves by springs wheels as doth a watch) have an artificial life? For what is the heart, but a spring; and the nerves, but so many strings; and the joints, but so many wheels, giving motion to the whole body, such as was intended by the Artificer? Art goes yet further, imitating that rational and most excellent work of Nature, man.

On the other hand, Descartes was critical on whether a machine would be able to imitate human actions:

> Although such machines could do many things as well as, or perhaps even better than, men, they would infallibly fail in certain others… For while reason is a universal instrument which can be used in all sorts of situations, the organs [of a machine] have to be arranged in a particular way for each particular action. From this it follows that it is morally impossible that there should be enough different devices [i.e., states] in a machine to make it behave in all the occurrences of life as our reason makes us behave (cited by Dreyfus, 1965, p. 69 (translation by Lafleur)).

But humans remain fascinated by synthesizing things, by imitating appearances of natural things, or by understanding non-artificial functionalities. The journey of AI has moved from the storytelling of Homer's tripods to philosophies of syllogism and logical reasoning and on towards a computation theory or manipulation of symbols by machine, thanks to luminaries such Aristotle, Leibniz, Boole, or Turing. The field flourished with important conferences such as the 1948 Interdisciplinary Conference held at Caltech that cemented the view that the brain might be compared to a computer, or the 1956 famous Summer Research Project on Artificial Intelligence at Dartmouth College – seen by many as the key gathering in the history of AI (for an overview, see Nilsson, 2010). Herb Simon, for example, shifted his interests and concerns

[1] Unless stated otherwise, in AI we refer to the whole collection of diverse methods which form the basis of symbolic and connectionist AI. This includes symbolic logical reasoning, knowledge systems, and rule-based systems as well as more recent developments in neural networks, machine learning, and deep learning. When referring to a specific AI method (e.g., knowledge systems) we explicitly state this.

[2] For a discussion, see, e.g., Nilsson (2010) and Rosheim (2006).

around administration and economics towards human problem solving to discover the symbolic processes that people use in their thinking. The computer was therefore used as a general processor for symbols. In other words, he found tools within computer languages that classical mathematical languages could not offer when exploring the processes of human thinking (Simon, 1991). The use of AI was therefore closely linked to attaining more rigor in the fields of behavioral and social sciences. Cybernetics – in the spirit of Nobert Wiener – has helped us put more weight on feedback and therefore to understand adaptive processes or how to maintain stability. Morgan (2003), for example, stresses that "under the influence of cybernetic thinking, the economic behaviour of each individual was pictured as being controlled by personal feedback loops" (p. 276). The field of cybernetics that inspired economics derived their insights from the study of messages, the development of computing machines and automata, psychology, and the nervous system (Wiener, 1954). Wiener (1954) stressed that "[t]o live effectively is to live with adequate information. Thus, communication and control belong to the essence of man's inner life, even as they belong to his life in society" (p. 18). Especially when viewed through a macroscopic lens, cybernetics allows us to avoid making assumptions about the contents, connections, and structure of economic systems beyond a simple input-output through transformation modelling approach (Cochrane & Graham, 1976; Billeter-Frey, 1996). This allows study of the sequences of economic events and path dependency; when calculating over the entire economic system where inputs are transformed by a black box economy into outputs and time and space, both local and global matter tremendously. In the end, feedback is a property of being able to adjust your future conduct based on past performance; and therefore, is a method of controlling a system by reinserting into the system the outcome of past performance (Wiener, 1954). This allows definition of various societal concepts, such as law, which in this context could be defined as the "ethical control applied to communication" (Wiener, 1954, p. 105).

Economics in the twentieth century emerged as a science in the "mould of engineering" (Morgan, 2003, p. 276), relying on a certain precision regarding how to represent the world with quantitative techniques rather than words and verbal arguments of the 19th century (Morgan, 2003, p. 287). Paul Samuelson (2004, p. 49), for example, recollects that when he

> began the study of economics back in 1932 on the University of Chicago Midway, economics was literary economics. A few original spirits—such as Harold Hotelling, Ragnar Frisch, and R. G. D. Allen—used mathematical symbols; but, if their experiences were like my early ones, learned journals rationed pretty severely acceptance of anything involving the calculus. Such

> esoteric animals as matrices were never seen in the social science zoos. At most a few chaste determinants were admitted to our Augean stables. Do I seem to be describing Eden, a paradise to which many would like to return in revulsion against the symbolic pus-pimples that disfigure not only the pages of Econometrica but also the Economic Journal and the American Economic Review? Don't believe it. Like Tobacco Road, the old economics was strewn with rusty monstrosities of logic inherited from the past, its soil generated few stalks of vigorous new science, and the correspondence between the terrain of the real world and the maps of the economics textbook and treatises was neither smooth nor even one-to-one.

Thus, as Morgan points out, the modelling and tool-based approach gave economics "an aura of scientific modernity" (p. 277) of a more advanced and proper science via the "desire to ape natural since" (p. 287) using, for example, mathematics to formulate general laws or statistics or econometrics to predict economic events (p. 277) or by engineering interventions in the economy (p. 305):

> The engineering metaphor also suggests that twentieth-century economics is best characterized as a science of applications and implies a technical art, one that relies on tacit knowledge and decidedly human input as in the eighteenth-century term "art of manufactures" (Morgan 2003, p. 276)

As a consequence, a form of social engineering evolved during the middle and late twentieth century (Morgan, 2003). Similarly, the use of AI may give the impression that Hayek's spontaneous order is a thing of the past. Big Data, machine learning (ML), and deep learning (DL) allow to ask whether economic calculation has become less impossible, supporting advancement towards more social planning. However, although we may end up with more reliable data about the initial conditions to predict the future, it will not give us enough theoretical understanding of the actual phenomena to be predicted, which is equally important for good predictions (Simon, 1996). Also, ML or Big Data cannot solve issues around the problem of utilization of knowledge (Hayek, 1945). Thus, there is a limit to how much of an "architect" an economist can be. Data points themselves are not free of the ambitions, power struggles, gaming aspects, or politics of societal decision making. AI has also taught us that simple heuristics of just "interestingness" can lead to powerful searches that result in realized activities or scientific discoveries (Simon, 1996). AI systems are interesting for economics due to their search for powerful problem-solving algorithms and for procedural rationality: "Procedural rationality takes on importance for economics in those situations where the 'real world' out there cannot be equated with the world as perceived and calculated by the

economic agent" (Simon, 1978, p. 505). Simon sees the power of a theory of computation in domains that are highly uncertain, rapidly changing, and therefore, too challenging to allow objectively optimal actions to be identified or implemented.

AI – like all fields at one point or another – has gone through many seasons of activity and focus in its long and winding history. The way AI is discussed and applied more specifically in economics and to the economic calculation debate is less explored. Haenlein and Kaplan (2019) use an analogy of four seasons (in turn) when recounting the history of the AI field: spring, summer, winter, and fall. Spring, led by the likes of Asimov, Turing, Minsky, McCarthy, Simon, and Newell, forms the roots of AI in automata, the antecedents of neural networks, and symbolic logical reasoning. AI summer began with the 1956 Dartmouth Project, followed by two decades of significant success and advances in the field (theory and practice). In 1973, US Congress argued for reducing the level of spend on AI research and the British Research Council grew increasingly cautious of optimistic AI researchers. This hallmarked the beginning of (the first) AI winter, a period where AI research (and funding for it) fell dramatically to almost a standstill as the early promises and hype of the field failed to materialise. As funding dried up, AI entered a 41-yearlong winter with little interest or activity in the field aside from the brief rise (and fall) of expert systems and other knowledge-based systems in the later 1970s. Statistical advances, increasing computational power, and data ubiquity began to increase by the 2000s, and AI researchers came to harvest the learnings from previous AI generations (i.e., AI fall), again with increasing interest from academia and industry and excitement in the general public. Neural networks, ML, and DL led the way in this (current) season. Others, however, argue this narrow focus falls short of *true* general AI; the sort imagined by early spring and summer AI researchers and science fiction more generally. Mostly, economists are focused on AI *fall* theories and methods, likely due to the complementary nature of their use and application (i.e., prediction, clustering, classifying) and strong preference for mathematics and procedural rationality. We expect this means missing out or ignoring what else can be learned from earlier attempts to create models of the human mind and nature.

