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Automation Risk, Innovative Capital, and Labour Market Outcomes: Evidence from Japan

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Abstract

This study provides an empirical assessment of the relationship between automation risk and labour market performance. To this aim, we use as a key original information the Automation Risk Index (ARI), a new dataset that quantifies the exposure of Japanese occupations and industries to artificial intelligence and robotic technologies at a highly disaggregated level. Our findings indicate that a higher intensity of innovative capital—including ICT infrastructure, AI technologies, and robotics—is associated with lower employment and wage levels. At the same time, these adverse effects are considerably attenuated in industries where occupations face a lower risk of automation, with the mitigating impact being particularly evident for highly educated, male, and younger workers. Overall, the evidence points to the importance of both reduced automation exposure and complementarities between workers' skills and advanced technologies in sustaining workers' bargaining position and limiting the negative labour market consequences of technological change.

Keywords: AI and Robotics; Automation Risk; ICT Capital; Labour Market
JEL Classification: J23, J24, J31, O33

1. Introduction

The rise of artificial intelligence (AI) and robotisation has intensified academic interest in their distinct and overlapping effects on employment and wages. While both technologies drive economic growth by boosting productivity, industrial robots mainly automate routine manual tasks, whereas AI systems extend automation into non-routine cognitive areas. Acemoglu and Restrepo (2022) conceptualise both AI and robotics as forms of task automation that produce displacement effects—by substituting labour—as well as reinstatement effects—by creating new tasks that enhance productivity. Artificial intelligence is widely recognized as a catalyst for profound and radical transformations within information and communication technology (ICT) paradigms, with the potential to engender a fundamental technological paradigm shift (Damioli et al., 2025).

Robotisation has been associated with job losses in routine-intensive sectors. Using U.S. data, Acemoglu and Restrepo (2020) estimate that each additional robot per thousand workers reduces both employment and wages, with particularly strong effects on routine manual occupations such as machinists, assemblers, material handlers, and welders. No significant effects, either positive or negative, were found for other occupational categories. Similarly, Graetz and Michaels (2018) show that while robots improve productivity across OECD countries, their labour market impacts are unevenly distributed.

In contrast, the labour market effects of AI are more heterogeneous. Most empirical analyses focus on the US case. Felten et al. (2019) demonstrate that exposure to AI correlates with employment growth, particularly in jobs characterised by a higher level of automation and those capable of leveraging the complementarities between AI and human tasks. Brynjolfsson et al. (2025) report that AI-powered conversational tools enhance the speed and output quality of less experienced and lower-skilled workers. Webb (2019) cautions that AI increasingly targets high-wage cognitive tasks, which may reduce demand for high-skilled labour and erode the skill premium. Acemoglu et al. (2022) note that AI-exposed establishments are hiring fewer workers for non-AI roles and are changing the skill requirements of remaining job postings. Nevertheless, the overall impact of AI on employment and wage growth remains too small to be clearly detected. In the EU context, Guarascio and Reljic (2025) find that employment gains from AI are concentrated in innovation-intensive countries and are significantly influenced by institutional factors and absorptive capacity. Guarascio et al. (2025) argue that contexts with strong innovation systems may see employment growth as AI enhances existing capabilities and production processes. In contrast, weaker contexts are likely to encounter structural barriers that could ultimately widen existing development gaps.

In summary, robotisation tends to displace routine labour, while AI's impact is more complex—balancing substitution with potential task augmentation. The net effect depends on occupational structures, innovation systems, and policy responses, but AI and robotics hold the potential to substantially reshape industrial organisation, labour and capital inputs, and the international division of labour. These dynamics are particularly relevant for Japan, where a shrinking working-age population makes automation a potential solution to severe labour shortages (Acemoglu and Restrepo, 2022b).

