Are Economists Open to AI?

Mapping Academic Research Trends to Professional Community Sentiment using Language Models

Yi Wang and Ray Ge

Quant @ Renmin University of China

June 21, 2026

Economists & AI

Economists' Opinions

Economists' Research Topics

Text-as-Data as Survey

Open Economists

Appendix

What Are Economists' View on AI

Background

As AI developed so fast, how people think about it?

- AI may increase productivity, thus a higher welfare
- AI may take away our jobs, or make it harder

What Are Economists' Views to AI

- They may be positive towards AI. (with a higher living condition & more interesting research by using AI)
- But negative when AI may take their job. (gatekeeping)

The Research Questions:

- How does the professional community perceive this AI shift? (gatekeeping or embracing?)
- Does the adoption of AI in top-tier economics, finance, business journals influence professional sentiment?

Traditionally, Hard to Get Economists' Views

- Surveys of economists are extremely expensive
- Small sample maybe biased (example: surveys done by graduate students)
- Economists may not reveal their true feeling during the daily talks

Our Solution: Millions of Posts from Economists

- Thinking: How ChatGPT or Gemini learned and almost know everything? (Human labels data are too expensive and limited)
- ChatGPT replies on huge textual information from the internet
- We borrow the same idea $\rightarrow$ collecting millions of opinions for the economists from the internet

Our Solution: Millions of Posts from Economists

Our idea

- Here we collected **millions of posts of economists** online from professional forum for economists aka **Economics Job Market Rumors**.
- Whether economists are gatekeeping or embracing AI, we can find out from their Opinions.

A Example on EJMR of Economists' Opinions toward AI

Example: Should the econ grad core include Generative AI, Reinforcement Learning, NLP? (2024)

Gatekeeping Views	**Open Views**
"Do you even know what reinforcement learning is?"	*"Seems like these are the future and econ hasn't changed since 1950."*
"RL is basically approximate dynamic programming—a staple of the curriculum since the 80s."	"To get hired in 2023 without an academic job, we're stuck taking Coursera and Udemy classes..."
"Making it "core" means qualifying exams on ML, which is nonsense.	...this is after 5 years post-undergrad in Econ. It's time to adapt."

Challenges: Unstructured Forum Data

Problem 1: Unstructured Nature of Posts

- Posts on EJMR contain informal language, jargon, sarcasm, food discussions
- No standardized format or labeling of research topics
- Posts mix multiple topics, making topic extraction difficult

Problem 2: Mapping to Research Fields

- Traditional keyword matching fails to capture semantic meaning
- Manual coding is time-consuming and not scalable to 1.3 million posts
- Context-dependent language requires understanding implicit relationships

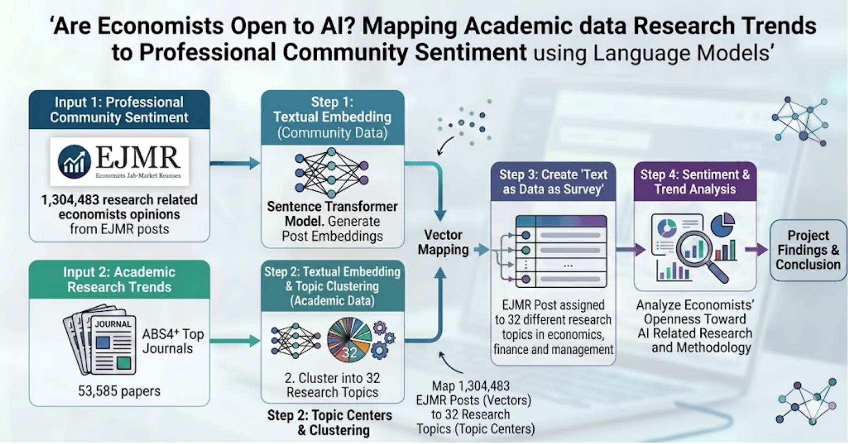
Our Research Workflow

1. **Data Acquisition**
   - Collected around 8 million economists' opinions from **EJMR**.
   - Extracted around 53,585 papers from top-tier **Econ & Finance & journals**.

2. **Cross-Datasets Textual Data Mapping by Encoder AI**
   - Mapping economists opinions with academic topics using **Encoder AI**.
   - 1.3 millions unstructured economists opinions → research themes

3. **Text as Data as Survey**
   - Economists' specific opinions on AI-related research topics are extracted and analyzed.

Workflow: Text as Data as Survey



Related Works

Tech reference: LLMs as Text-as-Data

- **Tech Background:** Transformer + scale/instruction tuning made this practical. (Vaswani et al., 2017; Brown et al., 2020; Ouyang et al., 2022)
- **Why useful:** context-aware semantics (negation, domain terms) + structured extraction (topics/stance/entities/evidence).
- **Where used:** earnings calls, filings, news (sentiment/stance, events, topics, risk); research workflow support.
- **NLP/LLMs in finance:** FinBERT; BloombergGPT; FinGPT. (Araci, 2019; Wu et al., 2023; Liu et al., 2023)

References: Vaswani et al. (2017) *Attention Is All You Need.*; Brown et al. (2020) *Language Models are Few-Shot Learners.*; Ouyang et al. (2022) *Training language models to follow instructions with human feedback.*; Araci (2019) *FinBERT.*; Wu et al. (2023) *BloombergGPT.*; Liu et al. (2023) *FinGPT.*

Related Works

Text-as-Data in Economics & Finance

- **Policy uncertainty indices:** Builds newspaper-based text indices to measure economic policy uncertainty and macro effects. (Baker, Bloom & Davis, 2016)
- **Misinformation in markets:** Identifies and quantifies financial misinformation using textual signals. (Fan, 2024)
- **Context-aware disclosure analysis:** Applies LLM-based methods to earnings texts to extract valuation-relevant information. (Siano, 2025)
- **Scalable textual factors:** Develops interpretable topic/sentiment models for empirical economic analysis. (Li, 2024; Lin, 2024)

Baker, Bloom & Davis (2016) *Measuring Economic Policy Uncertainty.*; Fan (2024) *Measuring Misinformation in Financial Markets.*; Siano (2025) *The News in Earnings Announcement Disclosures.*; Li (2024) *A Structural Topic and Sentiment-Discourse Model for Text Analysis.*; Lin (2024) *Textual Factors.*

Related Works

Empirical Research Using LLMs gererated data in Econ/Finance

- Uses ChatGPT 3.5 to classify forex news sentiment and links it to market returns. (Fatouros et al., 2023)
- Predicts stock movements from tweets and price data with ChatGPT, comparing it to regression models. (Xie et al., 2023)
- Analyzes LLM-derived sentiment and its bias for companies, linking it to stock returns. (Nakagawa, Hirano & Fujimoto, 2024)
- Analyzes financial news sentiment with GPT-family models, linking sentiment to stock returns. (Kirtac & Germano, 2024)

Fatouros, Soldatos, Kouroumali & Makridis (2023) *Transforming Sentiment Analysis in the Financial Domain with ChatGPT*.; Xie, Han, Lai, Peng & Huang (2023) *The Wall Street Neophyte: A Zero-Shot Analysis of ChatGPT Over Stock Movement Prediction*.; Nakagawa, Hirano & Fujimoto (2024) *Evaluating Company-specific Biases in Financial Sentiment Analysis using LLMs*.; Kirtac & Germano (2024) *Sentiment*

Related Works

Economic Job Market Rumors (EJMR) as Text Data

- **Gendered language in anonymous discourse:** Uses EJMR posts to quantify gendered lexical patterns; women are described with personal traits, men with professional attributes. (Wu, 2018; Cavallin, 2017)
- **Anonymous attention and abuse:** Studies how EJMR content and external links reflect attention dynamics, professional norms, and toxic speech in economics. (Ederer, Goldsmith-Pinkham & Jensen, 2025)

Cavallin (2017) *Gender Stereotyping in Academia*.
Wu (2018) *Gendered Language on the Economics Job Market Rumors Forum*.

Ederer, Goldsmith-Pinkham & Jensen (2025) *Anonymous Attention and Abuse*.

