

The Impact of AI and Robots on Employment, Wages, and Industrial Structure

Kyoji Fukao^{1,2}, Kenta Ikeuchi¹, Yoshiaki Nagaya³,
Cristiano Perugini⁴, Fabrizio Pompei⁴

¹ RIETI (J)

² Hitotsubashi University (J)

³ Nomura Research Institute (J)

⁴ University of Perugia (I)

Aims and scope

(i) Research aims:

- Investigate whether labour market outcomes in industries with low/high *Automation Risk Index* (ARI) have been more affected by the penetration of automation technologies presumably incorporating AI innovations.
- Focus on how ARI shapes the impact of innovative capital/investment intensity (software, computing equipment and communication equipment) on labour market outcomes, i.e., wages and hours worked

(ii) Data

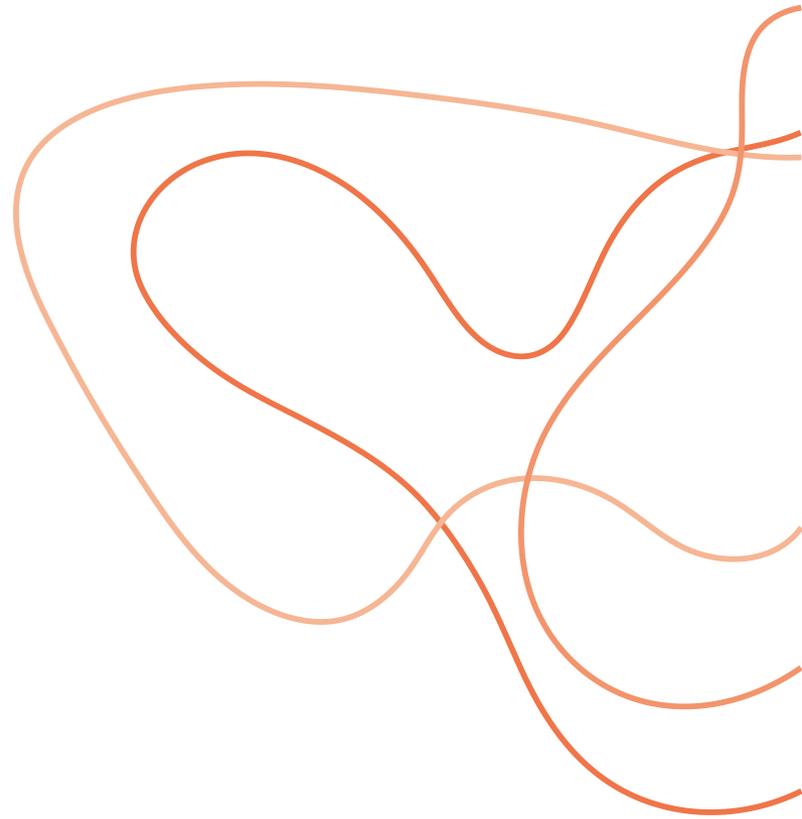
- Detailed industry-level data (JIP) in the decade before the pandemic (2009-2019)
- Detailed demographic group level labour market variables (wages, hours worked)
- ARI as a context variable (low/high ARI industries at the beginning of the period)

(iii) Methods

- Baseline panel FE model to investigate heterogeneity in the effects of innovative capital on wages and hours worked and across high/medium/low ARI Industries
- Simultaneous equations system to control for potential endogeneity of innovative capital and labour market outcomes

(i)

Background and methods



The Automation Risk Index (ARI) for Japan – Summary

We map 504 Japanese occupations based on the risk of being replaced by automation.

To this aim we use an experts survey as in Frey and Osborne (2017) but we expand the list of subjective assessments from 9 to 53 items (skills, abilities and nature of work) as in Paolillo et al. (2022)

ARI is based on primary data:

The survey is conducted on 13 experts and inquires about the extent to which AI is able to replace the 53 skills and abilities in 2024 and their estimate for 2030 and 2040

We then compare this ability of AI to the skills and abilities of humans needed for each occupation mapped in the Skills Evaluation Table of **Job Tag**

The **Job Tag** is the Japanese version of the **US O*NET** and reports data on skills, abilities, and the nature of work for 504 occupations based on a questionnaire survey of actual workers conducted by the Japanese Ministry of Health, Labour, and Welfare.

The ARI calculation for each occupation is based on Paolillo et al. (2022)

$$r_t = \frac{\sum_{j=1}^N m_{t,j} d(s_j - m_{t,j})}{\sum_{j=1}^N m_{t,j}}$$

r_t denotes the ARI for occupation t

t denotes occupation, $t=(1, 2, \dots, 504)$

j denotes Skills Evaluation Table elements, $j=(1, 2, \dots, 53)$

$m_{t,j}$ denotes necessary level of Job Tag Skills Evaluation Table element j for occupation t

s_j denotes the AI and robot skill level, (2024, 2030, 2040)

$d()$ denotes logistic distribution function with location and scale parameters set to 0 and 0.05, respectively.

The Automation Risk Index (ARI) for Japan – Extended explanation

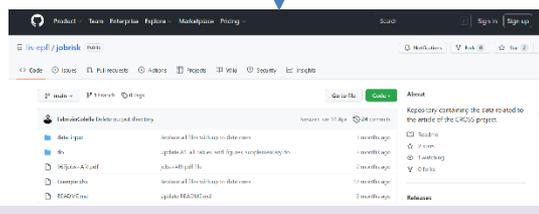
Prior research: 'How to compete with robots by assessing job automation risks and resilient alternatives,' in Science Robotics, April 2022.

- (i) Prof. Floreano et al., with support from the European Commission and others, investigate the impact of future robotics and AI on occupations
- (ii) They calculate workforce replacement potential by analyzing the skills and abilities required for each occupation and evaluating them against the technological maturity of robots and AI



How to compete with robots by assessing job automation risks and resilient alternatives

In about 1,000 job tasks. Figures showing the potential for replacement by robots



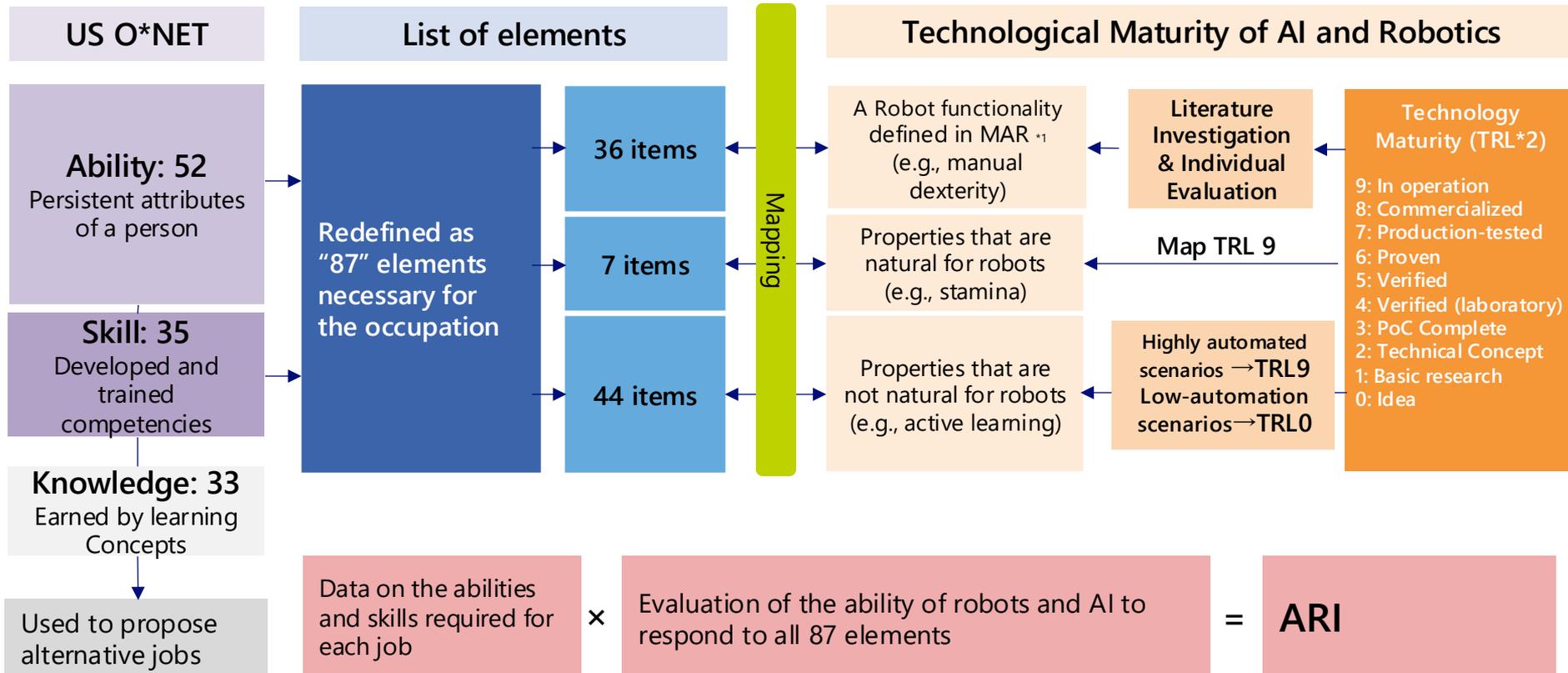
Detailed data used in the paper is available on GitHub. -Replacement potential rates for about 1000 jobs

ONETSCODE	Job (from ONET database)	Automation Risk Index
19-2012.00	Physicists	0.43
29-1069.04	Neurologists	0.48
29-1069.09	Preventive Medicine Physicians	0.48
19-3039.01	Neuropsychologists and Clinical Neuropsychologists	0.49
19-1069.07	Psychologists	0.49
15-2021.00	Mathematicians	0.50
11-2012.00	Chief Executives	0.50
29-1067.00	Surgeons	0.50
19-1029.02	Molecular and Cellular Biologists	0.51
19-1041.00	Epidemiologists	0.51
19-1021.00	Biochemists and Biophysicists	0.51
19-3091.01	Anthropologists	0.52
29-1023.00	Judges, Magistrate Judges, and Magistrates	0.52
19-2012.00	Astronomers	0.52
19-2012.00	Counseling Psychologists	0.52
19-1022.00	Microbiologists	0.52
19-2041.00	Chemical Engineers	0.52
29-1199.04	Naturopathic Physicians	0.53
29-1069.01	Allergists and Immunologists	0.53
17-2031.00	Biomedical Engineers	0.53
21-1014.00	Mental Health Counselors	0.53
29-1066.00	Psychiatrists	0.53
29-1069.05	Nuclear Medicine Physicians	0.53
29-1061.00	Anthropology and Archeology Teachers, Postsecondary	0.53
17-1011.00	Architects, Except Landscape and Naval	0.53
25-1132.00	Law Teachers, Postsecondary	0.53
17-1151.00	Mining and Geological Engineers, Including Mining Safety Engineers	0.53
19-3032.02	Clinical Psychologists	0.53
29-1069.03	Hospitalists	0.53
29-1031.00	Dietitians and Nutritionists	0.53
29-1069.06	Ophthalmologists	0.53
53-2021.00	Air Traffic Controllers	0.53
11-0121.00	Nature Sciences Managers	0.53
19-3041.00	Sociologists	0.53
25-1113.00	Social Work Teachers, Postsecondary	0.53
19-2041.03	Industrial Ecologists	0.53
19-1042.00	Medical Scientists, Except Epidemiologists	0.53
17-2081.01	Water/Wastewater Engineers	0.54
19-2021.00	Atmospheric and Space Scientists	0.54

source) <https://www.science.org/toc/scirobotics/7/65>
<https://github.com/lis-epfl/jobrisk>