The original contribution of our paper lies in the introduction of a novel dataset measuring automation risk at a detailed occupation and industry level in Japan—the Automation Risk Index (ARI). Building on the methodology of Paolillo et al. (2022), we construct the first granular, ability-based automation risk indicator for Japan that captures exposure to both AI and robotics. As explained in detail in Section 3, to this end we use the Job_Tag database—a Japanese counterpart to O*NET—which provides information on 53 worker abilities and skills across 500 occupations. Unlike Paolillo et al. (2022), however, we adopt a subjective approach to evaluating the capabilities of AI and robotics to replace human abilities. This subjective assessment is based on an ad hoc survey conducted among AI and robotics experts in Japan. We also provide a first empirical application of the novel indicator at a detailed industry level. Specifically, we investigate whether and how automation risk moderates the relationship between innovative capital intensity—comprising software, information and communication equipment, computer equipment, and robots—and key labour market outcomes (wages and working hours). Our findings show that higher innovative capital intensity tends to reduce working hours and directly suppress wages. However, these negative effects are significantly less pronounced in industries with lower ARI scores. Further analysis reveals that certain segments of labour (highly educated, young and male workers) are relatively less vulnerable to the adverse impacts of ICT/robot-driven innovation, and that low automation risk offers a relatively stronger protective effect for these labour segments.

The remainder of this paper is organised as follows: Section 2 reviews the existing literature and explains our original contribution. Section 3 describes the methodology and results related to the construction of the Automation Risk Index for Japan. Section 4 presents the dataset and the approach used in the empirical analysis. Section 5 illustrates and discusses its findings. Section 6 concludes.

2. Literature review and contribution

The current investigation into job automation risk is rooted in a long-standing debate on the relationship between technological change and employment. More than three decades ago, Vivarelli (1995), in a comprehensive literature review, systematized the labour-saving and labour-creating effects of technological change by distinguishing among different types of innovations. While process innovations can lead to worker displacement and unemployment, they may also trigger several compensating mechanisms. These include increased income and aggregate demand, cost reductions and productivity gains, or even wage adjustments that stimulate labour demand. In some cases, technological change may primarily affect working hours rather than employment levels, thereby mitigating job losses. By contrast, product innovations—often associated with the entry of new firms and the emergence of new industries—tend to generate clear positive effects on employment. Overall, the net impact of technological change depends on both the type of innovation and the strength of these compensatory mechanisms[1].

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[1] Recent broad-scope studies highlight how the employment effects of technological change vary depending on the type of automation considered. Vivarelli and Arenas Díaz (2025) revisit the long-standing debate on innovation and employment by explicitly incorporating AI into the analysis. While historical evidence suggests that compensatory mechanisms have typically offset job losses, they argue that the unprecedented speed and scale of AI diffusion may put these mechanisms under strain. By contrast, Guarascio et al. (2025), in a meta-analysis of robot adoption, find mixed effects on employment. Although automation can lead to job displacement in certain sectors, it may also generate productivity gains and foster new job creation, resulting in heterogeneous outcomes across industries and institutional settings. Overall, these contributions reinforce the view that technological change is neither inherently job-destroying nor job-creating; rather, its effects depend on broader economic conditions and adjustment processes.

During the 1990s and 2000s, a parallel strand of literature shifted attention from the nature of technologies to the characteristics of workers' skills and tasks. Within this framework, and taking information and communication technologies (ICT) as the defining feature of the latest wave of automation, the skill-biased technological change (SBTC) hypothesis argued that ICT complements highly educated workers. This complementarity increases wage inequality between high- and low-skilled workers, particularly when highly educated labour is scarce, while also displacing workers in jobs requiring only primary or secondary education (Katz and Murphy, 1992; Goldin and Katz, 2008; Acemoglu and Autor, 2012).