Related Works

Dynamic Research Topics

- **Text as data** Reviews growth of text-as-data methods in economics, highlighting rising empirical work using textual analysis. (Gentzkow, Kelly & Taddy, 2019)
- **Bibliometric analysis** Examines publication trends, co-word structures, citation patterns, and uses NLP-based measures to analyze research similarity, promotion outcomes, and gender representation. (Lu & Wang, 2022; Bianchi, 2024; Bello, Casarico & Nozza, 2025)

Bello, Casarico & Nozza (2025) *Research Similarity and Women in Academia*.; Gentzkow, Kelly & Taddy (2019) *Text as Data: Survey of Textual Analysis in Economics*.; Lu & Wang (2022) *A Decade for the Books: Bibliometric Analysis of Economics Letters*.; Bianchi (2024) *Text Mining arXiv: A Look Through Quantitative Finance Papers*.

Our Contributions: Challenges

Challenges in Current Approaches

- Traditional survey data has become costly in the big data era.
- Most LLM-based text economics and finance research uses general models rather than field-specific models
- Many studies focus on single corpus analysis, no cross-corpus semantic retrieval.

Our Contributions: Solutions

Our Contributions

- We develop a scalable framework combining encoder AI with cross-datasets semantic retrieval.
- Enables integration of multiple corpora (academic papers + forum posts) for richer insights.
- Demonstrates how unstructured online data can substitute for expensive surveys.

Our Innovations: Text-as-Data as Survey

Cross-Domain Semantic Retrieval

- Focus on cross-domain semantic retrieval, enabling effective integration of multiple corpora.
- Extract richer "survey insights" from unstructured forum textual information.
- Economists' professional forum $\rightarrow$ Survey of economists' opinions toward AI-related research topics or methodology.

8 millions Economists' Opinions

- **EJMR** (Economics Job Market Rumors) is a widely known online forum in the economics academia.
- It serves as an anonymous platform for:
  - Exchanging opinions on economics, academia, and policy.
  - Discussing job market news, research, and professional gossip.
- Our dataset consists of all publicly available posts from EJMR, spanning from 2010 to 2024.

Economics Job Market Rumors
https://www.econjobrumors.com

XJMR - Forum for Economics, Math, Sociology and Political Science

XJMR. The largest forum for Economics, Math, Sociology and Political Science. Come and discuss the job market, conferences, journals and more

Finance Job Rumors

New Topic in this Forum Send Post »

Join

*Currently accepted emails: .edu, .ac.uk, .ac.jp, .edu.cn, .ac.kr, ac.mw, sass.org.cn, ...

China Job Market

New Topic in this Forum Send Post »

Log In

Password Recovery To recover your password, enter your information below.

Chat (0)

Chat - econjobrumors.com ... Chat

Economics

1 2 ... 3,254 Next » New Topic in this Forum

Cases: 2017

Instead of saying AI IS GONNA REPLACE ALL JERBS, please give algorithmic detail

Economist
53b4

What I know: deep learning has made advantages in quite tightly-defined domains:

- Image processing/classification - e.g. identifying types of eye disease in images using deep convolutional networks
- Deep reinforcement learning in ATARI games, and board games - using deep Q-learning
- Speech recognition/translation

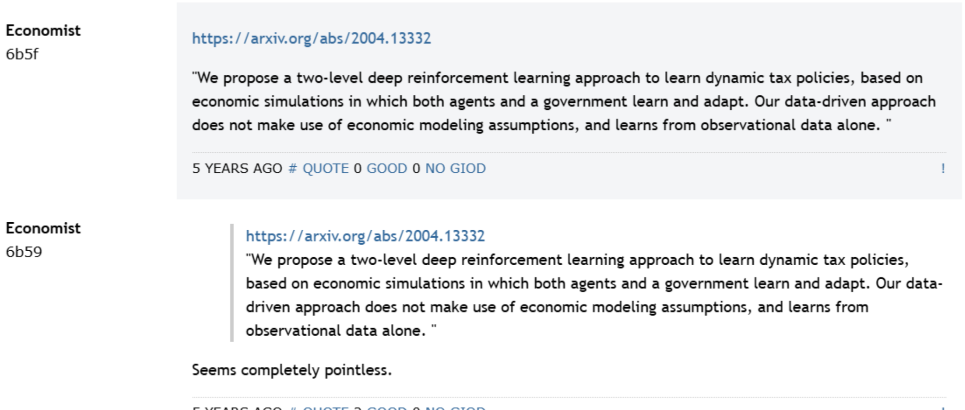
Please give me specific algorithmic details on how you are confident further advances in artificial intelligence will:

- Make AI good at more complex strategic games (e.g. RTS games) with long-term, multi-level objectives; currently, the existing set of algorithms cannot tackle these kinds of game, and instead only work on problems where the reward is fairly immediate, and where the state space is tight enough to discover with thousands/millions of iterations so that effective RL policy can be developed.

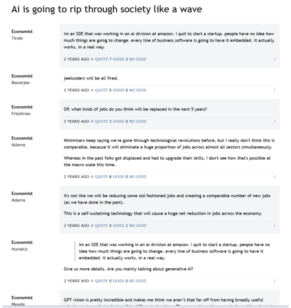
- Make AI good at transfer learning - that is instead of training a network from scratch for each game, the results of networks trained on one class of problem can be applied to another class of problem with +EV transfer benefits. Currently not much progress here - so no prospect of general-purpose AI yet.

Cases: 2020

Is all that progress in AI research really that useless for economics?



Cases: 2023



Ai is going to rip through society like a wave

Economist Tirole

im an SDE that was working in an ai division at amazon. I quit to start a startup. people have no idea how much things are going to change. every line of business software is going to have it embedded. it actually works, in a real way.

2 YEARS AGO # QUOTE 7 GOOD 2 NO GIOD !

Economist Banerjee

jeetcoders will be all fired.

2 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist Friedman

OP, what kinds of jobs do you think will be replaced in the next 5 years?

2 YEARS AGO # QUOTE 3 GOOD 0 NO GIOD !

Economist Adams

Minimizers keep saying we've gone through technological revolutions before, but I really don't think this is comparable, because it will eliminate a huge proportion of jobs across almost all sectors simultaneously.

Whereas in the past folks got displaced and had to upgrade their skills, I don't see how that's possible at the macro scale this time.

2 YEARS AGO # QUOTE 8 GOOD 0 NO GIOD !

Economist Adams

It's not like we will be reducing some old-fashioned jobs and creating a comparable number of new jobs (as we have done in the past).

This is a self-sustaining technology that will cause a huge net reduction in jobs across the economy.

2 YEARS AGO # QUOTE 0 GOOD 1 NO GIOD !

Economist Hurwicz

> im an SDE that was working in an ai division at amazon. I quit to start a startup. people have no idea how much things are going to change. every line of business software is going to have it embedded. it actually works, in a real way.

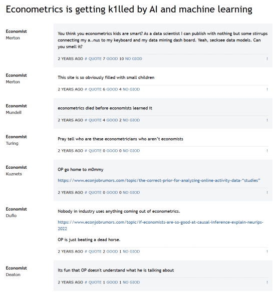
Give us more details. Are you mainly talking about generative AI?

2 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist Meade

GPT vision is pretty incredible and makes me think we aren't that far off from having broadly useful

AI is going to rip the society



Econometrics is getting k1lled by AI and machine learning

Economist Merton

You think you econometrics kids are smart? As a data scientist I can publish with nothing but some stirrups connecting my a..nus to my keyboard and my data mining dash board. Yeah, secksee data models. Can you smell it?

2 YEARS AGO # QUOTE 7 GOOD 10 NO GIOD !

Economist Merton

This site is so obviously filled with small children

2 YEARS AGO # QUOTE 6 GOOD 4 NO GIOD !

Economist Mundell

econometrics died before economists learned it

2 YEARS AGO # QUOTE 4 GOOD 2 NO GIOD !

Economist Turing

Pray tell who are these econometricians who aren't economists

2 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist Kuznets

OP go home to m0mmy

https://www.econjobrumors.com/topic/the-correct-prior-for-analyzing-online-activity-data-"studies"

2 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist Duflo

Nobody in industry uses anything coming out of econometrics.

https://www.econjobrumors.com/topic/if-economists-are-so-good-at-causal-inference-explain-neurips-2022

OP is just beating a dead horse.

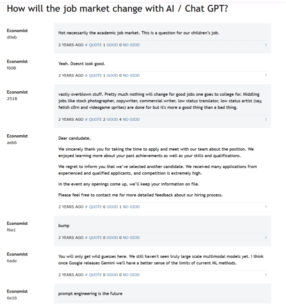
2 YEARS AGO # QUOTE 2 GOOD 1 NO GIOD !