Prior research: Prof. Floreano et al. methodology

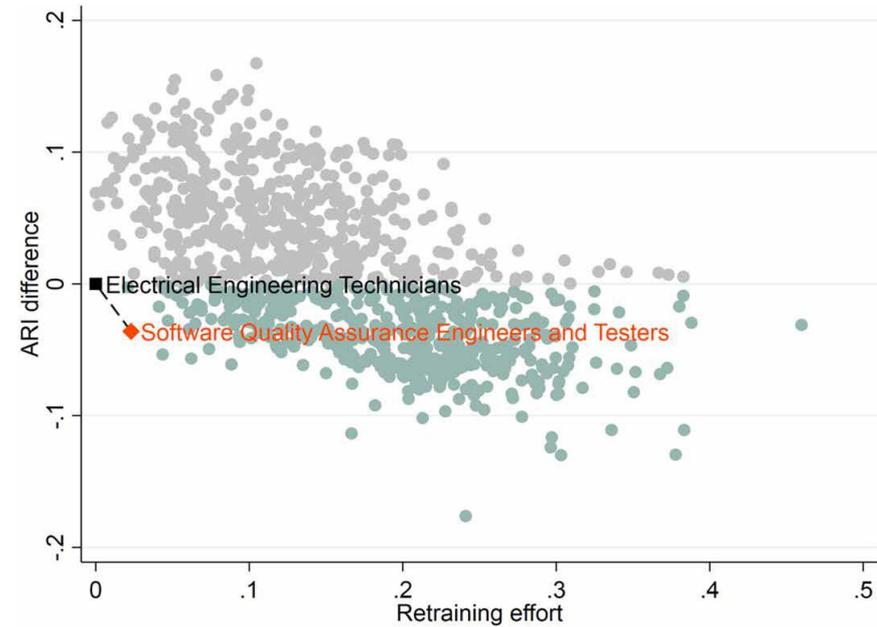
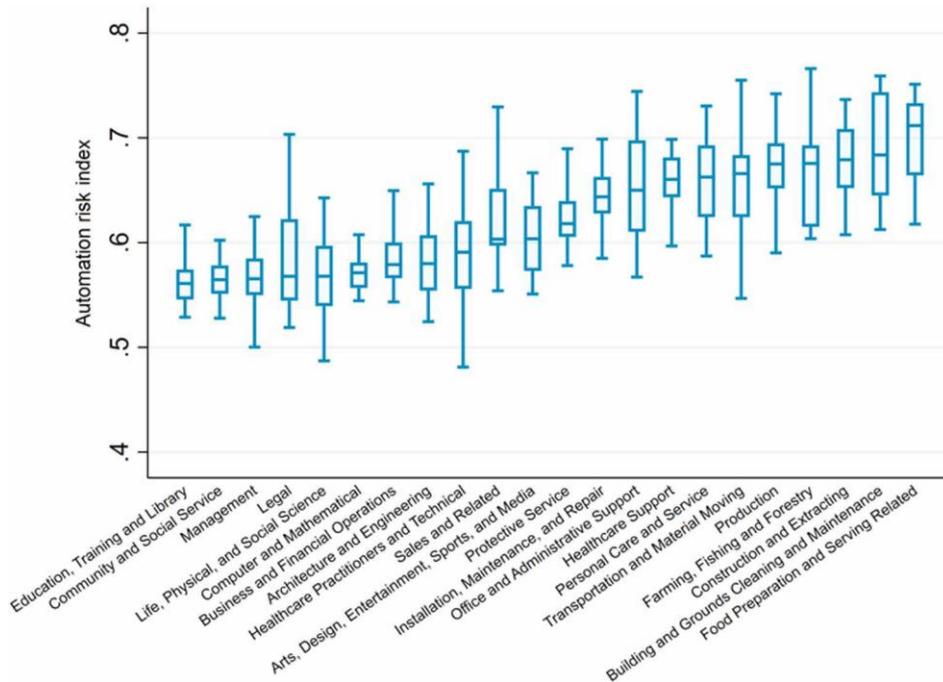
(i) The skills and abilities required for the occupations defined by **O*NET** are mapped to the functions of AI and robotics, and the technological maturity (TRL *2) of each robot and AI functionality is evaluated based on literature surveys such as MAR*1. The **Automation Risk Index (ARI)** is calculated for each occupation.



*1 European H2020 Robotics Multi-Annual Roadmap (MAR)

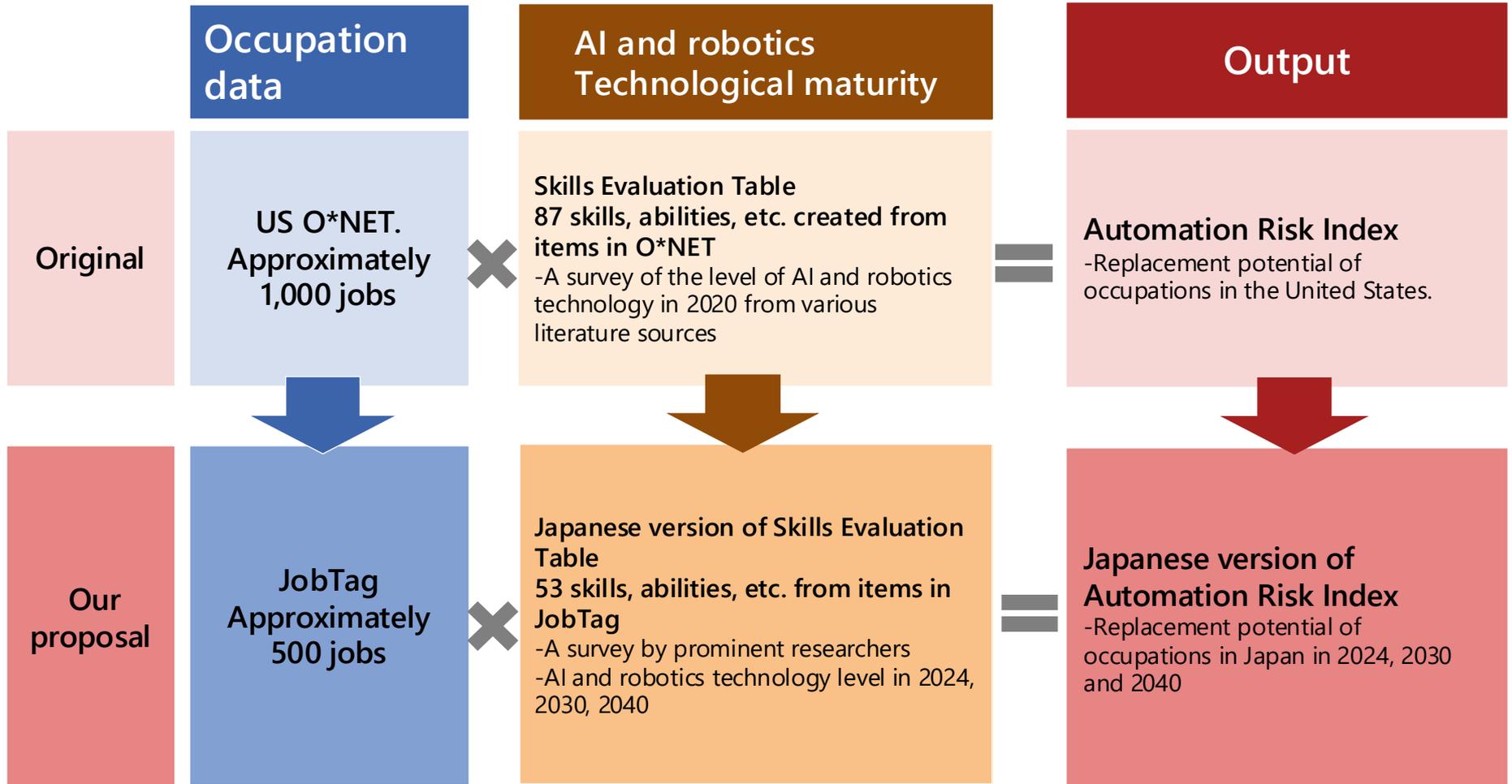
*2 Technology Readiness Levels, HORIZON 2020 – WORK PROGRAMME 2014-2015