This perspective was later refined by scholars such as Autor et al. (2003) and Autor and Dorn (2013), who emphasized that jobs are composed of tasks rather than homogeneous skill categories. They introduced the concept of routine-biased technological change (RBTC), according to which technological progress disproportionately replaces routine tasks—both cognitive and manual—while complementing non-routine cognitive, manual, and interpersonal activities. This framework helps explain the phenomenon of job polarization, characterized by a decline in middle-skill jobs alongside growth in both high- and low-skill occupations (Goos et al., 2014). Notably, Acemoglu and Autor (2012) show that SBTC adequately described the U.S. labour market until the mid-1990s. Thereafter, the narrowing wage gap between high- and low-educated workers reflected job polarization dynamics better captured by the RBTC framework.

Building on this literature, Frey and Osborne (2017)[2] focus on advances in machine learning (ML)—including computational statistics, data mining, and artificial intelligence—and mobile robotics (MR) as technologies capable of performing tasks previously considered uniquely human. They argue that machines are increasingly able to carry out non-routine cognitive tasks. To account for this, they extend the RBTC framework by redefining which tasks are susceptible to automation, based on three key "engineering bottlenecks": (i) perception and manipulation, (ii) creative intelligence, and (iii) social intelligence. Using task-level data from the O*NET database for the United States, they asked experts to classify occupations as automatable or not. They initially focused on 70 occupations for which expert agreement was high, and then extrapolated these classifications to 632 additional occupations using nine O*NET variables capturing the three bottlenecks (e.g., manual dexterity, originality, social perceptiveness). Their results suggest that 47% of U.S. jobs fall into a high-risk category, with a probability of automation exceeding 70%. Subsequent studies applied these occupation-level estimates to employment data in countries such as Germany (Brzeski and Burk, 2015), Finland (Pajarinen and Rouvinen, 2014), and across Europe (Bowles, 2014), often finding similar or even higher levels of automation risk.

These findings sparked considerable debate, with several scholars arguing that Frey and Osborne's methodology overestimates automation risk. A key critique, advanced by Arntz et al. (2016, 2017), concerns the reliance on an occupation-based approach. By assigning a single automation probability to each occupation, this method implicitly assumes that all workers within an occupation perform identical

[2] The first version of this study was available from a working paper published in 2013.

tasks and face the same risk of automation. In reality, workers within the same occupation often perform diverse tasks and are therefore differently exposed to automation. To address this limitation, Arntz et al. propose a task-based approach using individual-level data from the PIAAC database. They first estimate the relationship between job tasks and automation probabilities in the U.S., based on Frey and Osborne's results, and then apply this relationship to other OECD countries. Using this approach, they find that only about 9% of U.S. workers face a high risk of automation, compared to 47% under the occupation-based method. Similarly, estimated risks for European countries are substantially lower.

Following these critiques, more recent research focused on the US has increasingly adopted granular, task-level approaches, often leveraging detailed information from the O*NET database. For instance, Webb (2019) links AI-related patents to occupational tasks using natural language processing, while Felten et al. (2021) develop an index of occupational exposure to AI by matching AI capabilities and job tasks. Eloundou et al. (2024) provide one of the first systematic assessments of exposure to large language models (LLMs), and Felten et al. (2023) extend their earlier framework to generative AI, showing that knowledge-intensive sectors such as education, legal services, and media are particularly affected.
A related contribution is provided by Paolillo et al. (2022), who develop an automation risk index (ARI) for the United States based on a comparison between human abilities and the capabilities of advanced robotics. Their approach matches 87 human abilities listed in O*NET with a set of robotic abilities derived from the European H2020 Robotics Multi-Annual Roadmap (MAR) developed by SPARC, a public–private partnership between the European Commission and the robotics industry. For 44 human abilities,

however, no direct correspondence with robotic capabilities was available. The authors therefore construct two alternative scenarios—low and high automation—by assigning robotic abilities where necessary. They assess the substitutability between human and robotic abilities using the technological readiness level (TRL) scale defined by the European Union. The resulting ARI measures the proportion of human abilities required by a job that can be performed by machines. It does not represent a probability of automation but rather a relative measure: an ARI of 1 indicates that machines can perform all required abilities, while an ARI of 0 indicates that none can be automated.