In this paper, we explore the history and development of AI in economics, taking a scientometrics approach. Our descriptive study looks to shed light on the take-up of AI methods in economics through time and across locations, characterising the average and influential authors and institutions involved by economic subfield, academic age, country, gender, and the like. In particular, we centre our accompanying discussion of AI in economics around the

problem of economic calculation and social planning. It is still early days as to where AI in economics may take us – not to mention what world this might create and for what good (or bad). By characterising who and how AI methods have propagated through different sub-fields of economics (e.g., labour, environmental) we seek to uncover what resistance we may face as AI economists in the future and what hidden gems from a not-so-distant past may still remain ripe for picking.

2 Materials and Methods

2.1 Data Description

To gather the data needed to map this history of AI within and between economic sub-fields, we construct two datasets containing bibliometrics information of economics papers based on search query results from *Scopus* database and the *EconPapers* (and *IDEAs/RePEc*) repository. While the latter contains information on the JEL classifications (Journal of Economic Literature classification system) distinguish between 20 economics sub-fields, which provide us a much higher resolution analysis by field, we retain the *Scopus* data as this allows to explore the individual and institutional factors of research in similarly fine detail. We perform a search query (see Table) to retrieve relevant article records from the *Scopus* and *EconPapers* databases[3]. The query has been kept sufficiently broad to avoid the exclusion of relevant records from the search and also to ensure that results were not skewed towards more recent AI developments. The current AI literature is heavily focused on the connectionist approach, whereas in earlier times it was largely focused on symbolic/semantic reasoning and rule-based knowledge engineering. Our assumption is that economic publications that discuss, test, or apply AI are likely to mention more general AI terms (e.g., "machine learning", "artificial intelligence") as opposed to the computer science literature which discusses more specific AI terms (e.g., "support vector machines", "backward propagation") due to more nuanced definitions and specialisations.

Table 1. Search phrases for publication records retrieval

Search phrases
artificial intelligence, artificial general intelligence, intelligent machine, intelligent system, intelligent agent, machine learning, deep learning, neural network, statistical learning, natural language processing, expert system, knowledge system, knowledge-based system, knowledge engineering, and *semantic reasoning, symbolic reasoning, logical reasoning*

[3] The final search was performed on 31 August 2021.

Notes: Wildcards are also used in search terms (e.g., network*).

In *Scopus*, we conduct a "TITLE-ABS-KEY" search for the desired words in the title, abstract, and keywords of the texts, restricting to "SUBJAREA (ECON)" for only articles classified to the economics field[4]. Similarly, we searched the *EconPapers* database for the desired words in the title, abstract, and keywords of the texts. While the full collection in *EconPapers* also captures articles in a non-economics field, we restrict the search results to papers where JEL codes (see *Table A1* in *Appendix*) are identified. The final *Scopus* search retrieved 7,036 items[5] and 6,949 records are retrieved from the *EconPapers* database (contains 4,492 journal articles, 2,074 working papers, and 383 book or book chapters records).

Using the *pybliometrics* (Rose & Kitchin 2019) Python package[6], we also collect and collate, for each *Scopus* item retrieved, information of the authors (e.g., affiliation, first year of publication), articles (e.g., journal, number of authors), and journal (e.g., publication year). This results in a set of five derived datasets all linked to each other by document/author/affiliation *Scopus* IDs and by ISSN for the publication titles' information. See *Table S2* to *S4* in *Appendix* for further detail on variables retrieved by *Scopus* search.

2.2 Empirical Strategy

We first begin with some descriptive statistics, discussing the overall growth of AI in economics over time before delving deeper into details like growth and diffusion through different economic sub-fields (i.e., using JEL codes). We also differentiate between machine learning related and non-ML papers and map the co-occurrence of JEL classifications, seeing also the change in AI use and discussion over time by JEL classification. We then turn our focus to describing institutional/affiliation factors such as relative standing and AI productivity. Lastly, we describe the individual (i.e., author-level) factors of those publishing on AI in economics such as academic age and country of origin.

3 Results

Looking at the overall number of AI-related papers retrieved by *Scopus* with subject area *ECON*, we find that since 1986 the number of AI papers in economics have been steadily

[4] The four economic sub-fields in Scopus are broadly defined as *General Economics, Econometrics and Finance; Economics, Econometrics and Finance (miscellaneous),* and *Economics and Econometrics, Finance.*
[5] We excluded several Computer Science conference proceedings (e.g., AI conference 2011 2nd International Conference on Artificial Intelligence Management Science And Electronic Commerce (Aimsec)) as well as post-publication communications such as *Reply* and *Erratum*.
[6] https://pybliometrics.readthedocs.io/en/stable/index.html

increasing (see Fig. 1) coinciding with the major AI winter. Prior to this year, there were very few *ECON* papers published with AI-related content (*n*=11) matching our search term; perhaps corresponding to the rise (and fall) of expert systems with some slight lag. The share of all *ECON* papers with AI-related content in *Scopus* has also been steadily rising; up to approximately 2.4% in 2021 from 0.13% in 1986. One potential reason could be that advances in ML and neural networks were becoming more important in economics. In the early years, scholars such as Herb Simon and Allen Newell placed a strong emphasis on symbolic systems (Hunt, 2007; Cockburn et al., 2019). Simon, for example, recounts in his autobiography the achievement of the Logic Theorist (LT) that helped to prove some of the theorems in symbolic logic given by Russell and Whitehead in their Volume I of *Principia Mathematica*[7]:

> I have always celebrated December 15, 1955, as the birthday of heuristic problem solving by computer, the moment when we knew how to demonstrate that a computer could use heuristic search methods to find solutions to difficult problems. According to Ed Feigenbaum, who was a graduate student in a course I was then teaching in GSIA, I reacted to this achievement by walking into class and announcing, "Over the Christmas holiday, Al Newell and I invented a thinking machine." (If, indeed, I did say that, I should have included Cliff Shaw among the inventors.) Of course, LT wasn't running on the computer yet, but we knew precisely how to write the program (p. 206).

Early heuristic programs focused on aspects such as proving theorems in geometry or developing game-playing programs such as chess or checkers (Nilsson, 2010). Newell, Shaw,

[7] Correspondence with Bertrand Russell (see Simon, 1991, pp. 207-208).

Dear Earl Russell:

Mr. Newell and I thought you might like to see the enclosed report of our work in simulating certain human problem-solving processes with the aid of an electronic computer. We took as our subject matter Chapter 2 of Principia, and sought to specify a program that would discover proofs for the theorems, similar to the proofs given there. We denied ourselves devices like the deduction theorem and systematic decision procedures of an algorithmic sort; for our aim was to simulate as closely as possible the processes employed by humans when systematic procedures are unavailable and the solution of the problem involves genuine "discovery."

The program described in the paper has now been translated into computer language for the "Johnniac" computer in Santa Monica, and Johnniac produced its first proof about two months ago. We have also simulated the program extensively by hand, and find that the proofs it produces resemble closely those in Principia. At present, we are engaged in extending the program in the direction of learning (of methods as well as theorems) and self-programming.