Economist Deaton

Its fun that OP doesn't understand what he is talking about

2 YEARS AGO # QUOTE 1 GOOD 1 NO GIOD !

Econometrics is getting killed by AI and machine learning



How will the job market change with AI / Chat GPT?

Economist d0eb

Not necessarily the academic job market. This is a question for our children's job.

2 YEARS AGO # QUOTE 1 GOOD 0 NO GIOD !

Economist f608

Yeah. Doesnt look good.

2 YEARS AGO # QUOTE 1 GOOD 0 NO GIOD !

Economist 2518

vastly overblown stuff. Pretty much nothing will change for good jobs one goes to college for. Middling jobs like stock photographer, copywriter, commercial writer, low status translator, low status artist (say, fetish c0rn and videogame sprites) are done for but it's more a good thing than a bad thing.

2 YEARS AGO # QUOTE 2 GOOD 4 NO GIOD !

Economist aeb6

Dear candudate,

We sincerely thank you for taking the time to apply and meet with our team about the position. We enjoyed learning more about your past achievements as well as your skills and qualifications.

We regret to inform you that we've selected another candidate. We received many applications from experienced and qualified applicants, and competition is extremely high.

In the event any openings come up, we'll keep your information on file.

Please feel free to contact me for more detailed feedback about our hiring process.

2 YEARS AGO # QUOTE 6 GOOD 1 NO GIOD !

Economist f6e1

bump

2 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist 6ade

You will only get wild guesses here. We still haven't seen truly large scale multimodal models yet. I think once Google releases Gemini we'll have a better sense of the limits of current ML methods.

2 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist 6e16

prompt engineering is the future

How will job market change with AI

Cases: 2023 and later

Using ChatGPT for academic writing

Economist 102c
To the non-native English speakers out there - do you find ChatGPT useful for writing introduction/conclusion/response to referees?
2 YEARS AGO # QUOTE 2 GOOD 6 NO GIOD

Economist 0986
Yes, I draft and then use ChatGPT to correct.
2 YEARS AGO # QUOTE 2 GOOD 3 NO GIOD

Economist a924
> To the non-native English speakers out there - do you find ChatGPT useful for writing introduction/conclusion/response to referees?

ChatGPT hallucinates a lot, making up references, terms, etc. But it doesn't matter because Editors and referees are clueless these days. They don't check the legitimacy of anything.
2 YEARS AGO # QUOTE 18 GOOD 0 NO GIOD

Economist ca7c
how do you make the right prompts?
2 YEARS AGO # QUOTE 1 GOOD 2 NO GIOD

Economist 102c
Do you guys use GPT 3 or 4?
2 YEARS AGO # QUOTE 0 GOOD 1 NO GIOD

Economist b945
> To the non-native English speakers out there - do you find ChatGPT useful for writing introduction/conclusion/response to referees?

Using ChatGPT for academic writing(2023)

Do you use ChatGPT or other LLMs in your research or other academic activities?

Economist Akerlof
Are they becoming common tools among economists?
1 YEAR AGO # QUOTE 4 GOOD 0 NO GIOD

Economist Peter
If you do not use them, you will be left behind
https://www.econjobrumors.com/topic/the-intellectual-core-of-information-systems-security
1 YEAR AGO # QUOTE 4 GOOD 4 NO GIOD

Economist North
Consider this: ChatGPT can already do in a split second most of what is taught in econ/math/stats/CS grad school, and it will only get better in the future. And of course it has already replaced writers, translators and other similar jobs.
1 YEAR AGO # QUOTE 1 GOOD 7 NO GIOD

Economist Costanza
Generative AI for Economic Research: Use Cases and Implications for Economists
https://www-aeaweb-org.csulb.idm.oclc.org/articles?id=10.1257/jel.20231736
1 YEAR AGO # QUOTE 1 GOOD 2 NO GIOD

Economist Selten
Sure, 98% of my papers are written by Chad-Geppetto, I only change few things here and there.
1 YEAR AGO # QUOTE 1 GOOD 0 NO GIOD

do you use AI in your research (2024)

Possible to transition from econometrics to AI/ML?

Economist Card
You would have to think a deep understanding of advanced statistical techniques like instrumental variables is a huge advantage in these fields.
11 MONTHS AGO # QUOTE 0 GOOD 1 NO GIOD

Economist Meade
> You would have to think a deep understanding of advanced statistical techniques like instrumental variables is a huge advantage in these fields.

Perhaps you might think this, if you knew nothing about "these fields".
11 MONTHS AGO # QUOTE 2 GOOD 0 NO GIOD

Economist Nash
Before 2020 You can get into ML/Data Science/AI with just MA Econ.
Now you need phd in AI/Math/STEM
11 MONTHS AGO # QUOTE 0 GOOD 1 NO GIOD

Economist Imbens
> You would have to think a deep understanding of advanced statistical techniques like instrumental variables is a huge advantage in these fields.

LJL. All that is needed is freshman-level linear algebra. People used to joke that the field proceeds by "grad-student descent" -- basically a bunch of grad students randomly trying different things to see what works, no different than the old canard about a thousand monkeys with typewriters eventually discovering Shakespeare. Nowadays the field proceeds by the same process but with staff at AI firms.
11 MONTHS AGO # QUOTE 0 GOOD 0 NO GIOD

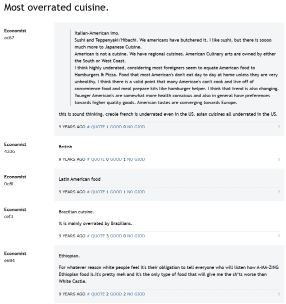
Economist Ostrom
Andrew Ng's Coursera classes are a good place to start. But maybe before that, maybe Python for Everybody by Dr. Chuck at the U of M (Coursera and FreeCodeCamp)
11 MONTHS AGO # QUOTE 0 GOOD 0 NO GIOD

Economist Vickrey
> Andrew Ng's Coursera classes are a good place to start. But maybe before that, maybe Python for Everybody by Dr. Chuck at the U of M (Coursera and FreeCodeCamp)

DataCamp is a good place to pick up python as well. Udemy of course as well.
11 MONTHS AGO # QUOTE 0 GOOD 0 NO GIOD

Possible to transit from econ to AI (2025)

Filter: opinions only related to research why?



Most overrated cuisine.

Economist ac67

> Italian-American imo.
> Sushi and Teppenyaki/Hibachi. We americans have butchered it. I like sushi, but there is soooo much more to Japanese Cuisine.
> American is not a cuisine. We have regional cuisines. American Culinary arts are owned by either the South or West Coast.
> I think highly underated, considering most foreigners seem to equate American food to Hamburgers & Pizza. Food that most American's don't eat day to day at home unless they are very unhealthy. I think there is a valid point that many American's can't cook and live off of convenience food and meal prepare kits like hamburger helper. I think that trend is also changing. Younger American's are somewhat more health conscious and also in general have preferences towards higher quality goods. American tastes are converging towards Europe.

this is sound thinking. creole french is underrated even in the US. asian cuisines all underrated in the US.

9 YEARS AGO # QUOTE 1 GOOD 0 NO GIOD !

Economist 4336

British

9 YEARS AGO # QUOTE 0 GOOD 1 NO GIOD !

Economist 0e8f

Latin American food

9 YEARS AGO # QUOTE 1 GOOD 1 NO GIOD !

Economist cef3

Brazilian cuisine.

It is mainly overrated by Brazilians.

9 YEARS AGO # QUOTE 3 GOOD 0 NO GIOD !

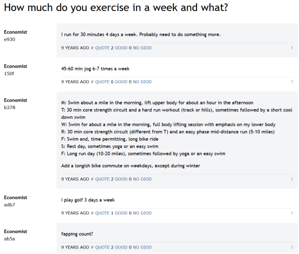
Economist e684

Ethiopian.

For whatever reason white people feel it's their obligation to tell everyone who will listen how A-MA-ZING Ethiopian food is.It's pretty meh and it's the only type of food that will give me the sh*ts worse than White Castle.

9 YEARS AGO # QUOTE 2 GOOD 2 NO GIOD !

food



How much do you exercise in a week and what?

Economist e930

I run for 30 minutes 4 days a week. Probably need to do something more.