The availability of detailed task and ability data, along with subjective or objective methods for identifying AI and robotic capabilities, has shaped research on automation risk beyond the United States. Dengler and Matthes (2018), for example, adopt a fully task-based approach using a German version of the O*NET database, which assigns around 8,000 tasks to 3,900 occupations. They estimate automation risk as the share of tasks within an occupation that can be performed by computers. For cross-country comparisons, Lewandowski et al. (2025) adapt the Felten et al. (2021) index to worker-level PIAAC data and extend it globally using comparable surveys and regression-based methods.

Our study builds primarily on the framework developed by Paolillo et al. (2022), applying it to the Japanese labour market. To our knowledge, this is the first attempt to construct a granular, ability-based automation risk indicator for Japan that captures exposure to both AI and robotics. We use the Job_Tag database—a Japanese counterpart to O*NET—which provides information on 53 worker abilities and skills across 500 occupations. Unlike Paolillo et al. (2022), we adopt a subjective approach based on expert assessments to evaluate the capabilities of AI and robotics and compare them to human abilities. This allows us to establish a complete correspondence across all 53 abilities, avoiding the need for arbitrary assumptions required in objective approaches when classifications do not align.

At the same time, subjective approaches such as ours have limitations, as expert judgments may not be fully replicable and can be influenced by researchers' biases. However, compared to earlier studies such as Frey and Osborne (2017), our approach relies on a much broader and more detailed set of abilities, providing a more comprehensive representation of the requirements of different jobs.

3. Measuring Automation Risk in Japan: A Novel Dataset

Our approach builds on Frey and Osborne (2017) by adopting a subjective framework that ensures close alignment between human and machine capabilities. At the same time, it draws extensively on Paolillo et al. (2022) to broaden the spectrum of human, ICT/AI, and robotic abilities considered, allowing for a more granular, ability-based assessment. On this basis, we construct a novel Automation Risk Index (ARI) for Japan at a detailed occupational level. As explained in more detail in Fukao et al. (2025), the index is developed by combining information from two key sources: (i) the Occupation Information Database: Simplified Numerical Data Download Version ver. 5.0, compiled by the Japan Institute for Labour Policy and Training (JILPT) and available on the JobTag website (hereafter referred to as JobTag-OID) [https://shigoto.mhlw.go.jp]; and (ii) an original expert survey on current and forecasted capacities of AI and robotics, designed by the authors and implemented by the Research Institute of Economy, Trade and Industry (RIETI) [www.rieti.go.jp] in collaboration with the Nomura Research Institute (NRI) [www.nri.com]. The JobTag-OID serves as the Japanese counterpart to the U.S. O*NET system and provides a structured classification of required skills, abilities, knowledge, and job characteristics for over 500 occupations. In this study, we identify 53 indicators—comprising skills, abilities, and job adaptability attributes—that are instrumental in assessing the substitutability of tasks by AI and robotics. Skill indicators are rated on a 7-point scale, while abilities and adaptability measures are evaluated on a 5-point scale.

In the survey, we asked experts to assess the extent to which AI and robots could replace the 53 identified skills, abilities, and job adaptability attributes in the years 2024, 2030, and 2040, using the same evaluation scales as those employed in the JobTag-OID. The survey was conducted between August and October 2024 and involved both a structured questionnaire and face-to-face interviews. A total of 38 experts were invited to participate in the survey. These individuals were selected based on their affiliation with national councils, research institutes, and related organisations in Japan, and their active involvement in advanced research on AI, robotics, and related fields. Of the 38 experts contacted, 13 agreed to participate in the survey.

Following Paolillo et al. (2022), the Automation Risk Index (ARI) for each occupation r_t listed in JobTag-OID database is defined as follows:

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

Where:

- j denotes skill, ability or adaptability attribute (with j =1, 2, ..., 53);
- $m_{t,j}$ represents the level of skill/ability/adaptability j required for occupation t according to JobTag-OID;
- s_j refers to the level of skill/ability/adaptability estimated to be achievable by AI and robot, based on expert survey responses for the year 2024, 2030, and 2040;
- $d(\cdot)$ denotes a logistic function, used to model the likelihood of technological substitution human labour, with location parameter of 0 and a scale parameter of 0.05.