Prior research: Results

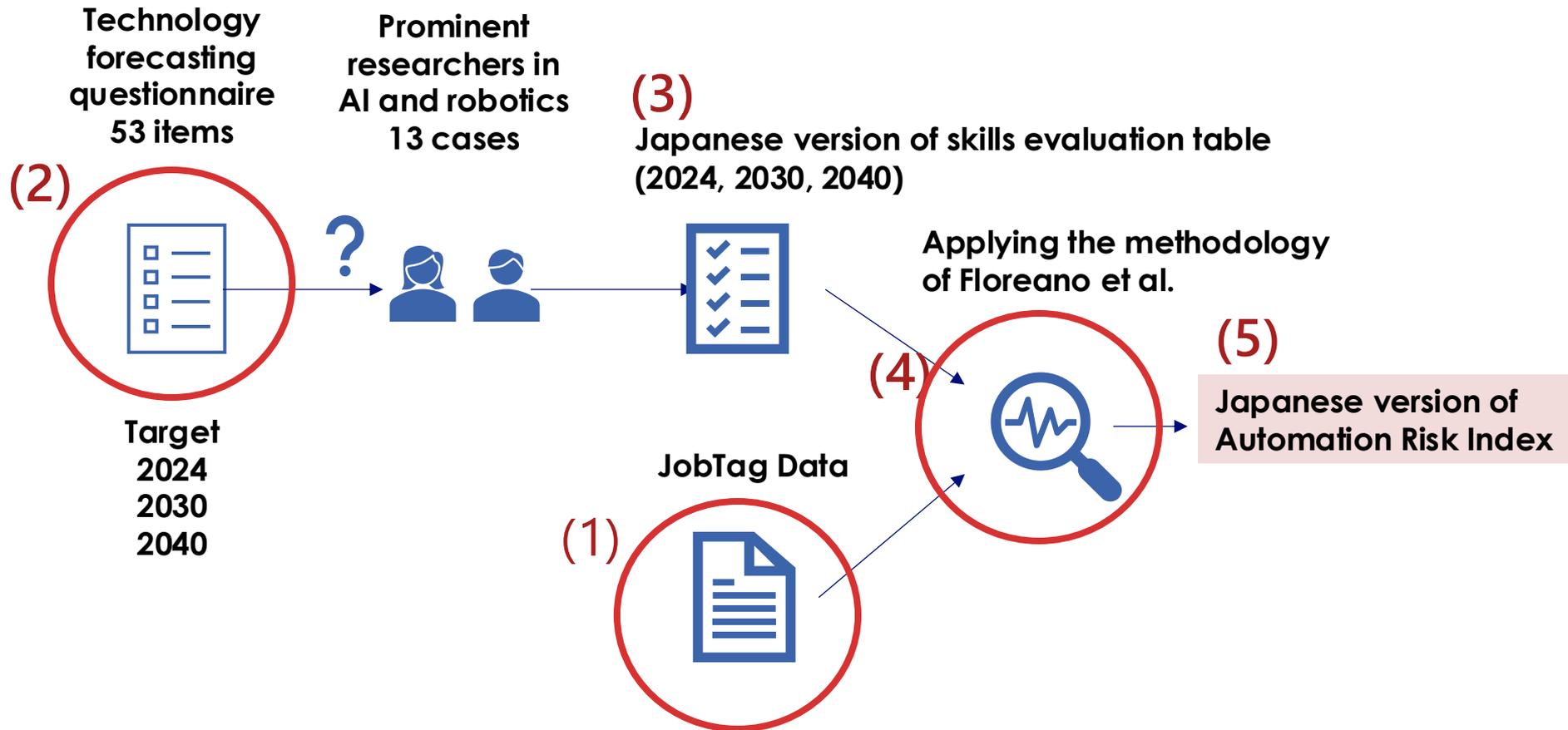


- ✓ Prior research, based on US occupational data O*NET.
- ⇒ Japanese occupational data (JobTag) & technological maturity in 2024, 2030 and 2040.

Our proposal: Methodology



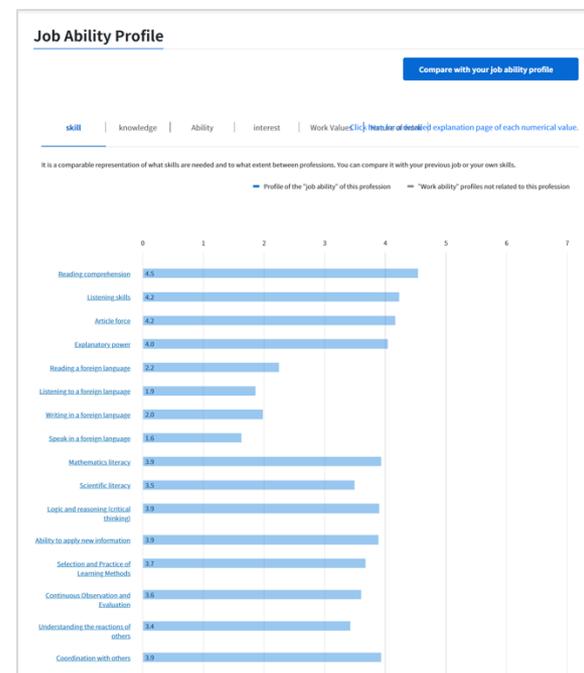
Overview of the creation of the Japanese ARI



(1) JobTag

- (i) JobTag is an occupational information website operated by the Japanese Ministry of Health, Labour and Welfare (**Japanese version of O-NET**)
- (ii) Developed with reference to US O*NET. Data on skills, abilities, knowledge, nature of work, etc. for about 500 occupations, based on questionnaire survey of actual workers
- (iii) Available as **open data**

The screenshot shows the JobTag website interface for the occupation 'Electrical Engineer'. At the top, there are navigation links: 'About this site', 'How to use it', 'Self-Diagnostic Tool', 'Occupation Search', 'Know your industry and occupation', and 'Links:'. Below these is a 'Frequently Asked Questions' section. The main heading is 'Electrical Engineer', with buttons for 'Save to My List', 'print', and 'Sources of Numerical Data'. Underneath, there are sections for 'Occupation aliases', 'Occupational classification', and 'Industries to which it belongs'. A navigation menu includes 'What kind of work?', 'How to get a job?', 'Features of working conditions', 'Job Ability Profile', 'Similar professions', and 'Related Links'. The 'What kind of work?' section contains text describing the role and a video thumbnail.



Source: <https://shigoto.mhlw.go.jp/User/Occupation/Detail/272>

(1) JobTag

Occupation information download

About Occupation Information Data

The data files of "Vocational Commentary" and "Numerical Information on Occupations" that can be downloaded from this page are the research and development products of the National Institute for Labour Policy and Training (the "Occupation Information Database").

All rights to the copyright of this database are reserved by the Organization. Please comply with the "Terms of Use" and use it so as not to infringe on the copyright of the Organization.

If you use the downloaded data file to write or publish a book, paper, etc., please be sure to include the source as follows. It is also necessary to include the file name and version number of the "Occupation Information Database".

Example of < when citing >

Source: "Occupational Information Database Commentary Download Data ver.1.8" created by the Japan Institute for Labour Policy and Training (JILPT) Downloaded

on July 6, 2020 from the job information site (Japan version O-NET) <https://shigoto.mhlw.go.jp/User/download>

<Example of a case where the data is edited, processed, retabulated, etc. for secondary use>

Created by the Japan Institute for Labour Policy and Training (JILPT) "Occupation Information Database Simplified Numerical System Download Data ver.1.8" Downloaded

on May 8, 2020 from the job information site (Japan version O-NET) (<https://shigoto.mhlw.go.jp/User/download>)

With the renewal on March 27, 2024, we have updated the occupational information data, including adding 10 occupations to the individual occupation information, and we have also changed the occupational classification of some occupations when the occupational classification correspondence table is posted on May 14, 2024. Version 5.00 has been released to reflect these changes.

List of occupational information data

Item No.	File Name	version	File Format	Published on
01	Detailed Numerical System Download Data (Occupational Interest)	5.00.01	csv	October 11, 2024
02	Detailed Numerical System Download Data (Occupational Interest)	5.00.01	xlsx	October 11, 2024
03	Detailed Numerical System Download Data (Work Values)	5.00.01	csv	October 11, 2024

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	1	Japanese O-NET "Input data."			*Terms of use										
2	2	Input data for the occupational information network of Japan			names of the professions listed and classification										
3	3	[Simplified numerical system download data]. This data is only as of the date of the last update on the left.													
4	4	version 5.00													
5	5														
6	6				Only occupations with numerical information in one of the areas are included in this data. For this reason, there are missing numbers in the "Recorded numbers".										
7	7	(Last updated: 2024.04.01)			See sheet 3 for existing data areas per occupation. (Excel version only)										
8	8														
9	9				Occupations with "1" in the "Task content validity concern flag" have no task information.										
10	10	(Produced and written by: National Institute for Labour Policy and Training (NILPT))			In some occupations, the representation rate is left blank for various reasons for certain tasks.										
11	11														
12	12				list of variables and the corresponding "IPD number" (see "Input data details") on Sheet 2 (Excel version only)										
13	13														
14	14				For numerical systems, in addition to the means and proportions of this data, sample size, standard error, 95% confidence intervals, etc. are included.										
15	15				The "Detailed Version Download Data" is scheduled to be published additionally, approximately once for each major version.										
16	16														
17	17	record number	Occupation name	realistic	scholarly	artistic	social	enterprising	customary	sense of accomplishment	autonomy (job/loosely)	Social recognition/status	Good interpersonal relations	Working conditions (stability of remuneration)	occupational safety and health
18	18	IPD_01_01_001	IPD_02_01_001	IPD_04_01_001	IPD_04_01_002	IPD_04_01_003	IPD_04_01_004	IPD_04_01_005	IPD_04_01_006	IPD_04_02_001	IPD_04_02_002	IPD_04_02_003	IPD_04_02_004	IPD_04_02_005	IPD_04_02_006
19	19	1	Total product set	2,743	2,771	2,626	2,657	2,657	2,699	2,571	2,714	2,571	2,600	2,714	2,699
20	20	2	Real product set	2,472	2,496	2,352	2,386	2,386	2,428	2,300	2,404	2,300	2,352	2,428	2,428
21	21	3	Contact industry set	3,349	3,000	2,845	3,299	3,339	3,459	3,418	3,202	3,289	3,418	3,418	3,418
22	22	4	Japanese context	3,464	3,018	2,873	3,374	3,412	3,193	3,281	3,018	2,857	3,179	2,844	3,173
23	23	5	Industry product set	3,519	3,060	2,860	3,179	3,070	3,562	3,400	3,300	3,162	3,226	3,179	3,263
24	24	6	Manufacture of	3,661	3,497	2,541	3,351	2,838	3,458	3,169	2,978	2,891	3,139	3,166	3,244
25	25	7	Primary occupations	3,474	3,170	2,692	3,289	2,871	3,553	3,357	3,053	2,959	3,226	3,119	3,183
26	26	8	Prepared food set	3,426	3,306	2,292	3,111	2,636	3,443	3,361	2,984	2,619	3,191	2,941	3,121
27	27	9	Service business set	3,959	3,109	2,796	3,768	3,059	3,211	3,356	3,411	2,842	3,184	2,842	3,843
28	28	10	Business product set	3,204	3,000	2,542	3,022	2,659	3,196	3,391	3,195	2,872	2,283	3,196	2,283
29	29	11	Low-Skill Product	3,067	3,031	2,515	3,077	3,077	3,449	3,419	3,395	2,844	3,292	3,353	3,292
30	30	12	Product set of H	3,304	2,759	2,542	3,039	2,652	3,292	3,370	2,978	2,261	3,412	3,329	3,304
31	31	13	H in product set	3,238	2,720	2,568	3,238	2,599	3,279	3,329	3,259	3,183	3,259	3,469	3,063
32	32	14	Industrial sector	3,658	3,469	3,031	3,313	3,019	3,519	3,509	3,344	3,192	3,469	3,313	3,569

Source: <https://shigoto.mhlw.go.jp/User/Download>

(2) The design of questionnaire items

Questionnaire items asking about skills and competencies needed by workers by JobTag

Questionnaire items on AI and robot technology forecasts.

JobTag*1
Questionnaire



Worker



JobTag
data



Technology
Forecasting
Questionnaire



Prominent researchers
in AI and robotics



Technology
Forecast



53 items were extracted and set up as survey items.

What is the level of mathematical skill in AI?

e.g.

Mathematical skill

Skills that utilize mathematics to solve problems.