Very truly yours,
Herbert A. Simon, Head
Industrial Management Department

Dear Mr. Simon,

Thank you for your letter of October 2 and for the very interesting enclosure. I am delighted to know that Principia Mathematica can now be done by machinery. I wish Whitehead and I had known of this possibility before we both wasted ten years doing it by hand. I am quite willing to believe that everything in deductive logic can be done by a machine.

Yours very truly,
Bertrand Russell

and Simon (1959) developed the General Problem-Solving (GPS) program which was part of an agenda to understand information processing and human problem solving (for a discussion see Torgler, 2021). GPS was, as Nilsson (2010) notes, an outgrowth of their earlier work on the Logic Theorist that was based on manipulating symbol structures via operators. According to Newell et al. (1959), GPS used means-ends systems of problem-solving heuristics, classifying "things in terms of the functions they serve, and oscillating among ends, functions required, and means that perform them" (p. 9). Means-ends analysis was therefore achieved by comparing the problem goal with the present situation and noticing the differences. This then leads to action(s) to reduce or eliminate such differences between goal and present states. Minsky (1986, 2006) also refers to means-ends analysis as a "difference-engine". In the 1970s, expert systems became dominant, pushed by a second generation of AI scholars such as Edward Feigenbaum and Ray Reddy, most of whom were more interested in knowledge representation than actual human intelligence (McCorduck, 2019). Expert systems can be defined as "computer programs, designed to make available some of the skills of an expert to non-experts" (Siler, 2005. p. xii). Those systems were attractive to businesses as consulting systems as they would be designed to help humans in their decision-making process and guide the uninitiated towards more favourable outcomes (for a discussion see Bickley, Chan et al., 2021). However, these systems generally break down when confronted with problems outside their area of expertise – or even within, if knowledge beyond the provided rules is required (Nilsson, 2010). Nilsson (2010, p. 326) refers to a story in which John McCarthy interacted with the famous medical expert system MYCIN by typing some information about hypothetical patients; namely, a male that underwent amniocentesis. MYCIN accepted those parameters without complaint as the fact that males cannot get pregnant was not included in the expert knowledge, thereby demonstrating a core limitation – *a lack of common sense*. As evident in Figure 1, the mid-to late 1980s was the period classified as the AI winter. Many AI sponsors (government and industry) ceased or reduced their funding, disappointed by exaggerated hopes, promises, and expectations.

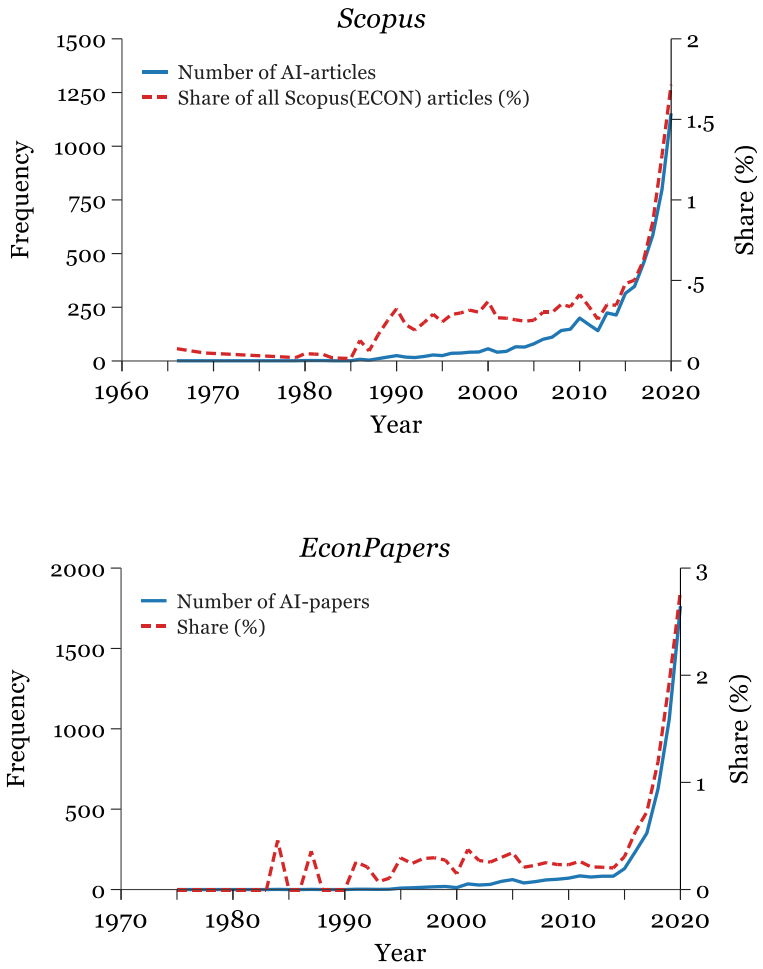

Fig. 1. Growth of AI-related economics papers in *Scopus* and *EconPapers* and relative (%) to overall number of economics papers over time.

A strong debate emerged during the long AI winter over whether the metaphor of the mind as a computer is useful or not. Reservations emerged about the comparability of mind and machine (for a discussion see Hunt, 2007, pp. 637-642). For scholars such as Herb Simon, both the human mind and the computer were symbolic systems. Others felt that the computation model was a poor fit, or simply inadequate, and became disillusioned with the information-processing models (Taube, 1961; Dreyfuss, 1965; Neisser, 1976). Dreyfuss emphasized that humans have uniquely human forms of information processing that are inaccessible to a mechanical system. He refers in particular to issues around the ill-structured data of daily life. Nilsson (2010, p. 314) summarizes the core criticisms:

- Computers have perhaps hundreds of processing units whereas brains have trillions.

- Computers perform billions of operations per second whereas brains perform only thousands.
- Computers are subject to crashes whereas brains are fault tolerant.
- Computers use binary signals whereas brains work with analog ones.
- Computers do only what their programmers tell them to do whereas brains are creative.
- Computers perform serial operations whereas brains are massively parallel.
- Computers are constrained to be 'logical' whereas brains can be 'intuitive'
- Computers are programmed whereas brains learn.

Jacob Schwarz (1986) raises the point that:

> … a basic goal of AI research has been the discovery of principles of self-organization robust enough to apply to a wide variety of information sources. Any such organizing principle would have to allow coherent structures capable of directly guiding some form of computer action to be generated automatically from relatively disorganized, fragmented input. The present state of AI research is most fundamentally characterized by the fact that no such robust principle of self-organization is as yet known, even though many possibilities have been tried (p. 491).

In the 1970s, scholars started to argue that thinking does not proceed serially (Hunt, 2007); therefore, scholars developed theories around parallel-processing systems (see, e.g., Rumelhart et al., 1986). Influenced by the brain structure, connectionists stressed that knowledge is stored in the connections among neurons, simulating the parallel processing of small neural networks (Hunt, 2007). Mitchell (2019) refers to an article published in *The Scientist* in 1988 citing a top official at the Defense Advanced Research Projects Agency (DARPA) – the agency that provided the majority of AI funding over the years – discussing the power of neural networks: "I believe that this technology which we are about to embark upon is more important than the atom bomb" (p. 34). As automated data-gathering techniques and inexpensive mass-memory storage apparatus became available and more accessible to the masses, ML techniques became even more important (Nilsson, 2010). AI researchers started to develop a large set of algorithms that enabled computers to learn from data, leading to the situation that ML became its own subdiscipline of AI (Mitchell, 2019). In recent years, learning-from-data approaches using, for example, deep neural networks have been very successful thanks to the better availability of Big Data. As the rise of Big Data has profound implications for the way science is done, such questions or comparisons are important; the manner in which data are collected, curated, and integrated into scientific modelling is essential in understanding our world (Coveney et al., 2016). Varian (2014), for example, stresses that

> [s]ince computers are now involved in many economic transactions, Big Data will only get bigger. Data manipulation tools and techniques developed for small datasets will become increasingly inadequate to deal with new problems. Researchers in machine learning have developed ways to deal with large datasets and economists interested in dealing with such data would be well advised to invest in learning these techniques (pp. 24-25).