9 YEARS AGO # QUOTE 2 GOOD 0 NO GIOD !

Economist 150f

45-60 min jog 6-7 times a week

9 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist b378

M: Swim about a mile in the morning, lift upper body for about an hour in the afternoon
T: 30 min core strength circuit and a hard run workout (track or hills), sometimes followed by a short cool down swim
W: Swim for about a mile in the morning, full body lifting session with emphasis on my lower body
R: 30 min core strength circuit (different from T) and an easy phase mid-distance run (5-10 miles)
F: Swim and, time permitting, long bike ride
S: Rest day, sometimes yoga or an easy swim
F: Long run day (10-20 miles), sometimes followed by yoga or an easy swim

Add a longish bike commute on weekdays, except during winter

9 YEARS AGO # QUOTE 2 GOOD 0 NO GIOD !

Economist adb7

I play golf 3 days a week

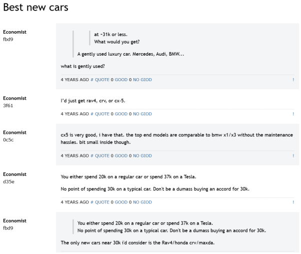
9 YEARS AGO # QUOTE 1 GOOD 0 NO GIOD !

Economist ab5a

fapping count?

9 YEARS AGO # QUOTE 2 GOOD 0 NO GIOD !

exercise



Best new cars

Economist fbd9

> > at ~31k or less.
> > What would you get?
>
> A gently used luxury car. Mercedes, Audi, BMW...

what is gently used?

4 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist 3f61

I'd just get rav4, crv, or cx-5.

4 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist 0c5c

cx5 is very good, i have that. the top end models are comparable to bmw x1/x3 without the maintenance hassles. bit small inside though.

4 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist d35e

You either spend 20k on a regular car or spend 37k on a Tesla.

No point of spending 30k on a typical car. Don't be a dumass buying an accord for 30k.

4 YEARS AGO # QUOTE 0 GOOD 0 NO GIOD !

Economist fbd9

> You either spend 20k on a regular car or spend 37k on a Tesla.
> No point of spending 30k on a typical car. Don't be a dumass buying an accord for 30k.

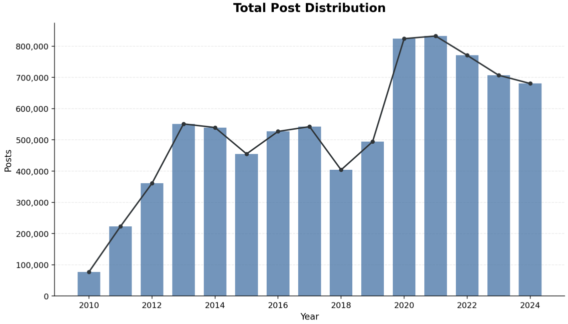
The only new cars near 30k i'd consider is the Rav4/honda crv/maxda.

cars

not all these threads are about research! life is full of a variety of topics.

8 Millions Economists' Opinions

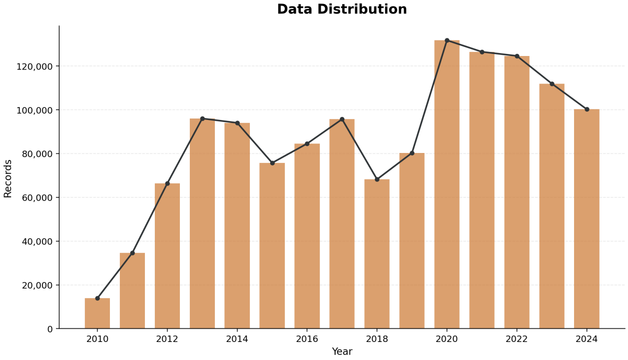
- Opinions (Posts): 7,989,637
- Words: 175,105,926
- Threads: 819,903
- Years: 2010 to 2024



distribution of posts

1.3 Millions Economists' Opinions Related to Research

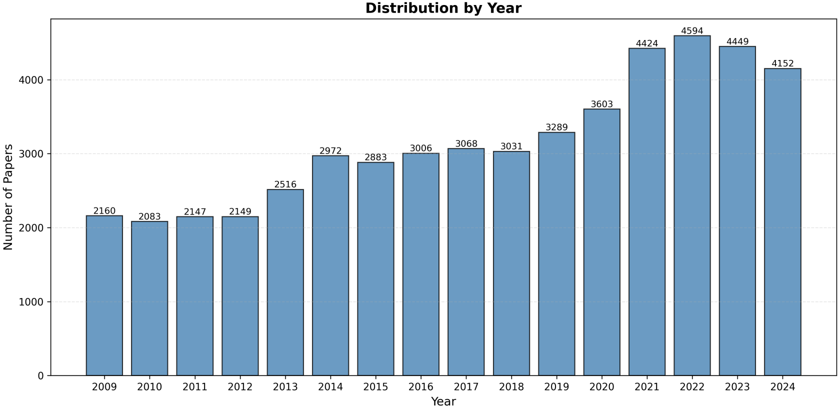
- Opinions (Posts): 1,304,483
- Words: 29,015,255
- Threads: 147,084
- Years: 2010 to 2024



- How we get the research topics including AI related economics research?
- How to get research trends for different topics?
- We turn to the top publications for our economists

Top Journals for Finance & Economics & Business

We have obtained information on 53,585 papers title and abstracts from **41 ABS 4* journals** through public sources (Google Scholar).



Description About Our Journals Data

The **ABS** journal list is a high-profile ranking system used to evaluate the quality of academic journals in the fields of business and management

Table: CABS Academic Journal Guide (AJG) Rating Hierarchy

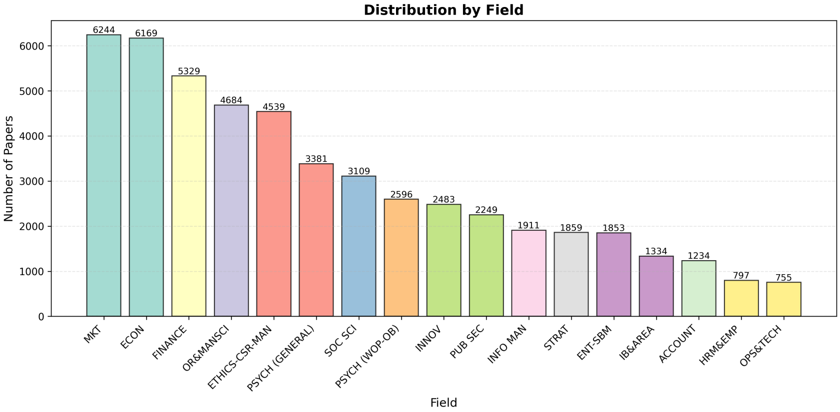
Rating	**Category**	**Description**
4*	Journals of Distinction	The "World Elite"
4	Top Journals	Global recognition
3	Highly Regarded	Solid recognized research
2	Well Regarded	Acceptable quality
1	Modest	Standards

ABS Journal Ranking (Association of Business Schools)

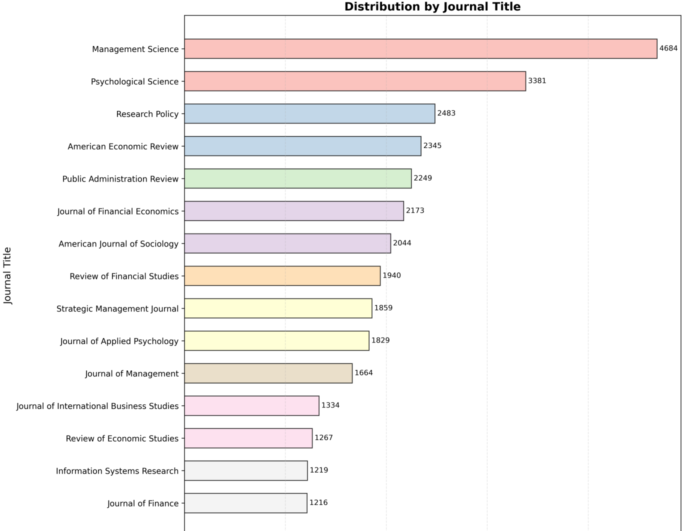
JOURNAL RANKING PORTAL

1944-7981	ECON	American Economic Review	American Economic Association	4*
2168-8966	ECON	Annals of Statistics	Institute of Mathematical Statistics	4*
1468-0262	ECON	Econometrica	Wiley-Blackwell	4*
1537-534X	ECON	Journal of Political Economy	University of Chicago Press	4*
1531-4650	ECON	Quarterly Journal of Economics	Oxford University Press	4*
1467-937X	ECON	Review of Economic Studies	Oxford University Press	4*

Description About Our Journals Data: Field Distribution



Description About Our Journals Data: Journal Distribution



From Man vs. Machine to Man plus Machine: The art and AI of stock analyses

Semantic search result

Cao, S; Jiang, W; (...); Yang, BZ

Oct 2024 | JOURNAL OF FINANCIAL ECONOMICS 160

An AI analyst trained to digest corporate disclosures, industry trends, and macroeconomic indicators surpasses most analysts in stock return predictions. Nevertheless, humans win "Man vs. Machine"when institutional knowledge is crucial, e.g., involving intangible assets and financial distress. AI wins when information is transparent but voluminous. Humans provide significant incremental value in "Man + Machine", which also substantially reduces extreme errors. Analysts catch up with machines after "alternative data"become available if their employers build AI capabilities. Documented synergies between humans and machines inform how humans can leverage their advantage for better adaptation to the growing AI prowess.