The Automation Risk Index (ARI) was successfully calculated for 487 out of 504 occupations. For the remaining 17 occupations, the calculation was not possible due to missing data in the JobTag-OID dataset. Table 1 presents the ten occupations with the highest and lowest ARI scores in the JobTag-OID classification for the year 2024 (the ARI level increases in the two future time horizons - 2030 and 2040 – due to the higher capacity of technology to replace human labour estimated by the experts; however, the ranking is substantially stable). Comparing our results with existing estimates based on alternative approaches is not straightforward, given differences in methodologies, occupational classifications, and levels of detail. Nevertheless, a high degree of consistency emerges when we benchmark our findings against those obtained using the most comparable approach based on U.S. O*NET data (see Frey and

Osborne, 2017)[3]. Our top ARI occupation (Data entry) features number 12 out of the 702 occupations considered by Frey and Osborne. Similarly, the remaining top ARI occupation of the Job-Tag list have their corresponding job in the upper tail of the Frey and Osborne taxonomy: we refer in particular to jobs related to logistics (drivers, shipping/receiving/traffic clerks, parking lot attendants), sales (sales workers, order clerks, telemarketers) and packaging (package and filling machine operators and tenders). Cleaning occupations also feature as high (hand grinding and polishing workers) or medium-high (Supervisors of housekeeping and janitorial workers, Maids and housekeeping cleaners) computerisable jobs. The consistency of the two rankings at the bottom of the distribution is even stronger, as we find all occupations with the lowest ARI at the bottom of the Frey and Osborn distribution too (medical/pharmaceutical science jobs, various types of engineers and researchers). Teachers and instructors also feature in the medium-low section of both distributions.

Table 1. Top and Bottom ARI occupations (JobTag-OID classification, year 2024)

	Top ARI Occupations	ARI	Bottom ARI Occupations	ARI
1	Data entry	0.5854	Civil and Building Engineering Researcher	0.0247
2	Newspaper delivery man	0.5562	International Cooperation Specialist	0.0379
3	Picking worker	0.5526	Securities Analyst	0.0470
4	Product Packaging Worker	0.5461	Pharmaceutical Researcher	0.0479
5	Building Cleaning	0.5454	IT Project Manager	0.0572
6	Packaging Worker	0.5427	Medical Researcher	0.0588

[3] Comparability with other existing studies (e.g., Felten et al., 2021; Webb, 2019; Mann and Püttmann, 2017) is lower due a substantially different methodological approach. The different approaches should, however, be regarded as complementary and can be useful to different researchers depending on the specific questions being asked.

7	Housekeeper (husband)	0.5416	Polymer Chemistry Engineer	0.0691
8	Station Kiosk Clerk	0.5369	Information Engineering Researcher	0.0777
9	Parking Manager	0.5281	Brewer	0.0796
10	Food Deliverer	0.5247	Space Development Engineer	0.0827

The 487 JobTag-OID occupations for which the ARI was calculated have been re-classified into the 144 occupations breakdown of the Basic Survey on Wage Structure (BSWS), to connect the ARI information to other major labour market and business databases available for Japan. The details of the methods used to compile the ARI dataset for the BSWS occupations are available in Fukao et al. (2025). Finally, we computed the industry-level ARI based on the detailed industry classification of the Japan Industry and Productivity (JIP) Database (version 2023, 100 industries). The industry-level ARI is obtained as the weighted average of the occupation-level ARI (in year 2024), using as weights the share of hours worked in each occupation in the industry/year drawn from the BSWS (and available in harmonised form from 2009 to 2023). Table 2 illustrates the top/bottom ARI industries in 2023; the sectors most populated with occupations at high risk of automation form a cluster of predominantly non-tradable, labour-intensive services, alongside some consumer goods industries, primarily serving final household demand. On the contrary, bottom ARI industries include a group of knowledge- and capital-intensive industries and infrastructure services that support production processes and technological development, including both tradable industrial inputs and essential utilities.