Economists are interested in ML as it is predictive. In general, data analysis in econometrics can be classified into four groups: 1) prediction, 2) summarization, 3) estimation, and 4) hypothesis testing (Varian, 2014). Traditional data analytics techniques cannot deal with Big Data as they are often noisy, and, unlike survey data, are not collected to answer specific questions. AI and Big Data analytics try to overcome such deficiencies. In addition, ML can be implemented first, followed by attempts to explain phenomena that better identify the underlying correlations and co-occurrences; hence, moving towards identifying a causal relationship. Mullainathan and Spiess (2017) stress that "machine learning provides a powerful tool to hear, more clearly than ever, what the data have to say" (pp. 103-104). Figure 2 indicates that a large share of AI papers in economics are using ML, and the rate is higher for *EconPapers*. In the 1990s (1990-1999), the share was 71.1%, followed by 79.9% in the first decade of the 21st century (2000-2010), and 80.5% in the following decade (2010-2020). For *Scopus*, the values are in the range of 40 to 50 percent (1990-1999: 40.5%; 2000-2010: 55.8%; 2010-2020: 49.7%) across the board.

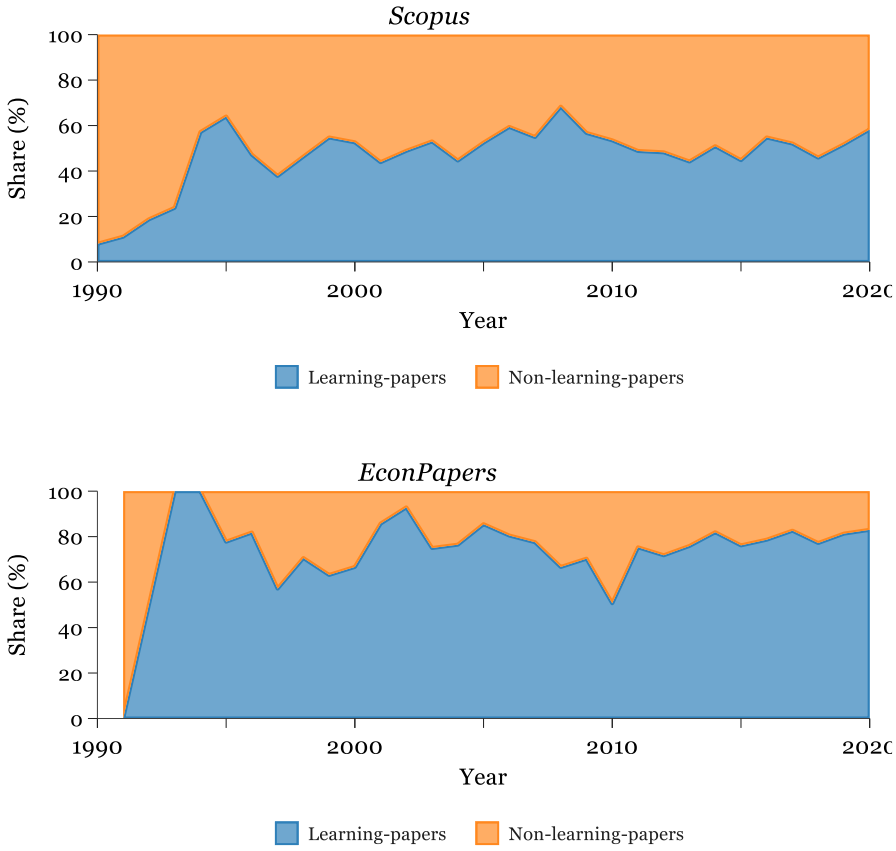

Fig. 2. Share of Learning-Based Articles. Search words: *machine learning*; *deep learning*; *statistical learning*; *supervised learning*; *reinforcement* learning; *neural network*; *natural language processing*; *genetic algorithm*; *metaheuristic*; *random forest*; *support vector machine*; *fuzzy logic*; *sentiment analysis*; *feature selection*; *support vector regression*; *boosting*; *genetic programming*; *bagging*; *deep belief network*.

Next, we look at the subfield differences in economics via JEL classification codes. To account for the total volume of papers published with each JEL classification, we obtain the number of papers with each JEL code in a single year where there is at least one AI-related paper, calculating the proportion of papers on the topic. A total of 734,819 records were returned with 329,795 journal articles (44.9%) (Table 2). We present results using fractional counting, meaning that we divide the paper by the number of JEL classifications listed in the paper. The correlation between the normal counting and fractional counting is (not surprisingly) quite high (ρ = 0.96). Overall, the 6,949 AI papers in the *EconPapers* dataset account for 0.95% of all economics papers based on our method of identifying AI papers.

Table 2. Share of AI-related papers in *EconPapers*

JEL code	*Classification*	Full counting			Fractional counting*		
		AI-papers	*Total*	*(%)*	*AI-papers*	*Total*	*(%)*
A	General Economics and Teaching	148	20274	0.73%	64.0	10548.9	0.61%
B	History of Economic Thought, Methodology, and Heterodox Approaches	118	17053	0.69%	34.1	7576.4	0.45%
C	Mathematical and Quantitative Methods	2371	149615	1.58%	1109.2	74152.7	1.50%
D	Microeconomics	616	138905	0.44%	232.0	62300.6	0.37%
E	Macroeconomics and Monetary Economics	583	113463	0.51%	207.1	58010.6	0.36%
F	International Economics	361	99744	0.36%	129.3	52511.1	0.25%
G	Financial Economics	1149	113319	1.01%	521.9	64267.9	0.81%
H	Public Economics	144	74694	0.19%	49.6	34504.5	0.14%
I	Health, Education, and Welfare	259	68023	0.38%	115.7	34660.8	0.33%
J	Labour and Demographic Economics	364	99799	0.36%	154.3	51069.6	0.30%
K	Law and Economics	167	24823	0.67%	58.3	12507.7	0.47%
L	Industrial Organization	455	79326	0.57%	182.4	37688.6	0.48%
M	Business Administration and Business Economics; Marketing; Accounting; Personnel Economics	531	48878	1.09%	234.3	28113.4	0.83%
N	Economic History	90	22084	0.41%	22.6	8723.6	0.26%
O	Economic Development, Innovation, Technological Change, and Growth	1768	143945	1.23%	840.0	66309.1	1.27%
P	Economic Systems	86	22161	0.39%	26.4	8069.4	0.33%
Q	Agricultural and Natural Resource Economics; Environmental and Ecological Economics	2945	124460	2.37%	2220.8	77256.2	2.87%
R	Urban, Rural, Regional, Real Estate, and Transportation Economics	374	49823	0.75%	149.8	27108.6	0.55%
Y	Miscellaneous Categories	37	4467	0.83%	8.7	1987.5	0.44%
Z	Other Special Topics	172	19270	0.89%	34.5	8118.7	0.43%
Overall		6,949	734,819	0.95%			

Notes: Total counts towards the number of *EconPapers* records in all years with at least one AI-paper. **Fractional counting* – paper is divided by the number of JEL classification listed in the paper.