2: Multiply the unit price of a product by the number of pieces and consumption tax to calculate the payment amount. (Nursing care office work 2.0)
4: Accurately calculate the floor area of a building under construction according to the actual shape, including curves. (Surveyor 4.047)
6: Build a mathematical model to simulate an engineering problem. (Data Scientist 5.1)

53 items, such as skills and competencies, nature of work, that have an impact on AI and robotics, were extracted; a questionnaire was sent to researchers to find out what level AI and robotics are at today and what level they could reach in the future, in 2030 and 2040.

*1 Prepared by the Japan Institute for Labor Policy and Training (JILPT).

(2) Japanese version of Skills Evaluation Table

Skill	Continuous observation and evaluation	Instrument monitoring	Ability	Nature of Work
Reading comprehension	Understanding the reactions of others	Operation & Control	Imagination about how things look	Work in groups and teams
Listening skills	Coordination with others	Maintenance & Inspection	Dexterity of the fingertips	Face-to-face discussions
Writing skills	Persuasion	Identification of the cause of failure, etc.	The speed of movement of the arms and legs	Contact with external customers
Explanatory power	Negotiation	Repair	Ability to generate many ideas and alternatives	Coordinate and lead with others
Reading a foreign language	Guidance	Quality checks	Ingenuity	Physical proximity to others
Listening to a foreign language	Personal assistance services	Rational decision-making		Freedom to make decisions
Writing in a foreign language	Complex problem solving	Analysis of the activities of companies and organizations		Self-setting priorities and goals
Speaking in a foreign language	Requirement analysis (Creation of specifications)	Evaluation of the activities of companies and organizations		Responsibility for the health and safety of others
Mathematical skill	Customization & Development	Time management		The impact of decisions on others and companies?
Scientific skill	Selection of tools, equipment and facilities	Money management		
Critical thinking	Installation and configuration	Materials management		
New information Application	Programming	Human resources management		
Selection and practice of learning methods				

(2) Survey Sheet



QUESTIONNAIRE ON AI AND ROBOT
TECHNOLOGY PREDICTION

August 2024

Research Institute of Economy, Trade and Industry / Nomura Research Institute, Ltd.

(2) Survey Sheet

About the purpose of this survey

The "Questionnaire on AI and Robot Technology Forecasting" asks about the skills and abilities that are already possible today or are expected to be realized in the future by mechanical devices and computer systems consisting of AI and robots, assuming 2024, 2030, and 2040.

The items asked are based on the items used in the questionnaire and the results of the questionnaire conducted by the Japan Institute for Labour Policy and Training (JILPT) to analyze the skills and abilities required for each occupation of workers in Japan*1*2.

About the questionnaire in general

- Your responses to the survey will not identify you.
- [As the results of questionnaire responses and attribute information, only the specialized field (AI, robot, etc.) and affiliation (university, general company) are associated and kept as records.

Points to note when answering the questionnaire items

- [Regarding feasibility, "a medium-sized company with about 500 employees can implement it within one year, and the expected reduction in labor costs and other costs from implementation exceeds the cost of implementation, so it is economically attractive."
- You don't need any supporting evidence to respond. It's okay to make a subjective judgment, so please let us know what you think. In addition, [depending on the target item, there may be items that are not specialized

Interview after the questionnaire

[After collecting the questionnaire, we will ask you to interview for one hour.] For specific interview items, please refer to "Interview Item .docx".

*1 Japan Institute for Labor Policy and Training (JILPT) "Numerical explanation page of job ability profile"

*2 Created by the National Institute for Labor Policy and Training (JILPT), "Occupational Information Database Simplified Numerical System Download Data ver.5.0."

(2) Survey Sheet

About the answer

- Please refer to the definitions of Level 2, Level 4, and Level 6 for skills, and answer on a 7-point scale from Level 1 to Level 7. In addition, as a reference value, typical occupations that require skills close to that level are listed. In the example below, it is a question about reading comprehension. If AI and robots find it difficult to "2: Read and understand the instructions on the questionnaire" in 2030, "1" and "2: Read and understand the instructions on the questionnaire." "2" is feasible and reasonable as a level, and "2: Read and understand the instructions on the questionnaire." "It does not extend to "4: Read and understand the document written about the management policy," and if the "middle" seems appropriate, "3" Please answer like this.

Example: Reading comprehension

Level 1:

Level 2: Read and understand the instructions on the questionnaire. (Building Cleaning 2.017)

Level 3:

Level 4: Read and understand documents written about management policies. (Bank Teller 4.016)

Level 5:

Level 6: Read and understand technical papers. (Computer Science Researcher 5.936, Judge: 6.615)

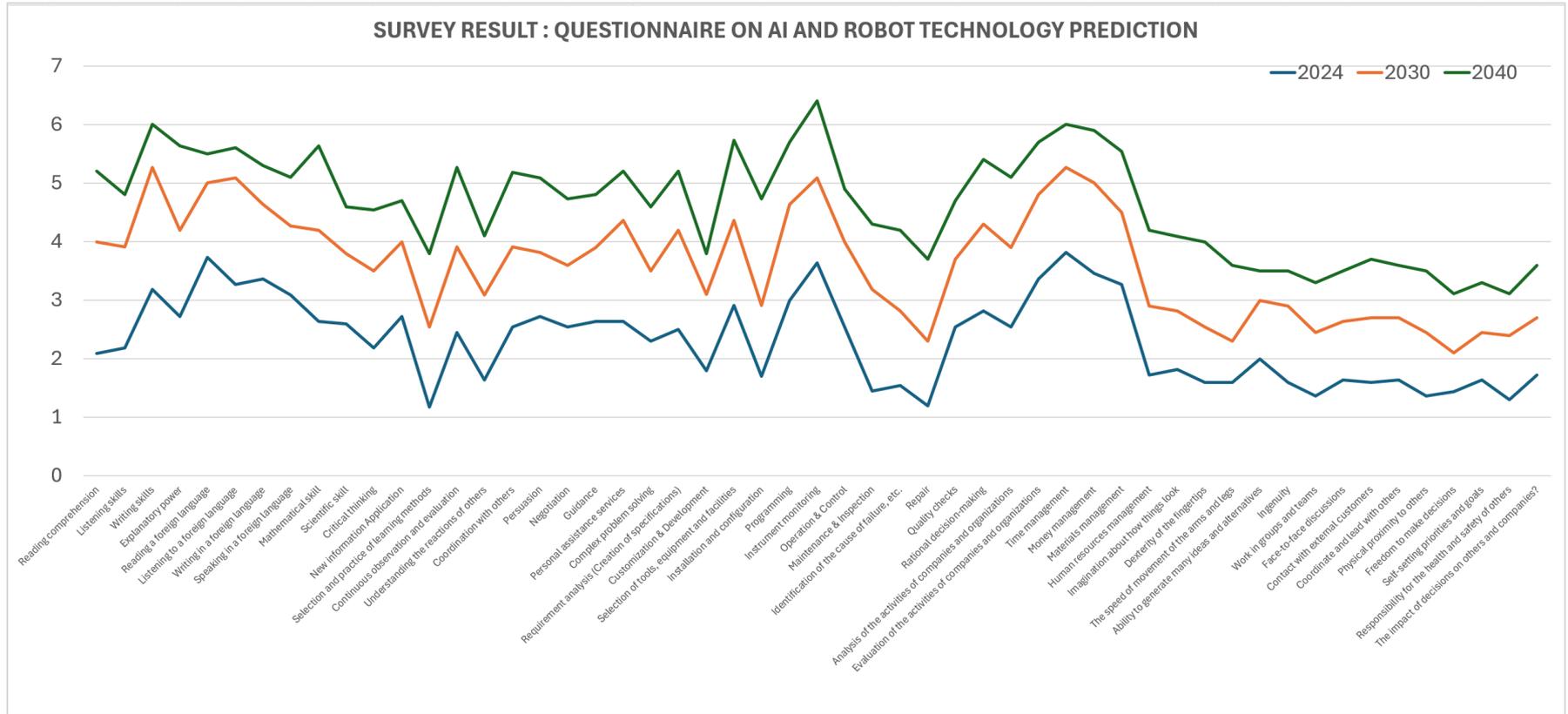
Level 7:

- The definition of the ability item is written for each level, so please answer the level that you think is feasible on a 5-level scale or 4-level level.
- The definition of the nature of work, typical occupations corresponding to the level are listed. Please rate the level that can be achieved by AI and robots

(2) Examples of questionnaire items

Skills	Substance	Level 1-7	2024	2030	2040
Reading comprehension	Skills to read and understand work-related documents.	2 : Read and understand the instructions on the questionnaire. (Building Cleaning 2.017) 4 : Read and understand documents written about management policies. (Bank Teller 4.016) 6 : Read and understand the content of technical papers. (Computer Science Researcher 5.936, Judge : 6.615)			
Listening skills	The skill of listening attentively, getting to the point, and asking the right questions when necessary.	2 : Take orders from customers at restaurants. (Product packaging worker 2.049) 4: Understand customer questions about products. (Illustrator 4.017) 6 : In a car accident, hear the details of the situation from the parties involved and witnesses. (Lawyer 5.949, Prosecutor 6.85)			
Writing skills	Skills to effectively convey information in writing tailored to the reader.	2 : Write down the message on the phone. (Trucker 2.02) 4: Write a new project outline to employees. (System Engineer (Fundamental Systems) 4.017) 6 : Write a technical explanation of your field of specialization in a book for the general public. (Patent Attorney 5.891, Judge 6.462)			

(3) Survey results: AI & robot technology prediction



(3) Survey results: AI & robot technology prediction

Category	Item (English)	Item(Japanese)	2024	2030	2040
Skill	Reading comprehension	読解力	2.09091	4	5.2
	Listening skills	傾聴力	2.18182	3.90909	4.8
	Writing skills	文章力	3.18182	5.27273	6
	Explanatory power	説明力	2.72727	4.2	5.63636
	Reading a foreign language	外国語を読む	3.72727	5	5.5
	Listening to a foreign language	外国語を聞く	3.27273	5.09091	5.6
	Writing in a foreign language	外国語で書く	3.36364	4.63636	5.3
	Speaking in a foreign language	外国語で話す	3.09091	4.27273	5.1
	Mathematical skill	数学的素養	2.63636	4.2	5.63636
	Scientific skill	科学的素養	2.6	3.8	4.6
	Critical thinking	論理と推論(批判的思考)	2.18182	3.5	4.54545
	New information Application	新しい情報の応用力	2.72727	4	4.7
	Selection and practice of learning methods	学習方法の選択・実践	1.18182	2.54545	3.8
	Continuous observation and evaluation	継続的観察と評価	2.45455	3.90909	5.27273
	Understanding the reactions of others	他者の反応の理解	1.63636	3.09091	4.1
	Coordination with others	他者との調整	2.54545	3.90909	5.18182
	Persuasion	説得	2.72727	3.81818	5.09091
	Negotiation	交渉	2.54545	3.6	4.72727
	Guidance	指導	2.63636	3.9	4.8
	Personal assistance services	対人援助サービス	2.63636	4.36364	5.2
Complex problem solving	複雑な問題解決	2.3	3.5	4.6	
Requirement analysis (Creation of specifications)	要件分析(仕様作成)	2.5	4.2	5.2	
	⋮	⋮	⋮	⋮	⋮
Nature of Work	Physical proximity to others	他者との身体的近接	1.36364	2.45455	3.5
	Freedom to make decisions	意思決定の自由	1.44444	2.1	3.11111
	Self-setting priorities and goals	優先順位や目標の自己設定	1.63636	2.45455	3.3
	Responsibility for the health and safety of others	他者の健康・安全への責任	1.3	2.4	3.11111
	The impact of decisions on others and companies?	意思決定が他者や企業に及ぼす影響力	1.72727	2.7	3.6