Table 2. Top and Bottom ARI industries (JIP classification, year 2023)

	Top ARI Industries	ARI	Bottom ARI Industries	ARI
1	Road transportation	0.4104	Research	0.1501
2	Waste disposal	0.3974	Water supply for industrial use	0.1829
3	Laundry, beauty and bath services	0.3869	Information services	0.1835
4	Hotels	0.3705	Sewage disposal	0.1947
5	Mail	0.3618	Ordnance	0.2050
6	Eating and drinking services	0.3575	Waterworks	0.2057
7	Tobacco	0.3564	Basic organic chemicals	0.2130
8	Other transportation and packing	0.3535	Organic chemicals	0.2131
9	Entertainment	0.3510	Chemical fertilizers	0.2134
10	Textile products (except chemical fibers)	0.3479	Image information, sound information and character information production	0.2136

For the reasons explained in the following section, we use in our empirical analysis the industry-level ARI in the year 2009, which describes each industry's exposure in 2009 to the potential risk of future automation, as a result of AI/robots technologies available in 2009 or introduced in the following years (until 2024).

4. Data and Empirical Approach

4.1 Data and Descriptive Facts

The aim of the empirical analysis is to identify the possible moderating effect of the labour replacement risk (measured by the ARI) on key labour market variables. To this purpose, we assemble an industry-level dataset for the Japanese economy, resorting again to the most recent release of the Japan Industry and Productivity (JIP) Database (version 2023); by so doing, we can match the ARI industry-level dataset, calculated on 94 JIP industries, with a large set of key and control variables. This version of the JIP dataset spans the period 1994–2021. For the purposes of our analysis, we restrict the sample to 2009 as the initial year—the first year for which the ARI can be computed—and 2019 as the final year. The years 2020 and 2021 are excluded due to the potentially confounding effects associated with the COVID-19 pandemic. Modelling a structural break (by means of a time dummy variable) over the entire period is unlikely to yield meaningful insights, given the limited length of the post-shock interval. The period of the analysis is suitable for the purpose of our analysis as, while robotisation started earlier, the diffusion of artificial intelligence began to accelerate in the 2010s, following the breakthrough of deep learning around 2012, which enabled rapid improvements in performance and facilitated the widespread deployment of AI applications across industries and consumer technologies (Brynjolfsson et al., 2017; Russell and Norvig, 2021; OECD, 2019)[4].

The dataset has a nested structure (see Table 3 for the list of variables and their definition). To account for worker heterogeneity, all key labour market variables—namely, hourly wages and hours worked—are measured at the demographic group level (defined by gender, age group, education, and employment status) within each industry and year. All remaining variables are defined at the industry level (across the 94 industries). They include the ARI metric already described and a measure of innovative capital intensity, computed as the real capital stock per hour worked for the following four components: software, computer equipment, communication equipment, and robots. The first three components are directly available in

[4] For example, Brynjolfsson et al. (2017) highlighted a significant decline in error rates between 2010 and 2016, achieved by software programs based on machine learning principles.

the online JIP dataset and can reasonably be considered enabling technologies for AI. This interpretation is well supported in the economics and ICT literature (Melina and Villa, 2025; Hiroyuki, 2025; Omicini et al., 2026), as AI systems fundamentally depend on: (i) software (algorithms, machine learning frameworks, and data-processing systems); (ii) computer equipment (computing power, servers, graphical processing units, data centers, and semiconductors); and (iii) communication equipment (networks, internet infrastructure, cloud connectivity, and data transmission). The metric of robot real capital stock was estimated using data provided by RIETI and a method consistent with the estimation of the other components[5]. A higher level of innovative capital intensity reflects not only a more direct and intensive use of AI technologies but also a greater use of robotics, both directly and indirectly, given the complementarity between ICT assets and robotic systems.