To better see the subfield differences, we first rank the fields by share of AI papers, which ranges from 0.19% (*H-Public Economics*) to 2.37% (*Q-Agricultural and Natural Resource Economics – Environmental and Ecological Economics*) (see Fig. 3). The relatively high rate of AI papers in *Q* could be driven by the fact that the ecological environment is a complex system that benefits from the use of Big Data and ML techniques[8]. Herb Simon (1995) defines AI as "complex information processing" (p. 939). In addition, it is a field that has a natural interest in knowledge-based systems. AI offers interesting opportunities for improved environmental management and global conservation. ML for example, has been important in the study of climate change. Deep neural networks have also helped to better map the biodiversity around the world (Dauvergne, 2020). As Figure 3 shows, a large proportion of the

[8] For a discussion on the importance of AI for sustainable entrepreneurship, see Bickley, Macintyre, and Torgler (2021).

papers use a ML approach (around 87% of the papers). Cambridge University has, for example, recently launched he UKRI Centre for Doctoral Training in the Application of Artificial Intelligence to the study of Environmental Risks (AI4ER). As they stress, their goal is to "train researchers uniquely equipped to develop and apply leading edge computational approaches to address critical global environmental challenges by exploiting vast, diverse and often currently untapped environmental data sets"[9]. Naturally, *C* (*Mathematical and Quantitative Methods*) has a high relatively share (compared to other fields) of AI papers, reporting the largest proportion of ML papers. Also, not surprisingly, fields such as *Financial Economics* (*G*) heavily rely on ML (88.3 percent of studies) and AI more generally.

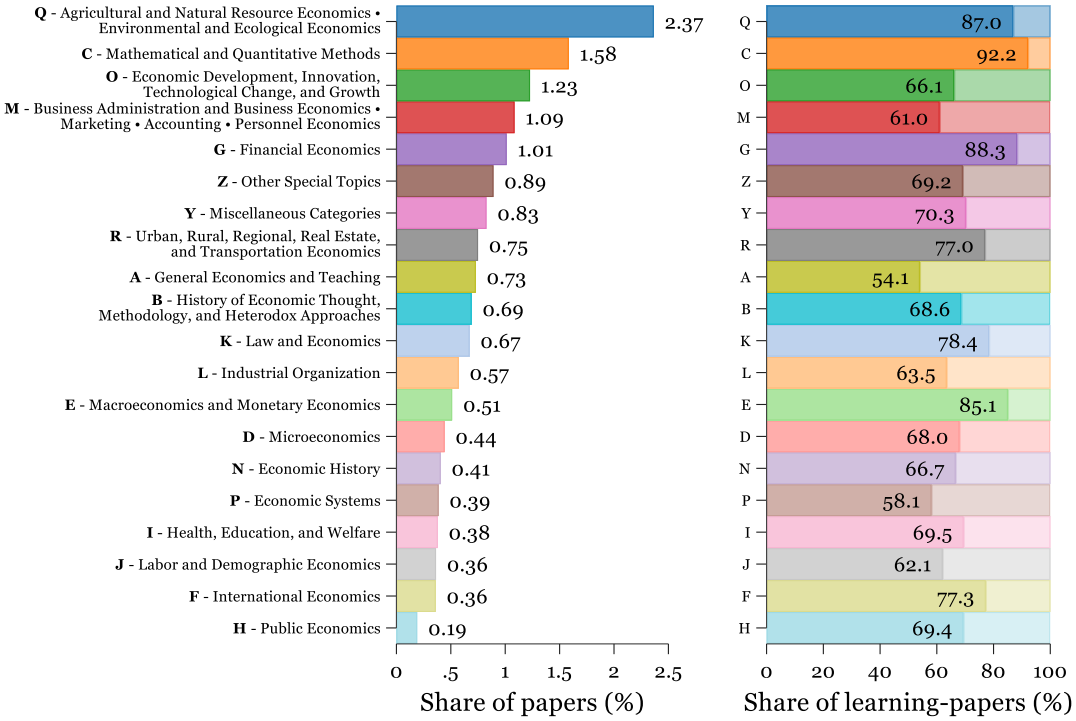

Fig 3. Share of AI-papers, by JEL code. Share is calculated based on full counting method. Share of learning papers (left panel) shows the proportion of ML-related papers (darker shade) and non-ML papers (lighter shade), respectively.

In Figure 4, we show how different combinations of JEL codes are used together in AI-related economics papers implementing a network analysis approach. The network graphs were created using Gephi with force-directed (Fruchterman-Reingold) layout. The nodes represent the 20 JEL classifications with size showing frequency with which the JEL classification was

[9] AI for the study of Environmental Risks (AI4ER) | UKRI Centre for Doctoral Training (cam.ac.uk)

used. Edges show the number of times a pair of JEL codes was used together (thickness and colour of the edge). Co-occurrence is weighted by the total number of JEL classifications used in the paper. Overall, we see a strong link between the *O* (*Economic Development*) and *Q* (*Agricultural and Environmental Economics*) pair, *C* (*Mathematical and Quantitative Methods*) and *G* (*Financial Economics*) pair, and *C* and *E* (*Macroeconomics and Monetary Economics*) pair. While *Q* is the most often used JEL classification among all AI-econ papers, *C* has the highest weighted degree, indicating that it is being used more often in conjunction with other JEL codes. This is particularly evident when the network is spilt into learning- and non-learning based papers (Fig. 5b and 5c) in which the strength of the connection between *C* and *E* and *G* is drastically reduced in the latter. In contrast, the connection strength between the pair *O* and *Q* is similar in the two subsets while *O* is most linked to other JEL classifications, often taking a more central position.