(4) Method of calculating the Japanese version of the ARI

(i) Calculation of the ARI based on Floreano et al.'s methodology

$$r_t = \frac{\sum_{j=1}^N m_{t,j} d(s_j - m_{t,j})}{\sum_{j=1}^N m_{t,j}}$$

r_t denotes the ARI for occupation t

t denotes occupation, $t=(1, 2, \dots, 504)$

j denotes Skills Evaluation Table elements, $j=(1, 2, \dots, 53)$

$m_{t,j}$ denotes necessary level of Skills Evaluation Table element j for occupation t

s_j denotes the AI and robot skill level, (2024, 2030, 2040)

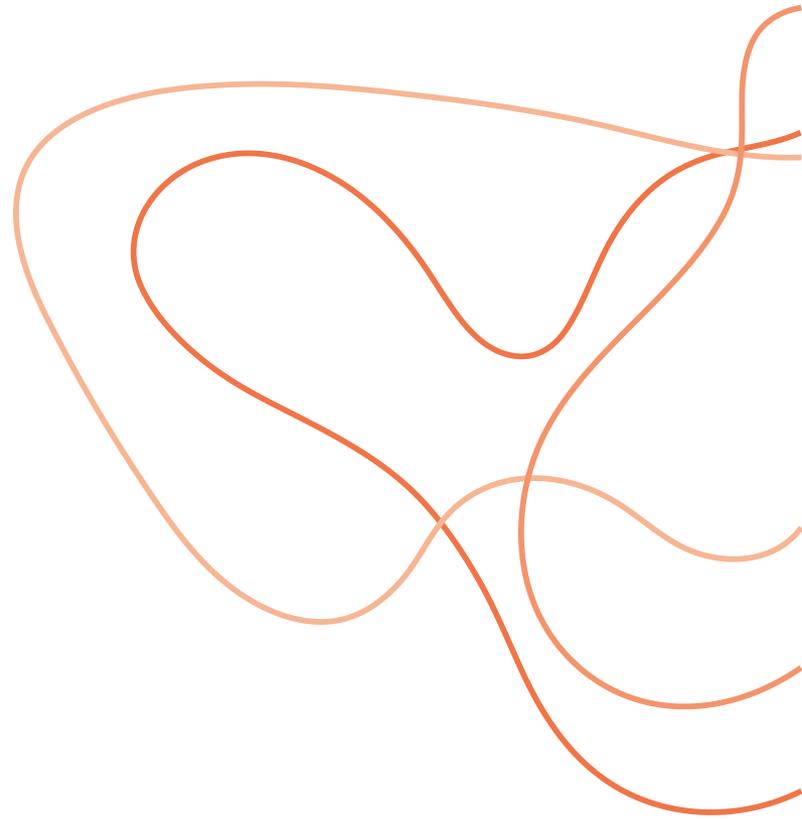
$d()$ denotes logistic distribution function with location and scale parameters set to 0 and 0.05, respectively.

(5) Survey results: Japanese version of the ARI

Occupation name	ARI 2024	ARI 2030	ARI 2040
Data entry	0.585439463	0.863875862	0.999920066
Newspaper (delivery) worker	0.55622461	0.879321925	0.892337935
Picking worker	0.552601134	0.819694823	0.999974336
Product packaging worker	0.546126853	0.767632358	0.993663736
Building cleaning	0.545352648	0.836714839	0.986626893
Packaging worker	0.54267578	0.808751057	0.998759835
Housekeeper (husband)	0.54159641	0.913558884	0.923716419
Station kiosk clerk	0.536863222	0.742636663	0.909583094
Parking management	0.528145852	0.829198741	0.961374641
Food delivery (food deliverers)	0.524704031	0.809307648	0.90050897
Factory worker	0.523261902	0.811501115	0.999954775
General business	0.519953244	0.820412446	0.992829898
Housecleaning	0.514918674	0.89813428	0.921312428
Receptionist	0.513194816	0.818414855	0.987794974
Security guard	0.509685206	0.82319018	0.997924129
⋮	⋮	⋮	⋮
Polymer chemistry engineer	0.069136524	0.272318122	0.677934567
Medical researcher	0.058833913	0.352539751	0.754477607
Project manager (IT)	0.057195786	0.313405561	0.675626652
Pharmaceutical researcher	0.047942909	0.2964388	0.696475828
Securities analyst	0.047016204	0.421758974	0.785946316
International cooperation specialist	0.03789681	0.365085813	0.807226659
Civil and building engineering researchers	0.024673767	0.267255519	0.68335739

(ii)

ARI
distributions



Matching the ARI by occupation with other data sources

- ARI by Jobtag occupations
 - 501 occupations
- Wage Census by occupation and industry
 - Establishment-level employee-employer matched data
 - Employment status, working hours, and wage
 - Firm and establishment size
 - 144 occupations
 - 500 industries (3-digit Japanese Standard Industry Classification)
- JIP database by industry
 - 100 industries (original classification) for 1994-2020
 - Gross output and value-added, labor and (tangible and intangible) capital inputs, productivity.

Automation Risk Index by occupation (Wage Census)

Highest ARI occupations

Occupation	ARI2024	ARI2030	ARI2040
1 Packaging Workers	0.5461	0.7676	0.9937
2 Building and Facility Cleaners	0.5454	0.8367	0.9866
3 General Office Workers	0.5200	0.8204	0.9928
4 Receptionists and Information Clerks	0.5132	0.8184	0.9878
5 Security Guards	0.5097	0.8232	0.9979
6 Other Transport, Cleaning, and Packaging Workers	0.5038	0.8145	0.9977
7 Other Transportation Workers	0.4891	0.8109	0.9396
8 Field Office Workers	0.4675	0.9228	0.9742
9 Commercial Freight Vehicle Driver (excluding Large Vehicle)	0.4622	0.8066	0.9932
10 Other Motor Vehicle Driver	0.4622	0.8066	0.9932

Lowest ARI occupations

Occupation	ARI2024	ARI2030	ARI2040
1 Steelmaking and Non-Ferrous Metal Smelting Workers	0.0001	0.4549	0.9250
2 Researchers	0.0494	0.2991	0.6931
3 Civil Engineers	0.0699	0.3347	0.7929
4 University Lecturer/Assistant Professor (including Technical College)	0.0703	0.3231	0.7059
5 University Professors (including Technical Colleges)	0.0703	0.3231	0.7059
6 University Associate Professor (including Technical College)	0.0703	0.3231	0.7059
7 Transport Equipment Engineers	0.0887	0.3346	0.7816
8 Systems Consultants and Designers	0.0957	0.4140	0.7721
9 Aircraft Pilots	0.1002	0.5079	0.8073
10 Other Machinery Mechanics and Repairers	0.1048	0.4469	0.7858

Notes: The occupational classification is based on the Wage Census's 144 occupations. The ARI is the average weighted by working hours.

Automation Risk Index by industry (JIP database)

Highest ARI industries

Industry	2020	2023	Diff.
1 Road transportation	0.4045	0.4098	0.0053
2 Waste disposal	0.3916	0.3962	0.0046
3 Laundry, beauty and bath services	0.3739	0.3868	0.0129
4 Hotels	0.3816	0.3699	-0.0117
5 Mail	0.3585	0.3613	0.0028
6 Eating and drinking services	0.3603	0.3572	-0.0030
7 Tobacco	0.3122	0.3562	0.0440
8 Other transportation and packing	0.3412	0.3507	0.0096
9 Entertainment	0.3447	0.3482	0.0036
10 Textile products (except chemical fibers)	0.3518	0.3470	-0.0048

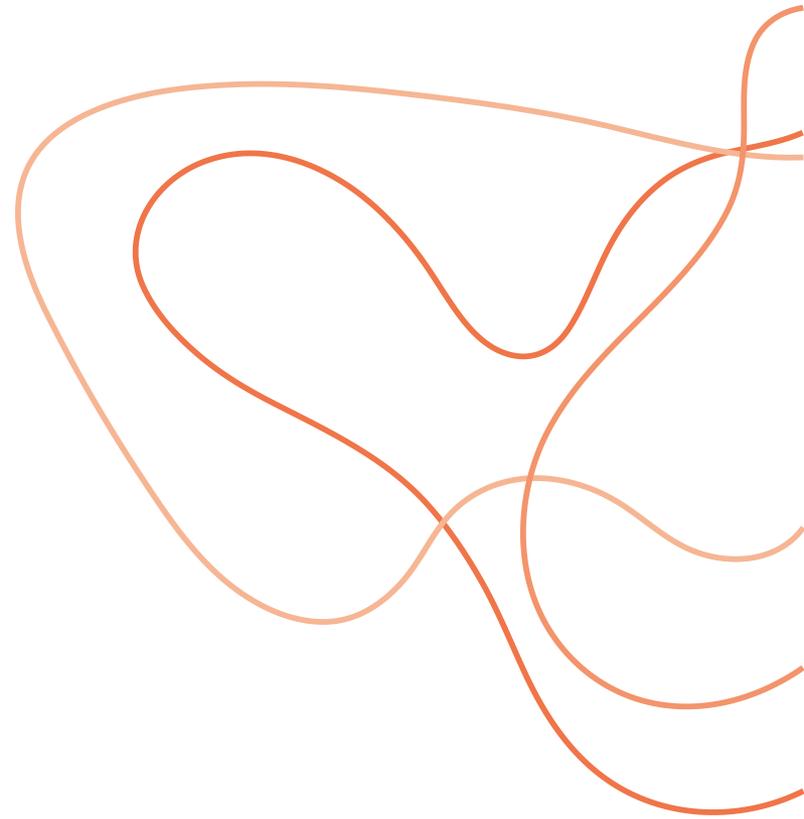
Lowest ARI industries

Industry	2020	2023	Diff.
1 Research	0.1318	0.1361	0.0043
2 Pig iron and crude steel	0.1471	0.1437	-0.0034
3 Smelting and refining of non-ferrous metals	0.1453	0.1446	-0.0007
4 Information services	0.1753	0.1710	-0.0044
5 Water supply for industrial use	0.2007	0.1766	-0.0241
6 Sewage disposal	0.2022	0.1803	-0.0218
7 Semiconductor devices and integrated circuits	0.1851	0.1839	-0.0013
8 Ordnance	0.2356	0.1865	-0.0491
9 Waterworks	0.1951	0.1911	-0.0040
10 Communication equipment	0.1982	0.1996	0.0013