Show less

Full text at publisher Full Text at Publisher ...

Journal of Financial Economics (ABS4*)

Dissecting Corporate Culture Using Generative AI

Semantic search result

Li, K; Mai, F; (...); Zhang, TF

Jan 2026 | REVIEW OF FINANCIAL STUDIES 39(1), pp.253-296

Enriched Cited References

We conduct the first large-scale study of how different stakeholder groups assess corporate culture and quantify the economic implications of those differences. We employ generative AI to analyze analyst reports, call transcripts, and employee reviews, and organize the

Full text at publisher Full Text at Publisher •••

Review of Financial Studies (ABS4*)

P2V-MAP: Mapping Market Structures for Large Retail Assortments

Semantic search result

Gabel, S; Guhl, D and Klapper, D

Aug 2019 | JOURNAL OF MARKETING RESEARCH 56(4), pp.557-580

The authors propose a new, exploratory approach for analyzing market structures that leverages two recent methodological advances in natural language processing and machine learning. They customize a neural network language model to derive latent product attributes by analyzing the co-occurrences of products in shopping baskets. Applying dimensionality reduction to the latent attributes yields a two-dimensional product map. This method is well-suited to retailers because it relies on data that are readily available from their checkout systems and facilitates their analyses of cross-category product complementarity, in addition to within-category substitution. The approach has high usability because it is automated, is scalable and does not require a priori assumptions. Its results are easy to interpret and update as new market basket data are collected. The authors validate their approach both by conducting an extensive simulation study and by comparing their results with those of state-of-the-art, econometric methods for modeling product relationships. The application of this approach using data collected at a leading German grocery retailer underlines its usefulness and provides novel findings that are relevant to assortment-related decisions.

Show less

Journal of Marketing Research (ABS4*)

The effect of subjectivity and objectivity in online reviews: A convolutional neural network approach

Semantic search result

Park, SK; Song, TK and Sela, A

Oct 2023 | JOURNAL OF CONSUMER PSYCHOLOGY 33(4), pp.701-713

Enriched Cited References

User reviews are now an essential source of information for consumers, exerting strong influence on purchase decisions. Broadly speaking, reviews rated by consumers as more helpful exert a greater influence downstream. The current research examines how the linguistic characteristics of a review affect its helpfulness score. Using a convolutional neural network (CNN), this research analyzes the linguistic subjectivity and objectivity of over 2 million reviews on Amazon. The results show that, ceteris paribus, both linguistic subjectivity and objectivity have a positive impact on review helpfulness. However, contrary to consumers' intuition, when subjectivity and objectivity are combined in the same review, review helpfulness increases less than their respective separate effects would predict, especially for hedonic products. We conceptualize that this results from the increased complexity of messages mixing subjective and objective sentences, which requires more effortful processing. The findings extend the literature on online reviews, word-of-mouth, and text analysis in marketing, and offer practical implications for marketing communication and facilitation of reviews.

Show less

Journal of Consumer Psychology (ABS4*)

Research AI by Using AI

- Matching 1.3 millions research-related economists' opinions to 53,585 top publications
- Sounds mission impossible by using traditional methods $(1,304,483 \times 53,585)$
- So, we turned to AI models for help

Why AI? The disadvantages of traditional survey methods

- **Costly and time-consuming:** Surveys require significant resources for design, distribution, and analysis, especially with large samples.
- **Limited sample size:** Surveys often have smaller, potentially biased samples that may not represent the broader population of economists.
- **Social desirability bias:** Respondents may not express their true opinions due to concerns about judgment or repercussions in a professional community.

Why AI? The advantages of using AI for sentiment analysis

- **Scalability:** AI can process and analyze millions of posts efficiently, far beyond the capacity of traditional surveys.
- **Rich contextual understanding:** AI models can capture nuanced sentiments, sarcasm, and domain-specific language that surveys may miss.

Our AI Method: Cross-Datasets Semantic Retrieval

- It's like using a "super-search" to find matching between research publications and economists' opinions
- Exactly. It's the same technology your ChatGPT uses to check the weather; it uses semantic retrieval to pull in the most relevant information from the internet.
- We use the same idea to map the research topics from top publications to economists' opinions

Background: Decoder AI vs Encoder AI

- The Decoder AI (The "Writer"): ChatGPT, Gemini, Deepseek (We are not using them)
- The Encoder AI (The "Reader"): **the AI model we are using**, it can understand the meaning of full context
- We use the Encoder AI (sentence transformer) to generate high-dimensional vectors for both economists' opinions and research publications

Textual Embedding by Encoder AI

1. **Document Embedding**: Generate document embeddings with encoder AI
   - Example: "I love machine learning" → [0.2, -0.5, 0.8, ...] (high-dim vector)
   - Similar documents have **smaller angles** between their vectors
   - Cosine similarity: $\cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$, where θ is the angle between vectors
2. **Clustering**: Cluster documents into groups with HDBSCAN

pipline: text → high-dimentional vector → reduction → cluster → extract topics

Comparison with Traditional Frequency/Dictionary Methods

Feature	Textual Embedding	Word Dictionary
Requires predefined categories	No	Yes
Handles semantic similarity	Excellent	Limited
Contextual understanding	Yes	No
Processing speed	Medium	Fast
Adapts to new terms/concepts	Yes	manual updates

- **Semantic over Lexical**: Discovers topics based on contextual meaning.
- **Automatic Discovery**: No need for manual keywords and dictionaries.
- **Context-Aware**: Groups by understanding contextual meaning.
- **Exploratory**: Identifies emerging themes without pre-definition.

Step1: Textual Embedding by Encoder AI

- Encoder AI + 1.3 million economists' opinions → 1.3 million meaningful vectors of economists' opinions
- Encoder AI + 53,585 top publication → 53,585 meaningful vectors about top publication
- **Automatic Topic Detection**: No need to specify number of topics

M. Grootel et al. (2020) | `https://github.com/MaartenGr/BERTopic`

Step 2: 53,585 Top Publications → Topics by Using AI Encoder (Sentence Transformer)

- But, 53,585 papers (semantic vectors) are still too many to analyze directly, we need to group them into research topics.
- So, we cluster the 53,585 top publications semantic vectors into research topics.
- Each topic is represented by a semantic vector (centroid of all papers in that topic)
- keywords for each topic cluster to check the meaning of each topic cluster and effectiveness of clustering

Step 2: Top Publications → Topics by Using AI Encoder

Unlike Previous works that use word dictionaries[1], we use textual embedding and cluster to collect **research topics** as "topic" indicator.

Table: topic selected from paper data

topic	keywords
AI	human ai, artificial intelligence, intelligent machines
gender	gender diversity, gender bias, gender equality
management	organization studies, management research, strategy research
innovation	patenting, innovation performance, open innovation

[1] Goldsmith-Pinkham. (2024) *Tracking the Credibility Revolution across Fields*.