The remaining variables listed in Table 3 are used as controls, and their inclusion is explained in the following subsection.

5 Specifically, we obtain nominal robot investment flows for benchmark years from the fixed capital formation matrix of the Input–Output Tables (Ministry of Internal Affairs and Communications; 2005, 2011, 2015, 2020). For non-benchmark years, investment is interpolated and extrapolated using the JIP series for 'other machinery and equipment.' Real robot capital stock is then estimated using the perpetual inventory method (PIM) based on the constructed nominal investment series. The investment deflator is derived from the JIP database, while depreciation rates follow Cabinet Office estimates

Table 3. Variables used in the empirical analysis

Label	definition	level
ln(h_wage)	log of real hourly wage	dg*/year
ln(hours)	log of annual hours worked	dg*/year
ln(innov_k_int)	log of real innovative capital (software + comp_equip + comm_equip+robot) 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
ln(comm_robot_int)	log of real robot capital stock per hour worked	industry/year
ud	union density: (union members/workers)	industry/year
mark-up	mark-up: (net gross output -variable costs)/net gross output	industry/year
lmt	labour market tightness: (job openings/job seekers)	industry/year
sh_work_100-	share of workers in small companies: (less than employees)	industry/year
sh_work_300+	share of workers in large companies: (more than 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_innov_k_int)	log of real non-innov capital (total capital - innov_cap) stock per hour worked	industry/year
ARI_2009	Automation Risk Index in 2009	industry
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

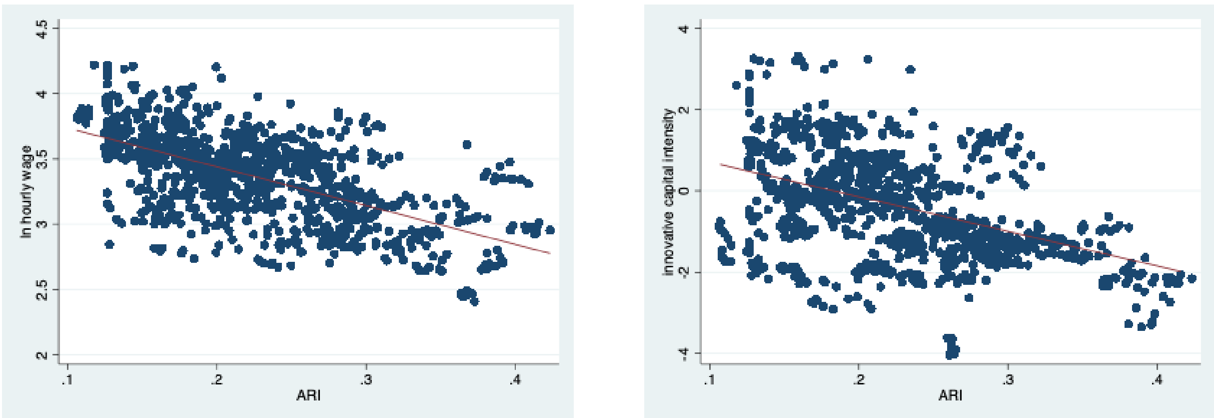
* Demographic groups (dg) are defined by gender/age/education/employment status at the following detail:

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

Notes: The industry classification is the 100 industries RIETI-JIP 2023 version (https://www.rieti.go.jp/en/database/JIP2023/). For the following industries it was not possible to calculate the ARI index due to missing data on the occupation shares on total employment in the BSWS data: 1. Agriculture, 3. Forestry, 4. Fisheries, 84. Housing, 91. Public Administration, 100. Activities not elsewhere classified. Data at the demographic group (dg) level is not available online and was provided by the JIP team in RIETI.