Notes: The industry classification is based on the 100 industries in the JIP database. The ARI of the industry is the weighted average of the ARI of the occupations in the industry, weighted by their share of total employment

(iii)

Data and
descriptive
evidence



Data

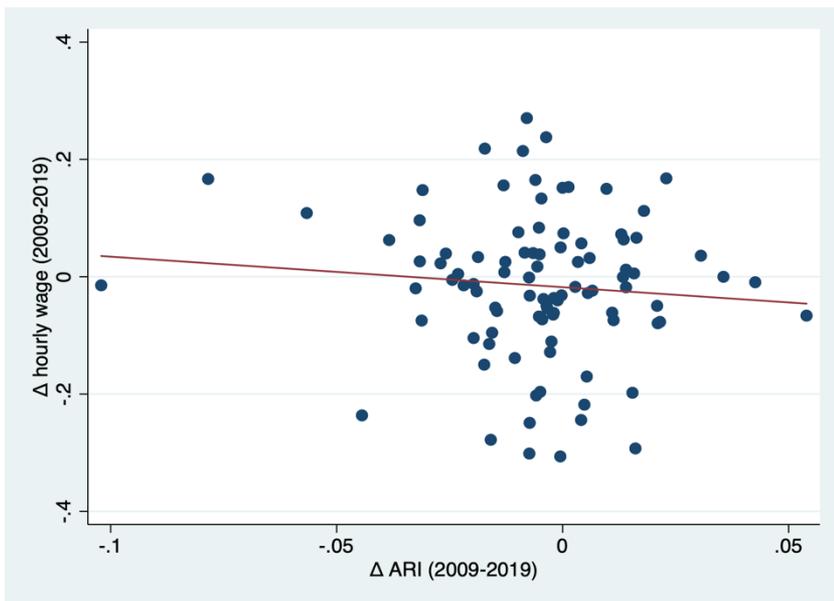
- ARI (2009 – 2019) computed weighting ARI in 2024 by the occupation composition in each industry/year
- JIP Industry 2023 (100 industries, 2009 – 2019)

Label	definition	level
ln(h_wage)	log of real hourly wage	cell/year
ln(hours)	log of annual hours worked	cell/year
ln(innov_cap_int)	log of real innovative capital (software + comp_equip + comm_equip) stock per hour worked	industry/year
ln(software_int)	log of real software capital stock per hour worked	industry/year
ln(comp_equip_int)	log of real computer equipment stock per hour worked	industry/year
ln(comm_equip_int)	log of real communication equipment stock per hour worked	industry/year
ud	union density: (union members/workers)	industry/year
mark-up	mark-up: (net_GO-variab_costs)/net_GO	industry/year
lmt	labour market tightness: (job openings/job seekers)	industry/year
sh_work_300+	share of workers in large companies: (300+ employees)	industry/year
offshoring	offshoring: (imported intermediate input / total intermediate input)	industry/year
ln(RD_int)	R&D intensity: (R&D real stock per hour worked)	industry/year
ln(non_IT_cap_int)	log of real non IT capital (total capital - innov_cap) stock per hour worked	industry/year
ln(inf_serv_int)	log of real expenditures in information services (from IO table) per hour worked	industry/year
ARI_bottom_50_ind09	Dummy variable =1 if in 2009 the industry had ARI < p50 of its distribution in 2009	industry
ARI_bottom_25_ind09	Dummy variable =1 if in 2009 the industry had ARI < p25 of its distribution in 2009	industry
ARI_2009	ARI in 2009	industry

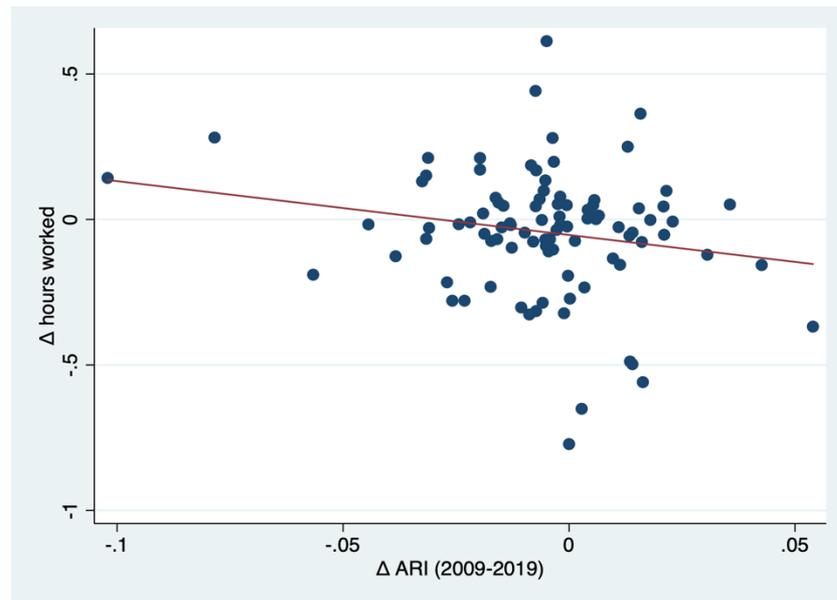
Cell definition	<i>Gender</i>	Male	Female				
	<i>Age</i>	15-24	25-34	35-44	45-54	55-64	65+
	<i>Education</i>	Primary	Lower Secondary	Junior College	College		
	<i>Employment status</i>	Regular	Non-regular	Self/Family			

Changes in ARI and key variables (2009-2019)

ARI - Hourly wage and hours worked



$\rho = -0.093$

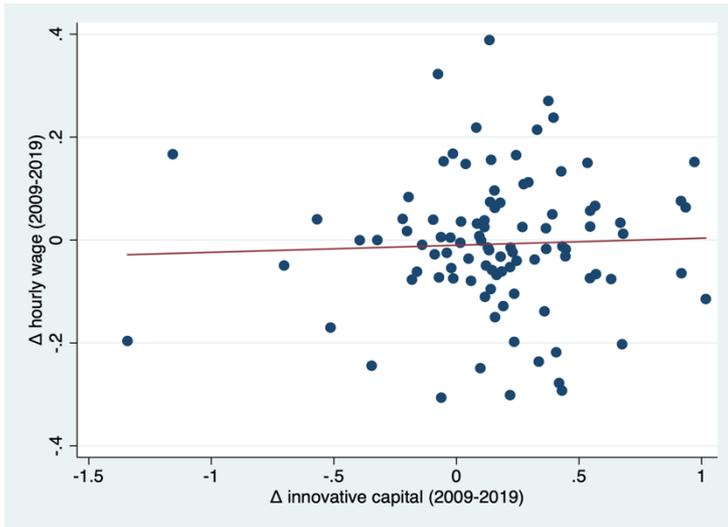


$\rho = -0.191^*$

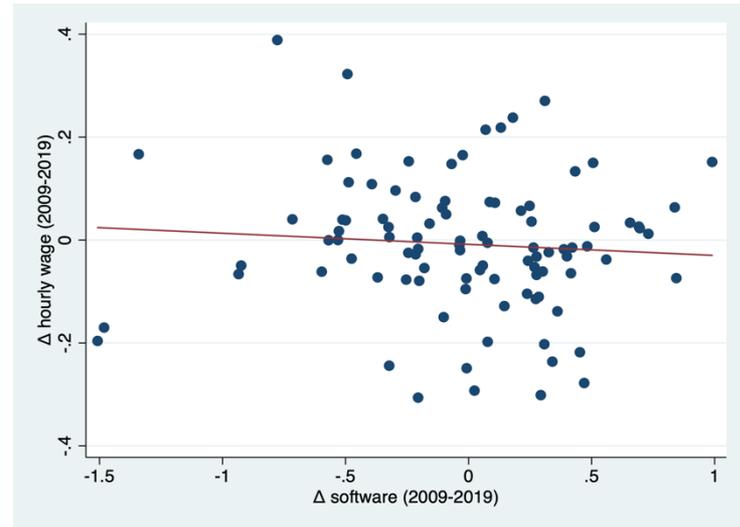
Clear association of automation risk with wages and labour demand