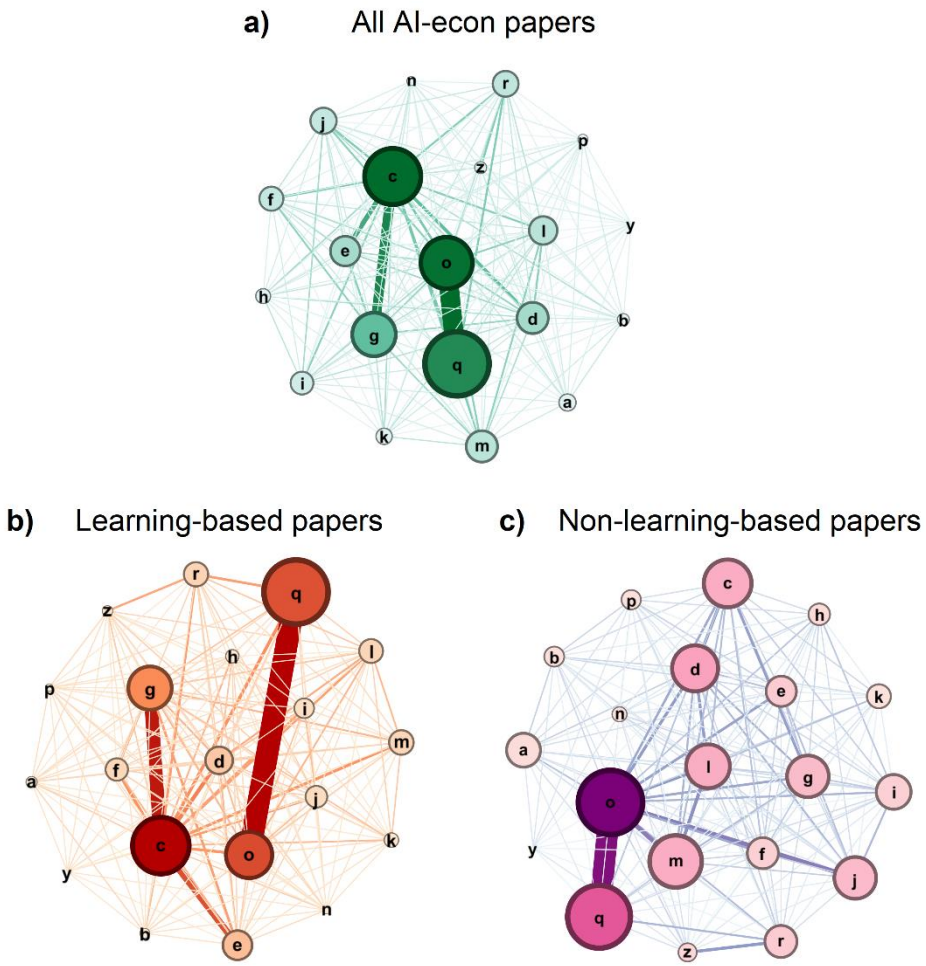

Fig. 4. Network analysis of JEL codes of AI-econ papers (*EconPapers*). Panel a shows the network of all 6,949 AI-econ papers and panels b and c shows the network of 'learning-based' papers (n = 5,607) and non-learning-based papers (n = 1,342), respectively.

In Figure 5, we take a look at changes over time. Overall, the share of economics papers using or discussing AI tends to increase in more recent years. This remains true across a number of fields, particularly for those disciplines reporting the highest shares in Fig. 3 (*C*, *Q*, *M*). Interestingly, the field of law and economics has increased the attention it pays to AI. Possibly this is due to the growing interest in how AI can affect society, which also asks questions around regulatory requirements and legal aspects of AI. Campedelli (2020), for example, shows that researchers are increasingly focusing on cyber-related crime topics, but also that relevant themes in algorithmic discrimination, fairness, and ethics are still rarely discussed.

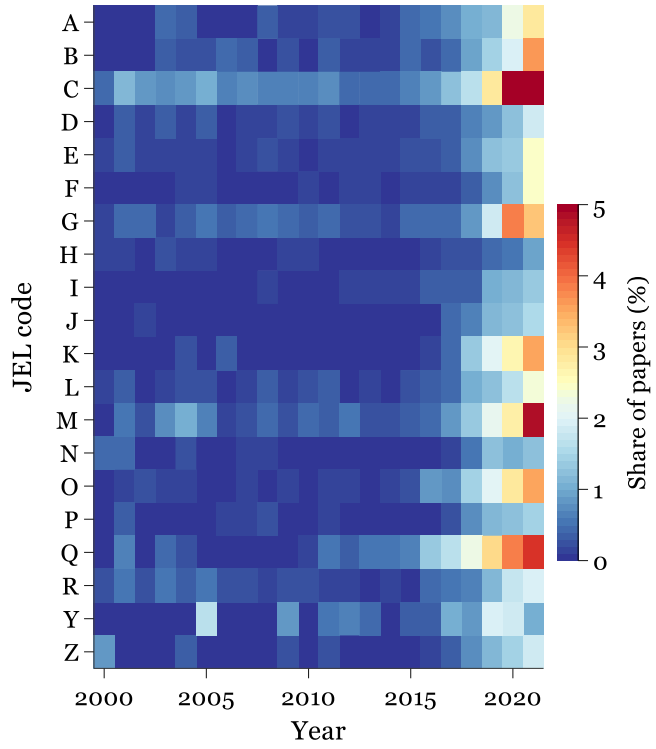

Fig. 5. Share of AI-papers over time, by JEL codes.

When looking at which institutions are pushing AI in economics (see Fig. 6), we can see a positive correlation between the quality of the university/institution and the ranking based on the number of AI papers produced; although, we did not normalize by the department size (ρ = 0.4, statistically significant at the 1% level). To measure the ranking information, we relied on Amir and Knauff (2008), whose method grades departments based not on research productivity, but on the strength of the Ph.D. program as measured by a department's ability

to place doctoral graduates in top-level economics departments or business schools. As they stress: "[w]ithin the respective context, faculty hires probably constitute a more reliable and stable indicator of influence than journal citations" (p. 185). As only 58 institutions were listed, we exclude the other university/institutions not listed in the ranking, which means that we only explore the relationship in relatively renowned departments. Those 58 institutions jointly publish 5.6% of all the AI publications in economics. For all the counting that we are doing (institutions, countries, authors' academic age), we employ a weighting approach by the inverse of the number of authors listed on the paper. Those investigations only rely on *Scopus* data. For example, if only one out of three authors is affiliated with Harvard, Harvard is credited with 33% of the contribution.

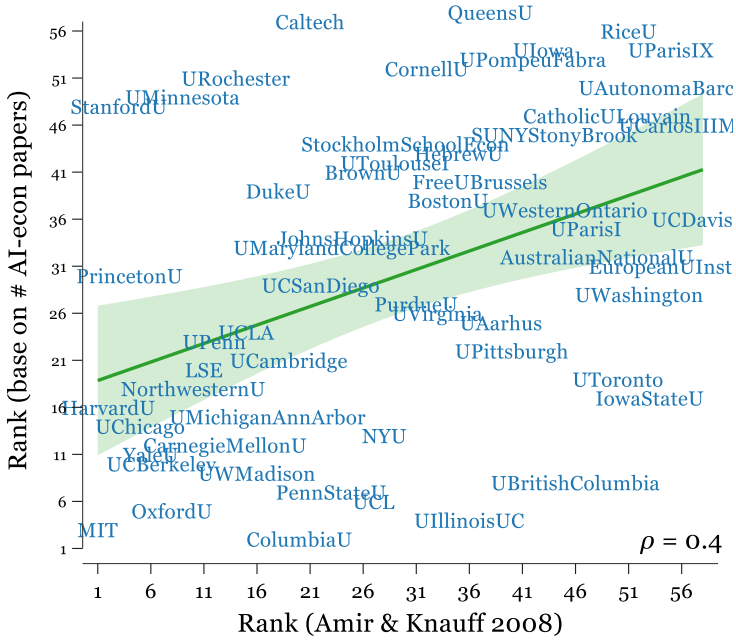

Fig. 6. Relationship between economic department ranking and AI-economics publication ranking among top institutions based on *Scopus* data.

Next, we take a closer look at the academic age of the scholars who publish in AI (Fig. 7). Academic age is defined as the number of years between year of publication and the year of the author's first publication recorded in *Scopus*. To calculate the authors' average academic age of each type of contribution within a given year, we apply the inverse of number of authors in each article as weights. For example, if an article is co-authored by two academics, then the weight is one-half (0.5). Overall, we observe that over the last three decades, economics

scholars publishing on AI are on average older. One possible explanation is that collaboration has increased in economics over time, meaning that the number of authors per paper has increased (Torgler & Piatti, 2013). However, there are differences between learning and non-learning papers. Scholars applying ML approaches are consistently younger than those who apply a non-learning approach.

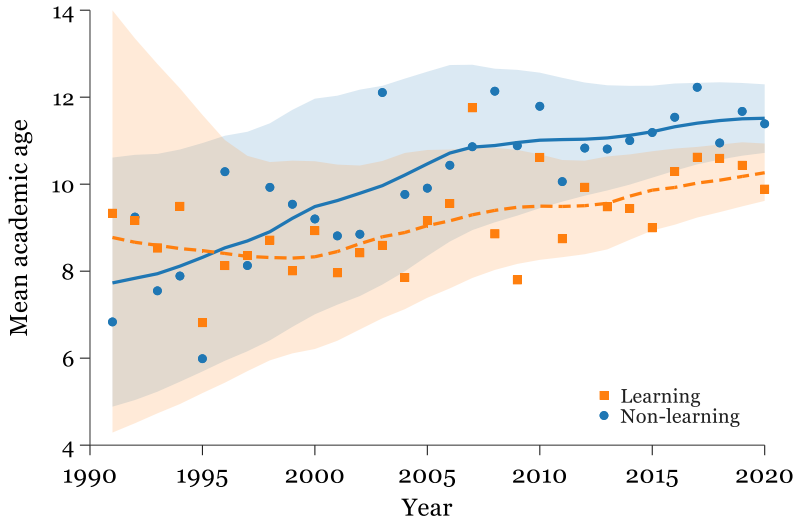

Fig. 7. Average academic age of authors, by types of contribution.