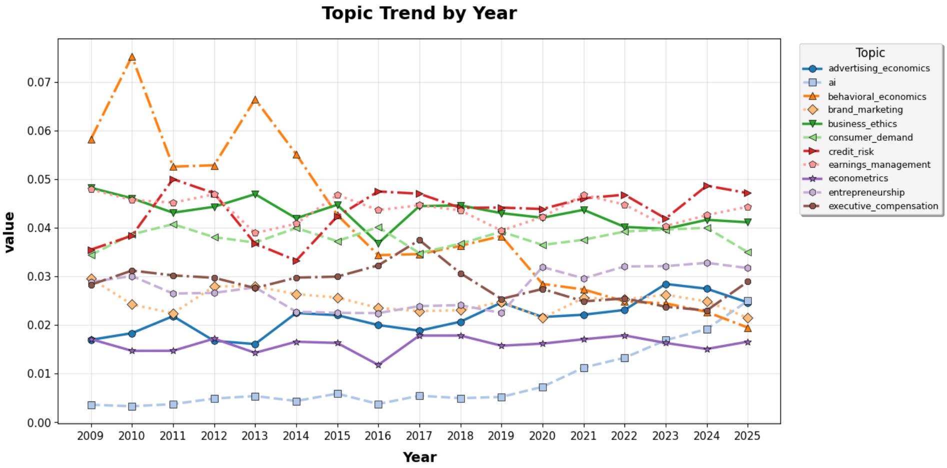
Step 2: Top Publications → Topics by Using AI Encoder

Topic	keywords
brand	consumers perceive, consumer psychology, purchase intentions
retail pricing	price competition, wholesale, dynamic pricing, inventory
racial	racial disparities, officers, police, black
online reviews	product reviews, sentiment, online reviews, rating systems
wage	wage, wages, minimum wage, unemployment, wage inequality
international business	multinational enterprises, international business, emerging markets
supply chain	supply chains, value chain, suppliers, supply chain
advertising	advertisements, advertisement, consumer search, ad, ads
personnel economics	human resource, hrm research, hr, organizational performance

Results: AI related Papers in Top Journals (Examples)

- "AI and the changing sources of competitive advantage": 0.9552,
- "Optimal Integration: Human, Machine, and Generative AI": 0.9400
- "Occupational, industry, and geographic exposure to AI: A novel dataset": 1.0000
- "Improving Human Deception Detection Using Algorithmic Feedback": 0.9893

Research Topics Trend : AI is rising quickly!



Step 2 Summary: Publications + Encoder AI

1. 53,585 publications $\rightarrow$ 32 semantic vectors representing each research topic
2. Trends of each research topics over 17 years

Step 3: Mapping Research Topics to Economists' Opinions

- 1.3 millions economists' opinions + Encoder AI → 1.3 million semantic vectors representing their opinions

Step 3: Mapping Economists' Opinions to Research Topics

- Step 3 is our innovative method by taking advantage of AI framework **Cross-Datasets Semantic Retrieval**
- It is Cross-Domain Semantic Retrieval, a new tech used by ChatGPT and Gemini
- Cross-Domain Semantic Retrieval helps ChatGPT to search the most relevant information from the internet news

Step 3: Mapping Research Topics to Economists' Opinions

- 1.3 million economists' opinions semantic vectors + 32 Research topics semantic vectors
- Calculate cosine similarity, then $\rightarrow$
- Semantic similarity for 1.3 million economists' opinions to 32 research topics
- A huge matrix of 1.3 million rows and 32 columns (Please see next page)

Data Description - Research Topics

VARIABLES	N	Mean	SD	Min	Max
ai	1,304,483	0.1068	0.1006	-0.1747	0.6756
econometrics	1,304,483	0.1116	0.1056	-0.1575	0.7293
health economics	1,304,483	0.0636	0.0774	-0.1713	0.6961
family business	1,304,483	0.0625	0.0761	-0.1623	0.6697
labor wages	1,304,483	0.0874	0.0962	-0.1567	0.6965
gender economics	1,304,483	0.0887	0.0867	-0.1831	0.6645
personnel economics	1,304,483	0.0576	0.0810	-0.1880	0.6176
public governance	1,304,483	0.0758	0.0810	-0.1711	0.5821
firm strategy	1,304,483	0.1131	0.1011	-0.1644	0.6777
behavioral economics	1,304,483	0.1307	0.0805	-0.1550	0.4953
venture capital	1,304,483	0.0876	0.0984	-0.1653	0.7507
entrepreneurship	1,304,483	0.0724	0.0803	-0.1615	0.7306
supply chain economics	1,304,483	0.0460	0.0817	-0.1848	0.5419
game theory	1,304,483	0.0747	0.0915	-0.1804	0.7145
mergers acquisitions	1,304,483	0.0725	0.0933	-0.1765	0.7974
executive compensation	1,304,483	0.0781	0.0924	-0.1916	0.7405
online reviews	1,304,483	0.0900	0.0849	-0.1801	0.6071
platform economics	1,304,483	0.0809	0.0911	-0.1628	0.7064

Results: Opinions for Different Topics (Examples)

AI

- "Exploring the Impact of Artificial Intelligence: Prediction versus Jud": 0.6754
- "Artificial Intelligence and Consumer Privacy | Ginger Zhe Jin": 0.6219

Platform Economics

- "Steering in Online Markets: The Role of Platform Incentives and Credib": 0.6757
- "Luigi Zingales and Tyler Cowen discuss the market powers of digital platforms": 0.656

International Business

- "Do Foreign Investors Improve Market Efficiency? | Marcin Kacperczyk,": 0.5921
- "Conference of the Multinational Finance Society, World Finance Conference, ...": 0.5029

Innovation

- "Patents and Cumulative Innovation: Causal Evidence from the Co | AFT": 0.782
- "A Survey of Empirical Evidence on Patents and Innovation | Bhaven N.": 0.7696

Mapping Economists' Opinions to Research Topics

Variable Construction Process

1. Apply texutual embedding and cluster to identify topics in ABS 4* Journal data
2. For each topic, compute the centroid using a sentence transformer
3. Encode all EJMR thread titles with the same sentence transformer
4. Compute cosine similarity between EJMR thread each title embedding and each topic centroid

TaDaS Output: Survey-like Cases

```
Analyze the economics dialogue and return JSON.

Task:
1. Evaluate ONLY A's attitude and affect.
2. Use Q only as contextual reference for A.
3. Use the bidirectional 0-1 scale.

Global scale:
0.0 = strong opposite pole
0.5 = no clear signal / neutral
1.0 = strong presence

Dimension anchors:
- openness:   0.0=closed,  0.5=neutral, 1.0=open
- negative:   0.0=non-neg, 0.5=neutral, 1.0=negative
- ...

Consistency rules:
- 0.5 means "no signal", not "medium".
- Do not raise poisonous/negative just because Q is toxic.
- ...

Return strictly JSON with keys:
{ "openness":..., "negative":...,... }

Q: {Question},A: {Answer}
```

Question: Causality vs Machine Learning

Answer: "You clearly don't understand not only economics or econometrics, but basic 1st year statistics."

Output

Dimension	**Score**
openness	0.2
negative	0.8
poisonous	0.8
arrogance	0.7
curiosity	0.3
confusion	0.2
AI	0.2457

Advantages of Cross-Domain Semantic Retrieval for Posts as Survey

- **Scalability:** Efficiently processes millions of posts and thousands of papers
- **Contextual Understanding:** Captures nuanced relationships beyond keyword matching

Dependent Variables: Sentiment

Sentiment Measures

- **Model:** `google/gemma-3-12b-it`
- **Sentiments:**
  - `negative score`: 0 to 1, higher means more negative sentiment
  - `openness score`: 0 to 1, higher means more open
  - other sentiment dimensions follow the same scale
- **Alternative model:** `cardiffnlp/twitter-roberta-base-sentiment`
- **Sentiment:** `negative score`: 0 to 1, higher means more negative sentiment

Sentiment and AI Adoption: Descriptive Statistics

Data Description

VARIABLES	N	Mean	SD	Min	Max
Sentiment					
openness	1,304,483	0.4556	0.2247	0.0000	1.0000
negative	1,304,483	0.5540	0.2353	0.0000	1.0000
poisonous	1,304,483	0.4878	0.2412	0.0000	1.0000
arrogance	1,304,483	0.5115	0.1885	0.0000	1.0000
curiosity	1,304,483	0.4082	0.2196	0.0000	1.0000
confusion	1,304,483	0.4325	0.1719	0.0000	1.0000
AI Adoption in Top Journals					
Trend ai	1,304,483	0.0086	0.0050	0.0033	0.0191

Other Control Variables

- Forum indicators (for example, `macro-job-market-rumors`)
- The 28 emotion indicators of the thread title (the question)
  - **Model:** `SamLowe/roberta-base-go_emotions`
  - Fine-tuned RoBERTa on Reddit data
  - Covers 28 emotion indicators such as admiration, amusement, and confusion
- Additional controls