Innovative capital and wages

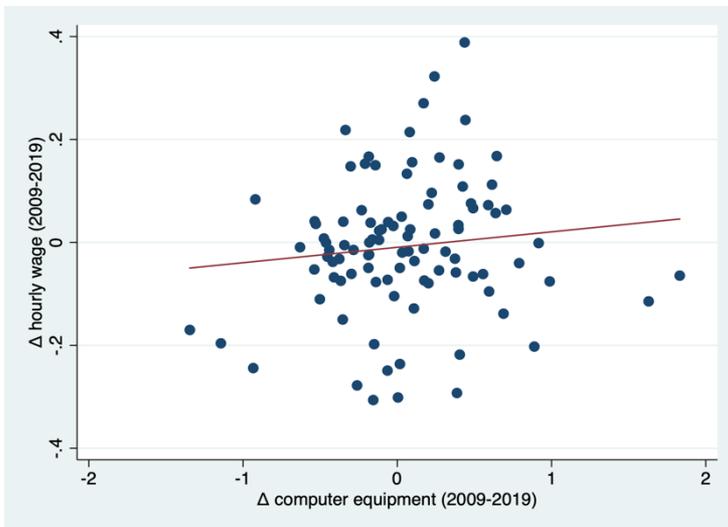
$\rho = 0.040$



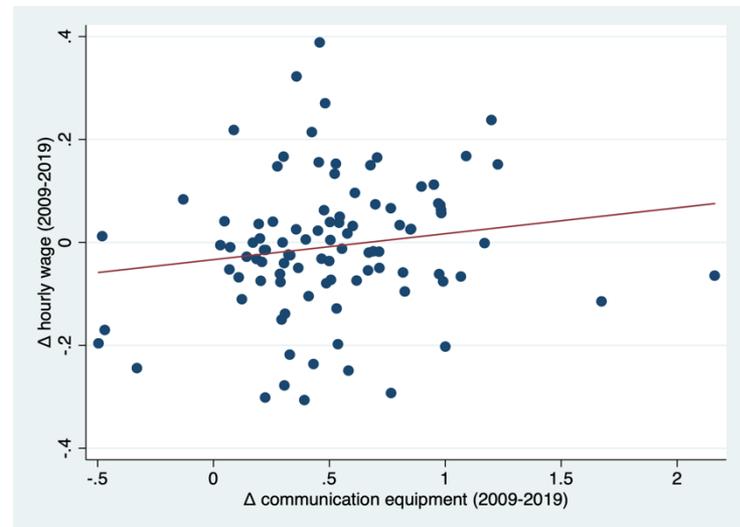
$\rho = -0.078$



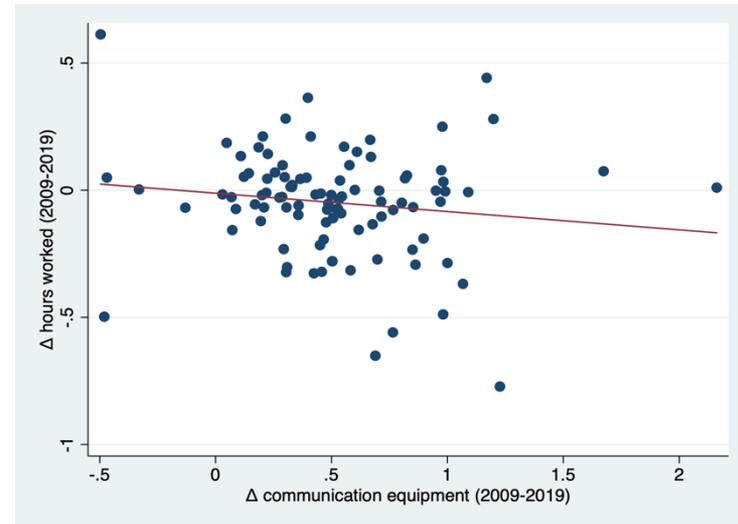
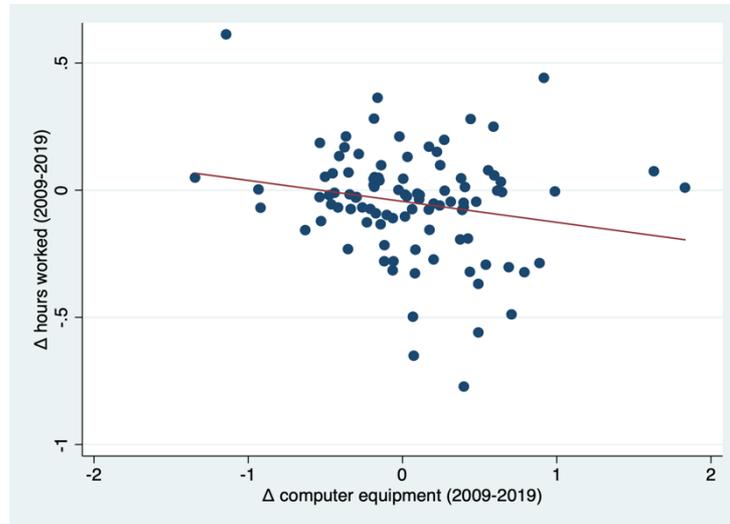
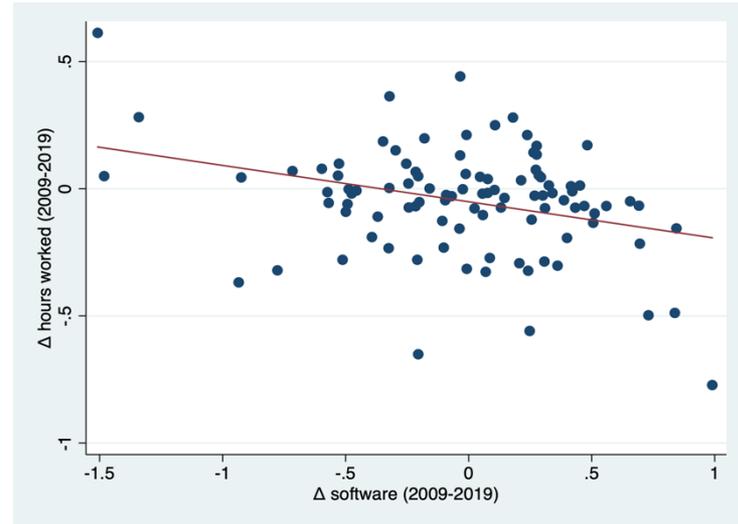
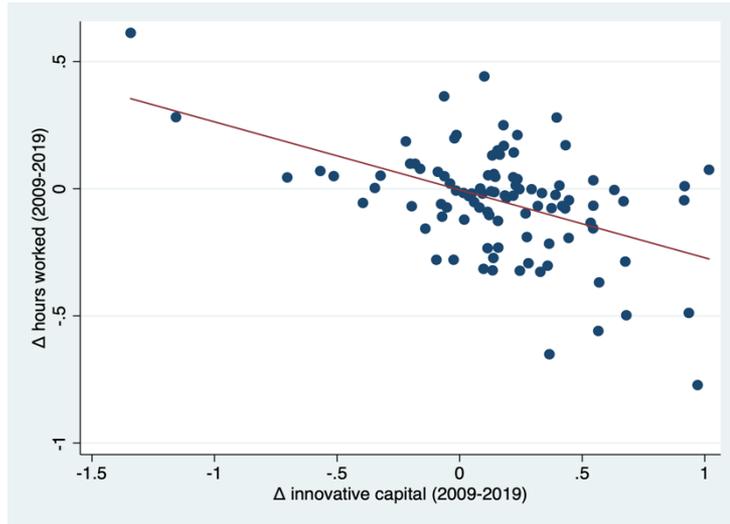
$\rho = 0.114$



$\rho = 0.156$

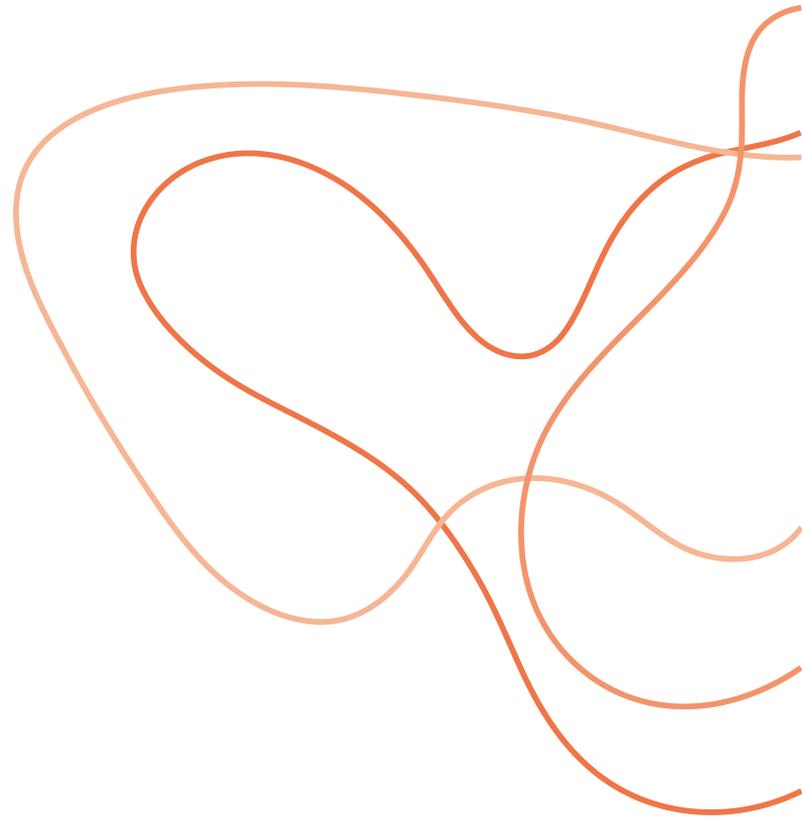


Innovative capital and hours worked



(iv)

Methods



Simultaneous equation approach

- We use a simultaneous equations system to control for potential endogeneity of innovative capital and labour market outcomes
- Hours worked affect wage rates and viceversa (Moffitt, 1982, 1984; Pencavel and Holmlund, 1988; Tummers and Woittiez, 1991; Mohanty and Golestani, 2017).
- Innovative capital can be endogenous and linked to wages and hours worked: higher wages encourage investments that lower labour costs. At the same time, the disutility of hours worked for high-wage earners or a decreasing labour supply due to demographic changes (Acemoglu, 2021) may drive the adoption of automation technologies that replace human labour.
- Relying on labour economics literature, we follow Mohanty (2019), who adopted a three-simultaneous equation approach to investigate the relationships between wages, hours worked, and job satisfaction.
- We replace job satisfaction with innovative capital, considering it alongside hourly wages and hours worked as dependent variables. These are viewed as endogenous and correlated with the disturbances in the system's equations.
- The exogenous variables are used as instruments for the endogenous variables.
- The system is identified such that for each equation (i), the total number of exogenous variables in the system, minus the exogenous variables employed in equation (i), exceeds the number of endogenous variables utilised in that equation (i) (Theil, 1971; Greene, 2018).

Simultaneous equation approach

$$hwage_{igcjk} = \alpha + \beta_1 hours_{igcjk} + \beta_2 innov_cap_{it} + \beta_3 (innov_cap \times ARI_{bottom50})_{it} + \beta_4 \gamma_{lmt}_{it} + \beta_5 markup_{it} + \beta_6 ud_{it} + \beta_7 sh_w_large_firms_{it} + \tau_t + \eta_{igcjk} + \varepsilon_{igcjk} \quad (1)$$

$$hour_{igcjk} = \alpha + \gamma_1 hwage_{igcjk} + \gamma_2 innov_cap_{it} + \gamma_3 (innov_cap \times ARI_{bottom50})_{it} + \gamma_4 offshor_{it} + \tau_t + \eta_{igcjk} + \varepsilon_{igcjk} \quad (2)$$

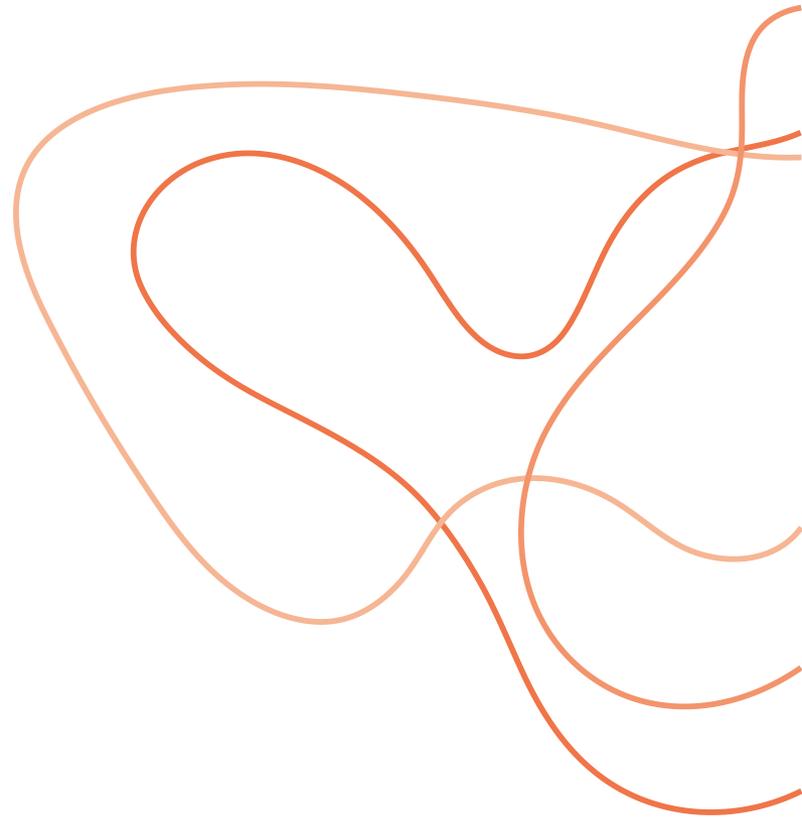
$$innov_cap_{it} = \alpha + \lambda_1 hours_{igcjk} + \lambda_2 hwage_{igcjk} + \lambda_3 RD_{it} + \lambda_4 non_IT_cap_{it} + \lambda_5 inf_serv_inp_{it} + \tau_t + \eta_{igcjk} + \varepsilon_{igcjk} \quad (3)$$