Finally, we also look at which countries are producing more AI papers (Fig. 8). Overall, the US leads the number of publications (18.54%), followed by China (9.03%), and the UK (5.89%). The top 10 countries are responsible for 57.64% of all the AI economics publications (*Scopus*). Among those nations with relatively high production of AI papers, China and India show a particularly high rate of ML research. If we correlate the share of ML papers in AI with the Human Development Index[10] – which assesses the development of a country by the key dimensions of human development (long and healthy life, being knowledgeable, and having a decent standard of living) – we observe a negative correlation of $\rho = -0.546$. This means that less developed nations are putting a lot of relative weight in applying ML (relative to other AI approaches). It should be noted we restricted that sample only to countries with more than 30 AI papers ($n = 41$).

[10] Human Development Index (HDI) | Human Development Reports (undp.org)

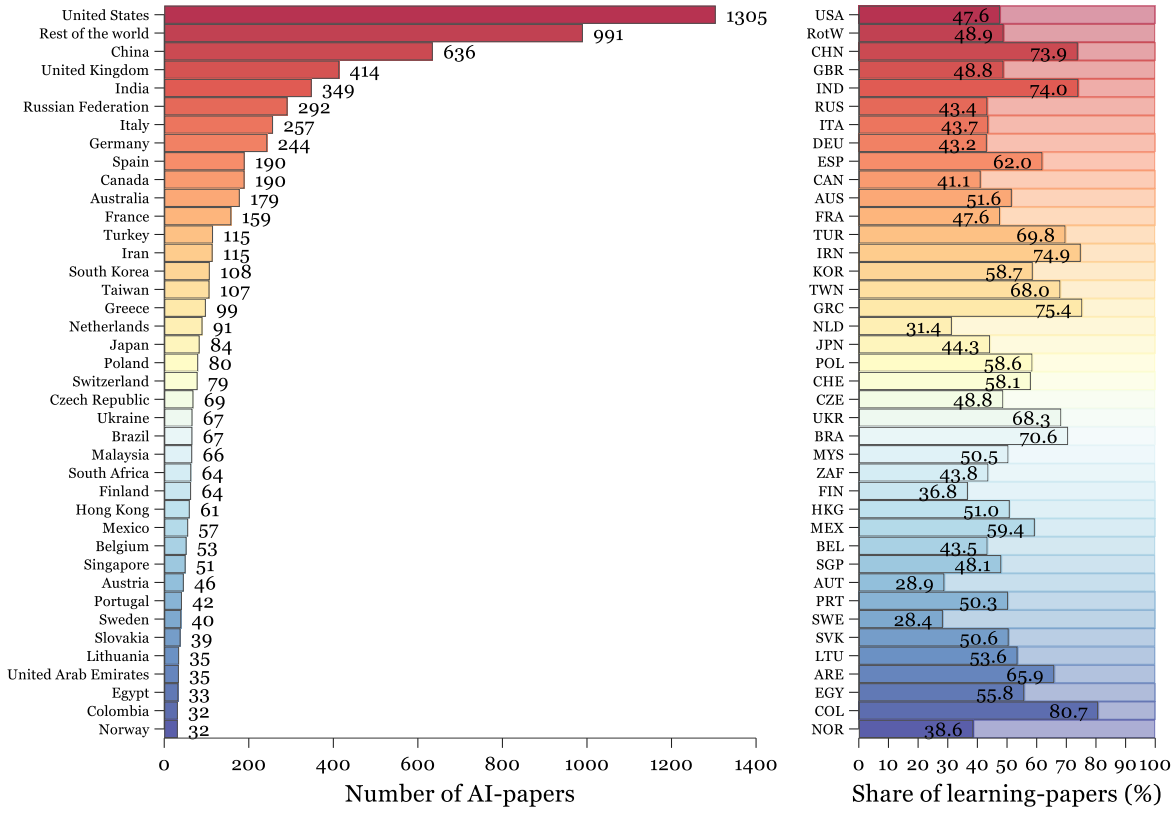

Fig. 8. Top 40 Country ranking by number of AI-papers.

4 Conclusions

The history of AI use and discussion in economics is long and winding, much the same as the evolving field of AI itself. Since its beginnings, economists have engaged with AI but in varying degrees and with changing focus over time and place. In general, our results provide insights regarding the evolution of AI in economics over time and place, between subfields, and comparing various author and affiliation demographics. As a next step, we may look to characterize how AI has propagated through and within other subject areas and fields beyond economics. In doing so, we start to understand the value, understanding, and use of AI methods across and within other fields, mapping the usefulness and many ways to think in AI.

More specifically, we have explored the diffusion of AI and different AI methods (e.g., ML, DL, neural networks, expert systems, knowledge-based systems) through and within economic subfields, taking a scientometrics approach. To map such a history of AI within and between economic sub-fields, we construct two datasets containing bibliometrics information

of economics papers based on search query results from the *Scopus* database and the *EconPapers* (and IDEAs/RePEc) repository. Such search results are obviously not free of issues as AI methods may have been applied in papers that we have not been able to identify with our search and classification strategy.

Our results indicate that AI in economics follows a similar trajectory (with slight delay) to the AI field itself: activity in the 70s, downturn in the 80s, and increasing interest in more recent times. Primarily, this appears driven by learning approaches. However, not all economic subfields engage equally in learning-based AI. Indeed, those that have come to conceptualise the economy as a complex system are usually more susceptible to AI and Big Data. In particular, environmental, agricultural, natural resource, and ecological economists focus in relative terms extensively on AI, especially on learning-based AI methods. Of those papers with AI-related content, those citing a mathematical and quantitative focus (JEL classification) most frequently occur in conjunction with other economics subfields, which makes sense considering the learning dominance in AI economics. There also appears to be some subtle undertone of the challenges and opportunities AI holds for topics such as the future of work, discussed in economics with papers often citing economic development, innovation, technological change, and growth JEL classifications. We find increasing interest in AI over time for those at the intersection of economics and law, possibly due to new regulatory and legal challenges that are emerging in this field. Others in the history of economic thought also look to be following suit, suggesting growing interest in reviving or revisiting the relevance of AI in economics.