DID Regression Model

Model Design

$$Y_{i,t} = \beta_0 + \beta_1 \cdot \mathit{AI\ Trend}_t + \theta \cdot (\mathit{AI\ Trend}_t \times \text{Topic AI}_i) + \sum_{k=1}^{K} \beta_k \cdot \text{Topic}_{i,k} + \mathbf{X}_i' \boldsymbol{\delta} + \epsilon_{i,t}$$

where:

- *AI Trend*$_t$: Treatment indicator which is the popularity of AI-related research on top-top econ journals
  - *AI Trend* The annual average semantic similarity to AI among all **publications**

DID Topic Coefficients

Table: DID Results:Interaction

	openness	negative	arrogance	confusion	curiosity	poisonous
ai	-0.1626***	0.3282***	0.3065***	-0.0389***	-0.0976***	0.0801***
	(0.0083)	(0.0086)	(0.0069)	(0.0063)	(0.0082)	(0.0087)
AI Trend	0.4726***	-0.5319***	-0.4684***	1.6945***	1.7223***	-0.0297***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
ai $\times$ AI Trend	15.6407***	-22.2936***	-17.8339***	-7.8842***	11.0471***	-20.5981***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Observations	1,304,483	1,304,483	1,304,483	1,304,483	1,304,483	1,304,483
Pseudo R^2	0.0016	0.0032	0.0008	0.0004	0.0013	0.0031

All columns include forum controls, year fixed effects, and additional controls.
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

DID Topic Coefficients

Table: Other Topics I

	openness	negative	arrogance	confusion	curiosity	poisonous
behavioral economics	-0.0731***	0.0106	-0.1419***	0.2195***	0.0613***	0.2047***
	(0.0132)	(0.0138)	(0.0110)	(0.0103)	(0.0132)	(0.0141)
business ethics	-0.7375***	1.3253***	-0.1785***	-0.2066***	-0.6420***	1.1079***
	(0.0391)	(0.0407)	(0.0322)	(0.0299)	(0.0392)	(0.0414)
econometrics	0.0444*	-0.1411***	-0.1580***	-0.1259***	0.0437*	-0.1851***
	(0.0236)	(0.0246)	(0.0199)	(0.0187)	(0.0237)	(0.0252)
gender economics	-0.7123***	0.7853***	0.4843***	0.1059***	-0.7527***	0.9256***
	(0.0278)	(0.0287)	(0.0225)	(0.0200)	(0.0282)	(0.0291)
health economics	-0.3488***	0.5302***	0.1300***	0.2148***	-0.2114***	0.4618***
	(0.0264)	(0.0276)	(0.0220)	(0.0203)	(0.0265)	(0.0280)

All columns include forum controls, year fixed effects, and additional controls.
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

DID Topic Coefficients

Table: Other Topics II

	openness	negative	arrogance	confusion	curiosity	poisonous
innovation and patents	0.0660**	0.2211***	-0.0820***	0.0693***	0.2046***	0.3623***
	(0.0286)	(0.0300)	(0.0238)	(0.0221)	(0.0287)	(0.0304)
labor and wages	0.4582***	-0.3250***	-0.2111***	0.0658**	0.2937***	-0.5542***
	(0.0395)	(0.0412)	(0.0329)	(0.0304)	(0.0397)	(0.0419)
platform economics	-0.1860***	0.4771***	-0.0112	0.1559***	-0.1349***	0.3353***
	(0.0285)	(0.0301)	(0.0238)	(0.0221)	(0.0286)	(0.0304)
venture capital	-0.1695***	-0.1066**	-0.0057	0.0641	-0.1985***	-0.1899***
	(0.0508)	(0.0532)	(0.0423)	(0.0396)	(0.0510)	(0.0540)

All columns include forum controls, year fixed effects, and additional controls.
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Platform-Trend Benchmark

Table: Platform-Trend Benchmark

	openness	negative	arrogance	confusion	curiosity	poisonous
platform economics	0.0113	0.1836***	0.1704***	0.0566***	0.0816***	0.0087
	(0.0093)	(0.0098)	(0.0078)	(0.0072)	(0.0093)	(0.0099)
platform economics Trend	0.5217***	-0.5637***	-0.4118***	1.3316***	1.9112***	-0.0232***
	(0.0010)	(0.0011)	(0.0009)	(0.0008)	(0.0010)	(0.0011)
platform economics × platform economics Trend	5.9023***	-7.2440***	-5.9722***	-1.5410***	2.8450***	-7.5527***
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Observations	1,304,483	1,304,483	1,304,483	1,304,483	1,304,483	1,304,483
Pseudo R^2	0.0015	0.0031	0.0006	0.0004	0.0013	0.0031

All columns include forum controls, year fixed effects, and additional controls.

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Gender-Trend Benchmark

Table: Gender-Trend Benchmark

	openness	negative	arrogance	confusion	curiosity	poisonous
gender economics	-0.4391***	0.7012***	0.5272***	0.0271***	-0.3855***	0.4979***
	(0.0098)	(0.0102)	(0.0081)	(0.0074)	(0.0098)	(0.0103)
gender economics Trend	1.0440***	-1.0662***	-0.6772***	2.8124***	3.0384***	-0.1549***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0007)
gender economics × gender economics Trend	-3.9797***	-2.4125***	-5.1248***	-0.0125***	-10.4633***	6.1271***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,304,483	1,304,483	1,304,483	1,304,483	1,304,483	1,304,483
Pseudo R^2	0.0018	0.0036	0.0009	0.0004	0.0014	0.0034

All columns include forum controls, year fixed effects, and additional controls.

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

All-Trends

Model Design

This model includes the full set of publication-side topic trends and their interactions.

$$Y_{i,t} = \beta_0 + \sum_{j=1}^{K} \theta_j \cdot \mathit{Topic\ Trend}_{j,t} + \alpha_j \cdot (\mathit{Topic\ Trend}_{j,t} \times \text{Topic}_{i,j}) + \sum_{k=1}^{K} \beta_k \cdot \text{Topic}_{i,k} + \mathbf{X}_i' \boldsymbol{\delta} + \epsilon_{i,t}$$

- Controls for the broader movement of the publication frontier
- AI coefficients are interpreted conditional on all comparison topic trends
- Tests whether the main pattern survives richer trend controls

All-Trends Results

Table: All-Trends Results

	openness	negative	arrogance	confusion	curiosity	poisonous
ai	-0.1499***	0.1603***	0.1847***	-0.1062***	-0.1851***	-0.0621***
	(0.0176)	(0.0183)	(0.0145)	(0.0136)	(0.0175)	(0.0186)
AI Trend	-0.0844***	0.0906***	-0.0644***	0.3534***	-0.1250***	0.0633***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
ai $\times$ AI Trend	16.6836***	-17.7953***	-15.1309***	-5.0255***	16.6836***	-19.5234***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Observations	1,304,483	1,304,483	1,304,483	1,304,483	1,304,483	1,304,483
Pseudo R^2	0.0022	0.0044	0.0012	0.0006	0.0019	0.0043

All columns include forum controls, year fixed effects, and additional controls.
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Pre-ChatGPT Sample Restriction

Model Design

We re-estimate the interaction specification on the pre-2023 sample to remove the direct ChatGPT shock.

- Same interaction specification as the main DDD-style design
- Sample restricted to the pre-2023 period
- Tests whether the pattern is already visible before ChatGPT's public release

Pre-ChatGPT Robustness

Table: Pre-ChatGPT Robustness

	openness	negative	arrogance	confusion	curiosity	poisonous
ai	-0.1948***	0.3718***	0.3514***	-0.0317***	-0.1255***	0.1168***
	(0.0092)	(0.0096)	(0.0077)	(0.0071)	(0.0091)	(0.0098)
AI Trend	1.9801***	-1.6427***	-0.7872***	1.9602***	6.6914***	-0.4813***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
ai × AI Trend	18.4095***	-24.9527***	-12.3310***	-14.2374***	6.2386***	-26.0659***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Observations	1,092,308	1,092,308	1,092,308	1,092,308	1,092,308	1,092,308
Pseudo R^2	0.0014	0.0030	0.0008	0.0005	0.0012	0.0029

All columns include forum controls, year fixed effects, and additional controls.
Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Innovation: Text as Data as Survey

- AI framework: cross-datasets semantic retrieval
- Unstructed professional forum data $\rightarrow$ Valuable Survey data
  - **Easy:** easy to apply in other fields (e.g., finance, management, marketing) even without professional AI hardware
  - **Efficient:** good at extracting relevant opinions from unstructured textual data
  - **Time sensitive:** can capture real-time changes in opinions and trends (Better than GPT as a survey)

Conclusions

- Economists becoming more open to AI
- Maybe, leading economics, finance, and business journals can accelerate the adoption of emerging technologies and innovative methodologies among early-career researchers.
- **Text-as-Data-as-Survey (TaDaS)** framework can be a powerful tool for extracting insights from unstructured text data for economics, finance, management, marketing, quant trading and etc, even without professional AI handware.