Where:

- industry i ($i = 1, \dots, 100$), gender g ($g = 1, 2$), age group j ($j = 1, \dots, 6$), educational attainment k ($k = 1, \dots, 4$), contract c ($c = 1, \dots, 3$), year t ($t = 1, \dots, 11$).
- hourly wages, hours worked and innovative capital are the endogenous variables
- β_2 and γ_2 are the effects of innovative capital in industries with ARI above the median in 2009
- $(\beta_2 + \beta_3)$ and $(\gamma_2 + \gamma_3)$ are the effects of innovative capital in industries with ARI below the median in 2009
- labour market tightness, mark up, union density and share of workers in large firms are control (exogenous) variables in the wage equation (1)
- offshoring is the control (exogenous) variable in the labour demand equation (2)
- research and development assets, non-IT capital and information input services are control (exogenous) variables in the innovation equation (3)
- τ_t, η_{igcjk} are time and cell-level fixed effects

(v)

Results



Baseline Model

- Protective effects of low exposure to ARI on the detrimental effects of innovative capital intensity on wages and hours worked
- Expected effects of the endogenous and exogenous drivers of wages, hours worked and innovative capital

VARIABLES	ln(h_wage)	ln(hours)	ln(innov cap_int)
	innov cap	innov cap	innov cap
ln(innov_cap_int)	-0.081*** (0.005)	-0.682*** (0.016)	
ln(innov_cap_int)*ARI_bottom_50_ind09	0.030*** (0.002)	0.043*** (0.010)	
ln(software_int)			
ln(software_int)*ARI_bottom_50_ind09			
ln(comp_equip_int)			
ln(comp_equip_int)*ARI_bottom_50_ind09			
ln(comm_equip_int)			
ln(comm_equip_int)*ARI_bottom_50_ind09			
ln(hours)	-0.108*** (0.005)		
ud	0.001*** (0.000)		
mark-up	-0.378*** (0.009)		0.401*** (0.010)
lmt	0.033*** (0.002)		
sh_work_300+	0.073*** (0.006)		0.040*** (0.006)
ln(h_wage)		-1.242*** (0.071)	
offshoring		-1.044*** (0.062)	
ln(RD_int)			0.076*** (0.004)
ln(non_IT_cap_int)			0.652*** (0.003)
ln(inf_serv_int)			0.243*** (0.002)
Constant	-0.030*** (0.002)	-0.165*** (0.007)	-0.178*** (0.002)
Observations	138,432	138,432	138,432
R-squared	-0.151	-0.066	0.484

Standard errors in parentheses; cell and time fixed year effects included

*** p<0.01, ** p<0.05, * p<0.1

Innovative capital and its components

VARIABLES	ln(h_wage) innov cap	ln(hours) innov cap	ln(h_wage) software	ln(hours) software	ln(h_wage) comp equip	ln(hours) comp equip	ln(h_wage) comm equip	ln(hours) comm equip
ln(innov_cap_int)	-0.081*** (0.005)	-0.682*** (0.016)						
ln(innov_cap_int)*ARI_bottom_50_ind09	0.030*** (0.002)	0.043*** (0.010)						
ln(software_int)			-0.039*** (0.008)	-0.599*** (0.028)				
ln(software_int)*ARI_bottom_50_ind09			0.051*** (0.006)	0.125*** (0.025)				
ln(comp_equip_int)					-0.094*** (0.005)	-0.401*** (0.019)		
ln(comp_equip_int)*ARI_bottom_50_ind09					0.061*** (0.005)	0.117*** (0.018)		
ln(comm_equip_int)							-0.089*** (0.004)	-0.696*** (0.016)
ln(comm_equip_int)*ARI_bottom_50_ind09							0.023*** (0.002)	0.071*** (0.007)

- Protective effects of low exposure to ARI confirmed for all components ...
- ... but relatively stronger for software, the component more closely related to AI
- Results are confirmed for sectors below p25 of the ARI distribution in 2009

Heterogeneity by workers' attributes (total innovative capital)

(i) Education

VARIABLES	Education Level				Junior College		College	
	ln(h_wage)	ln(hours)	ln(h_wage)	ln(hours)	ln(h_wage)	ln(hours)	ln(h_wage)	ln(hours)
ln(innov_cap_int)	primary	primary	secondary	secondary	jun coll	jun coll	college	college
	-0.069***	-0.792***	-0.113***	-0.669***	-0.113***	-0.663***	-0.054***	-0.598***
	(0.009)	(0.033)	(0.008)	(0.025)	(0.011)	(0.030)	(0.010)	(0.026)
ln(innov_cap_int)*ARI_bottom_50_ind09	0.020***	0.016	0.038***	0.064***	0.030***	0.044**	0.034***	0.029*
	(0.005)	(0.021)	(0.004)	(0.016)	(0.005)	(0.020)	(0.005)	(0.017)

- The detrimental effect of innovative capital is weaker for college graduates and the protective effect of low ARI is relatively stronger

(ii) Gender

VARIABLES	Male		Female	
	ln(h_wage)	ln(hours)	ln(h_wage)	ln(hours)
ln(innov_cap_int)	male	male	female	female
	-0.078***	-0.637***	-0.079***	-0.715***
	(0.006)	(0.021)	(0.007)	(0.023)
ln(innov_cap_int)*ARI_bottom_50_ind09	0.043***	0.094***	0.014***	-0.019
	(0.003)	(0.014)	(0.004)	(0.015)

- Male workers are significantly better sheltered compared to female workers

Heterogeneity by workers' attributes (total innovative capital)

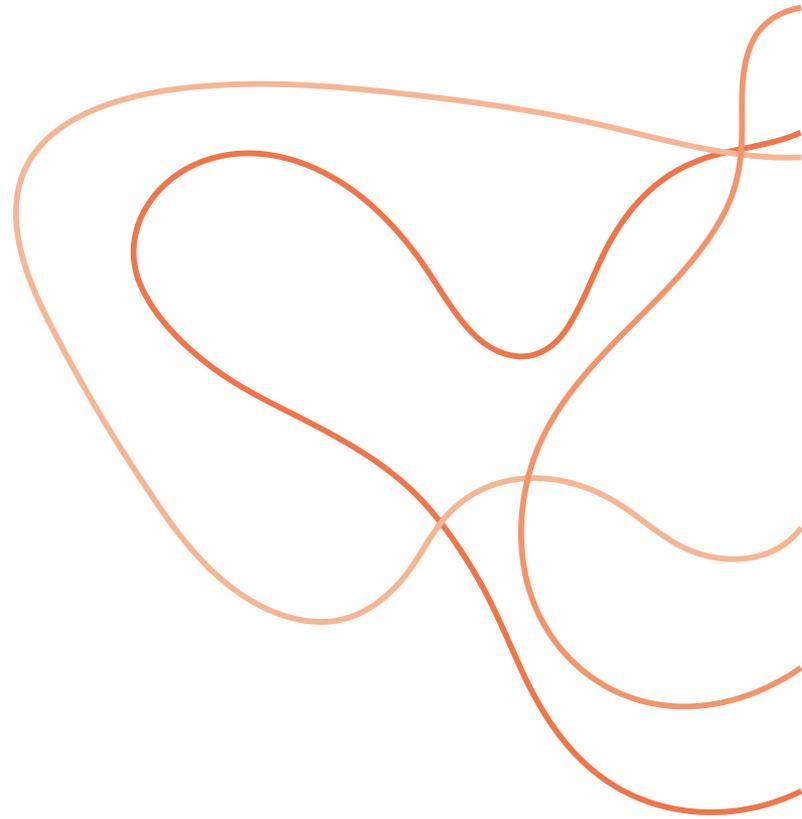
(iii) Age

VARIABLES	15-34 yo		35-54 yo		over 55 yo	
	ln(h_wage)	ln(hours)	ln(h_wage)	ln(hours)	ln(h_wage)	ln(hours)
ln(innov_cap_int)	-0.053***	-0.639***	-0.091***	-0.677***	-0.105***	-0.693***
	(0.006)	(0.024)	(0.007)	(0.025)	(0.012)	(0.030)
ln(innov_cap_int)*ARI_bottom_50_ind09	0.022***	0.047***	0.023***	0.055***	0.043***	0.009
	(0.004)	(0.016)	(0.004)	(0.017)	(0.005)	(0.020)

- The detrimental effect of innovative capital on wages is weaker for young workers, but older workers are more sheltered by working in low ARI industries
- Results are confirmed (and reinforced) for sectors below p25 of the ARI distribution in 2009 (*ARI_bottom_25_ind09)
- Results are confirmed for the single components of innovative capital
- For Software, in particular, the protective role of low ARI sectors is significantly stronger

(vi)

Final remarks



Final Remarks

- Our main empirical evidence indicates that increasing intensity of innovative capital exerts a decreasing effect not only on employment (labour demand, via a substitution effect), but also on wages
- In the wage equation, the impact of innovative capital intensity on wages can be interpreted as follows:
 - Indirect effect (via labour demand): higher intensity of innovative capital decreases hours worked and, consequently, hourly productivity and wages increase
 - Direct effect: hours worked being equal, higher intensity of innovative capital negatively affects the bargaining power of those workers not (yet) replaced by capital, who accept wage moderation due to the threat of being replaced
- This interpretation is supported by the fact that in industries where occupations with a low automation risk index are predominant, the negative impact on wages is less pronounced because the threat of being replaced is weaker
- Future research efforts will aim at disentangling such effects using microdata (matched employer-employee data - BSWS, BSJBSA, EEC)
- We will investigate how the risk of automation replacement (at the individual worker level) affects the relationship between innovative investment-driven gains in productivity and wages and how this effects depends on the characteristics of workers that shape their bargaining power