Moreover, those institutions at the productive forefront of AI economics are those scholars in higher ranked universities and institutions. This shows the big players (or at least the affiliate members of the big players) have their sights set on how AI may transform their own research and ways of the world. We also found that economists engaging with AI are also getting older over time; possibly due to more frequent collaborations, which would require us to normalize by the overall trend in economics to identify its importance for AI research. However, those engaging with learning-based AI approaches are consistently younger than those who wield the non-learning methods. Further, we find those countries with lower scores on the Human Development Index appear more concerned or focused on learning-based AI, perhaps because they are coming later to the game and hence, starting primarily from where the AI field is focused now. However, future developments require an understanding about what a method is able to achieve and what it cannot. Historically, there has never been a time

with more efficient means to systematically collect and analyse information. However, what is lacking is AI with common sense and many ways to think or reason about the world beyond narrow or highly specialised domains. In other words, combining the many methods of AI developed throughout history (e.g., ML, expert systems, symbolic logical reasoning), i.e., a neuro-symbolic approach. Most AI of today will fail once it meets the messiness of the real world. Beyond statistical randomisation, for human-like organic interactions and spontaneous order to take place, AI must send price signals indistinguishable from human-kind. In other words, AI will need to mimic the behaviours of individuals in markets, and markets of markets and other socioeconomic systems so we know they can participate in a truly human world. Sensitive to the quality and quantity of data inputs, learning-based AI approaches require to find signals in data among noise and other interferences that are inherent in Big Data. In general, as Marcus and Davis (2019) point out, "deep learning, is fabulous at learning but poor at compositionality and the construction of cognitive models; the other, classical AI, incorporates compositionality and the construction of cognitive models, but it is mediocre at best at learning" (p. 94). As cognitive models are an important element for economics, the field cannot afford to disregard this factor. This is particularly important when working towards an AI that is robust, reliable, and able to function in a complex and ever-changing world. Humans are uniquely spontaneous and creative when faced with new and unexpected circumstances, which means that no training data are available and the data we do have is often imperfect. AI systems need to be able to work in an open system that constantly changes. Marcus and Davis (2019, p. 16) are right in emphasizing that we cannot practice every situation in advance, nor are we able to foresee what sort of information and data we need when acting in any given situation. Common sense is still a core hurdle to overcome. As Marvin Minsky often reminds us, AI systems do not really know why they cannot push a string. We generally do not think to ask ourselves these questions as their answers seem obvious. The sorts of knowledge in experience we describe as intuition and common sense.

Engineers and planners will be more fashionable in the AI world. AI may encourage a shift towards pushing or arguing for more central planning, thanks to now having access to the kind of "supermind" that would probably cause Hayek to turn over in his own grave. Hayek warned us about the subjective character of the data, and in the end, our data or facts are only ideas or concepts. It is naïve to assume, as he stresses, that "all the sense qualities (or their relations) which different men had in common were properties of the external world", meaning that

> it could be argued that our knowledge of other minds is no more than our common knowledge of the external world… knowledge and beliefs of different people, while possessing that common structure which makes communication possible, will yet be different and often conflicting in many respects… But the concrete knowledge which guides the action of any group never exists as a consistent and coherent body. It only exists in the dispersed, incomplete, and inconsistent form in which it appears in many individual minds, and the dispersion and imperfection of all knowledge are two of the basic facts from which the social sciences have to start (pp. 48-50).

AI and Big Data will not solve the problem of compatibility of intentions and expectations of different people. Global networks create a complexity and allow potential instabilities that are impossible to manage by a top-down planning approach, which suggests that we need to rely on flexible adaptation to local needs (Helbing, 2015, p. 88). As Gmeiner and Harper (2021) point out, there is difference between economic calculation and planning as planning also requires making decisions in the realm of the political, and decision-making processes are not per se efficient, as evident in the Public Choice literature. Aspects around incentives, power and authority can corrupt the benefits of AI – as Gmeiner and Harper (2021) point out – "planning creates more data, which feeds calculation. Data problems can cascade through this feedback loop and could even corrupt deep learning algorithms, which are only as good as the data that train them" (p. 6). This lends us towards more consideration of the many ethics of AI. Unintended consequences remain important, given black box AI, and manipulation of information and knowledge flows to AI, which decide on behalf of humans, or which may cause harm (financial, health, or otherwise). The good, the bad, and the ugly are all parts of current and future AI and how goals are defined and decided upon all have major implications when AI is involved.

There is also a danger that AI and Big Data may also disregard qualitative phenomena by emulating natural sciences, "replacing the picture of the world in terms of sense qualities by one in which the units are defined exclusively by their explicit relations…It not only leads frequently to the selection for study of the most irrelevant aspects of the phenomena because they happen to be measurable, but also to 'measurements' and assignments of numerical values which are absolutely meaningless" (Hayek 1979, p. 89). In general, Hayek (1979) reminds us that "the great lesson of humility which science teaches us, that we can never be omnipotent or omniscient, is the same as that of all great religions: man is not and never will be the god before whom he must bow down" (p. 182). Not even when the Golem becomes a reality.

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Appendix

Table S1. Main Journal of Economic Literature (JEL) codes

Code	Category
A	General Economics and Teaching
B	History of Economic Thought, Methodology, and Heterodox Approaches
C	Mathematical and Quantitative Methods
D	Microeconomics
E	Macroeconomics and Monetary Economics
F	International Economics
G	Financial Economics
H	Public Economics
I	Health, Education, and Welfare
J	Labour and Demographic Economics
K	Law and Economics
L	Industrial Organization
M	Business Administration and Business Economics; Marketing; Accounting; Personnel Economics
N	Economic History
O	Economic Development, Innovation, Technological Change, and Growth
P	Economic Systems
Q	Agricultural and Natural Resource Economics; Environmental and Ecological Economics
R	Urban, Rural, Regional, Real Estate, and Transportation Economics
Y	Miscellaneous Categories
Z	Other Special Topics

Table S2. Key variables returned by *Scopus* Search (*ScopusSearch*)

Variable	Description
EID	Unique academic work identifier assigned in *Scopus* bibliographic database.
DOI	The DOI (Digital Object Identifier) of the document.
PII	The PII (Publisher Item Identifier) of the document.
Pubmed ID	The PubMed ID of the document.
Title	Title of the document.
Submission Type	Type of the document. Refer to the *Scopus* Content Coverage Guide for a list of possible values. Short version of submission type description.
Submission Type Description	Long version of submission type.
Creator Name	Name of document corresponding author.
Author Count	Number of document authors.
Author IDs	The author(s) *Scopus* IDs.
Affiliation IDs	The author affiliation(s) IDs.
Cover Date	The date of the cover the document is in.
Cover Display Date	The date displayed on the cover the document is in.
Publication Name	Name of source the document is published in.
ISSN	ISSN of source the document is published in.
Source ID	*Scopus* source ID of the document.
Aggregation Type	Aggregation type of source the document is published in.
Description	Return the description of a record. Note: If this is empty, try property abstract instead.
Author Keywords	List of author-provided keywords of the document.

Cited By Count	Number of articles citing the document.
Open Access	Whether the document is available via open access [‘1’] or not [‘0’].

Table S3. Returned by Author Search (*AuthorRetrieval*)

Variable	Description
Identifier	The author's *Scopus* ID.
Indexed Name	Author's name as indexed by *Scopus*.
Surname	Author's preferred surname.
Given Name	Author's preferred given name.
Start Publication Year	Year of author’s first publication.
Last Publication Year	Year of author’s last publication.
H Index	The author's h-index.
Citation Count	Total number of citing items.
Cited By Count	Total number of citing authors.
Document Count	Number of documents authored (excludes book chapters and notes).
No. Subject Areas	Number of unique subject areas of author’s publications.
Co-author Count	Total number of co-authors.
Affiliation Current ID	A list of *Scopus* Affiliation IDs for author’s current affiliation(s).
No. Historical Affiliation(s)	Number of unique historical affiliations.
ORCID	The author's ORCID.

Table S4. Returned by Affiliation Search (*AffiliationRetrieval*)

Variable	Description
Identifier	The *Scopus* ID of the affiliation.
Affiliation Name	The name of the affiliation.
Address	The address of the affiliation.
City	The city of the affiliation.
Country	The country of the affiliation.
Author Count	Number of authors associated with the affiliation.
Document Count	Number of documents for the affiliation.
Organisation Type	Type of the affiliation. Requires the STANDARD view and only present if profile is org profile.
Date Created	Date the *Scopus* record was created.