Thank You! Please Help Us Spread the Words!

- **Lei Ge**
  gelei@ruc.edu.cn
  github.com/tigercut2017

- **Yi Wang**
  wy_139@ruc.edu.cn
  github.com/onecloud139

- www.openeconomist.com
  - Still under construction, but will be available soon. We will also share our data and code there soon.
  - Open to new tech and new ideas
  - Open sourced data and code

Acknowledgements

Special thanks to:

Iván Blanco Sánchez
Pedro Alberto Chauffaille Saffi
Carlo Chiarella
John Coah
Eric Duca
Pablo García Estévez
Sergio Javier García Saiz
Salomón García Villegas
Juan Pedro Gomez
Manuel López Martín de Blas

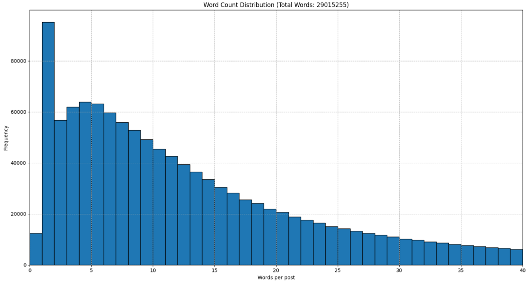
Textual Embedding by Encoder AI (Detailed Pipeline)

1. **Document Embedding**: Generate document embeddings with transformers
   - Example: "I love machine learning" $\rightarrow$ [0.2, -0.5, 0.8, ...] (n-dim vector)
   - Similar documents have **smaller angles** between their vectors
   - Cosine similarity: $\cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}$, where θ is the angle between vectors
2. **Dimensionality Reduction**: Reduce dimensions with UMAP
3. **Clustering**: Cluster documents with HDBSCAN
4. **Topic Representation**: Create topic representations with c-TF-IDF

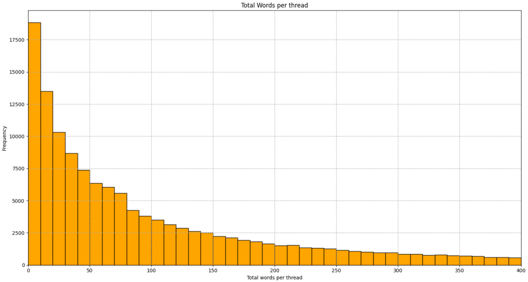
Document Embedding $\rightarrow$ Dimensionality Reduction $\rightarrow$ Clustering $\rightarrow$ Topic Representation

pipline: text $\rightarrow$ high-dimentional vector $\rightarrow$ reduction $\rightarrow$ cluster $\rightarrow$ extract topics

Description About Our Data



distribution of words per post



distribution of words per thread

Variable	N	Mean	SD	Min	Max
forum china-job-market	1304483	0.0062	0.0783	0.0000	1.0000
forum conferences	1304483	0.0012	0.0352	0.0000	1.0000
forum econ-lounge	1304483	0.0240	0.1531	0.0000	1.0000
forum econometrics-discussion	1304483	0.0374	0.1897	0.0000	1.0000
forum economics-discussion	1304483	0.1653	0.3714	0.0000	1.0000
forum european-job-market	1304483	0.0024	0.0485	0.0000	1.0000
forum finance-job-rumors	1304483	0.0465	0.2106	0.0000	1.0000
forum from-the-blogs	1304483	0.0055	0.0739	0.0000	1.0000
forum general-economics-job-market-discussion	1304483	0.0539	0.2259	0.0000	1.0000
forum industry-rumors	1304483	0.0060	0.0771	0.0000	1.0000
forum latest-research-discussion	1304483	0.0097	0.0982	0.0000	1.0000
forum macro-job-rumors	1304483	0.0015	0.0387	0.0000	1.0000
forum macroeconomics	1304483	0.0078	0.0881	0.0000	1.0000
forum math-job-market	1304483	0.0040	0.0632	0.0000	1.0000
forum math-lounge-off-topic	1304483	0.0177	0.1320	0.0000	1.0000
forum micro-job-rumors	1304483	0.0016	0.0406	0.0000	1.0000
forum microeconomics	1304483	0.0039	0.0623	0.0000	1.0000
forum off-topic	1304483	0.4850	0.4998	0.0000	1.0000
forum political-economy	1304483	0.0148	0.1208	0.0000	1.0000
forum political-science-discussion	1304483	0.0002	0.0145	0.0000	1.0000
forum political-science-job-market	1304483	0.0000	0.0038	0.0000	1.0000
forum political-science-lounge-off-topic	1304483	0.0001	0.0106	0.0000	1.0000
forum questions-from-prospective-grad-students	1304483	0.0175	0.1310	0.0000	1.0000
forum registered-users-forum	1304483	0.0000	0.0012	0.0000	1.0000
forum research-journals	1304483	0.0223	0.1475	0.0000	1.0000
forum sociology-discussion	1304483	0.0016	0.0403	0.0000	1.0000
forum sociology-job-market	1304483	0.0000	0.0060	0.0000	1.0000
forum sociology-lounge-off-topic	1304483	0.0000	0.0061	0.0000	1.0000
forum software-and-programming-for-research	1304483	0.0114	0.1062	0.0000	1.0000
forum sport	1304483	0.0030	0.0549	0.0000	1.0000
forum teaching	1304483	0.0098	0.0986	0.0000	1.0000
forum technology	1304483	0.0385	0.1923	0.0000	1.0000
forum trash	1304483	0.0009	0.0307	0.0000	1.0000

Variable	N	Mean	SD	Min	Max
Question admiration	1304483	0.0354	0.1474	0.0003	0.9585
Question amusement	1304483	0.0083	0.0657	0.0002	0.9565
Question anger	1304483	0.0107	0.0548	0.0002	0.8517
Question annoyance	1304483	0.0306	0.0770	0.0010	0.8037
Question approval	1304483	0.0341	0.0705	0.0017	0.9252
Question caring	1304483	0.0049	0.0359	0.0002	0.9157
Question confusion	1304483	0.0953	0.1500	0.0003	0.9412
Question curiosity	1304483	0.1845	0.2657	0.0002	0.9069
Question desire	1304483	0.0075	0.0537	0.0003	0.8438
Question disappointment	1304483	0.0221	0.0762	0.0005	0.8670
Question disapproval	1304483	0.0254	0.0859	0.0004	0.8974
Question disgust	1304483	0.0055	0.0329	0.0002	0.8480
Question embarrassment	1304483	0.0023	0.0170	0.0001	0.8128
Question excitement	1304483	0.0074	0.0355	0.0002	0.8384
Question fear	1304483	0.0044	0.0389	0.0001	0.9115
Question gratitude	1304483	0.0025	0.0295	0.0001	0.9904
Question grief	1304483	0.0008	0.0026	0.0001	0.0837
Question joy	1304483	0.0077	0.0489	0.0003	0.9134
Question love	1304483	0.0062	0.0549	0.0001	0.9641
Question nervousness	1304483	0.0018	0.0136	0.0000	0.6433
Question optimism	1304483	0.0075	0.0322	0.0005	0.9336
Question pride	1304483	0.0007	0.0045	0.0000	0.4629
Question realization	1304483	0.0155	0.0435	0.0015	0.8787
Question relief	1304483	0.0010	0.0042	0.0001	0.2478
Question remorse	1304483	0.0019	0.0248	0.0001	0.8293
Question sadness	1304483	0.0154	0.0768	0.0003	0.9265
Question surprise	1304483	0.0070	0.0419	0.0002	0.8987
Question neutral	1304483	0.5947	0.3247	0.0045	0.9737