Before describing our empirical model, we present some descriptive evidence related to the core of our empirical analysis. Diagram 1 illustrates the relationship between automation risk and wage (left panel) and automation risk and innovative capital intensity (right panel) across Japanese industries, drawing on the JIP dataset and pooling 94 sectors over the period 2009–2019. A clear pattern emerges: sectors with greater exposure to automation risk tend to be characterised by lower average wages and lower innovative capital intensity (that is, higher levels of employment intensity). This finding is consistent with the hypothesis that a higher risk of task automation exerts downward pressure on wages, as workers in these sectors face increased substitutability by capital. This wage moderation is likely to reduce labour costs relative to investments in innovative or automation technologies. As a result, incentives to invest in innovation are weaker when labour remains sufficiently inexpensive, reinforcing the persistence of lower capital intensity (and, conversely, higher labour intensity) in sectors with elevated automation risk.

Diagram 1. ARI, hourly wages and innovative capital intensity

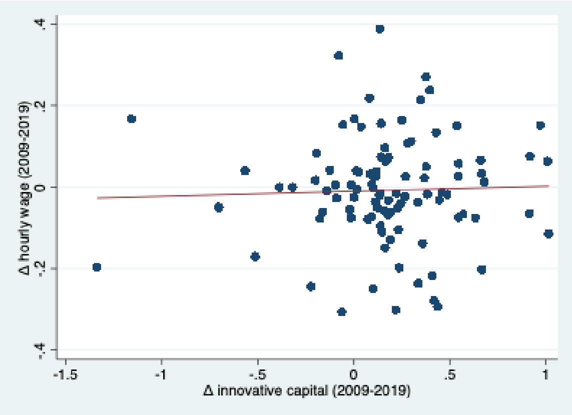


ρ = -0.6022 (p-value = 0.000) ρ = -0.4775* (p-value = 0.000)

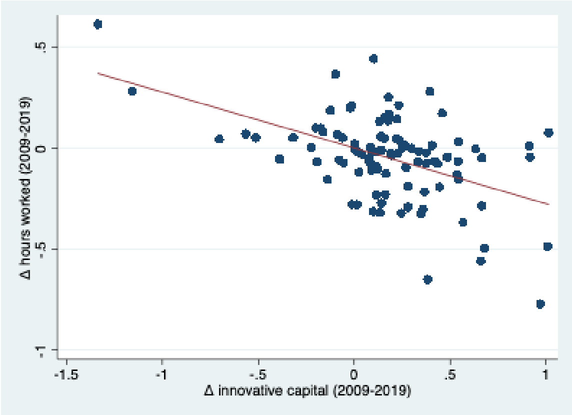
Diagram 2 illustrates the relationship between changes in innovative capital intensity over the period considered and the growth of wages and hours worked. An increase in innovative capital intensity is associated with weaker growth—or even a decline—in labour input (right-hand panel). At the same time, workers who remain employed in sectors experiencing rising innovative capital intensity do not experience wage declines (the correlation is indeed positive but very weak). This pattern is consistent with several possible explanations. On the one hand, it may reflect a standard productivity effect stemming from a higher capital–labour ratio. On the other hand, the workers who remain employed are likely to possess skills that complement innovative capital, making them less susceptible to displacement and defending their bargaining power.

The evidence presented thus far is primarily descriptive and does not directly address the central focus of our research, namely, the moderating role of automation risk in shaping the relationship between innovative capital and labour market outcomes. A more structured analytical approach is therefore required to investigate these aspects, as outlined in the following subsection.

Diagram 2. Innovative capital intensity, wages and hours worked



ρ = 0.0355* (p-value = 0.000)



ρ = -0.4929* (p-value = 0.000)

4.2 Model Specification and Empirical Strategy

The relationship between labour market outcomes and innovative capital intensity is inherently bidirectional, and using simple regression techniques can lead to significant consistency and efficiency issues in the estimators. To address this endogeneity, simultaneous equation models are commonly employed in the literature (Moffitt, 1984; Mohanty, 2019).

Building on this approach, we develop a model that jointly captures the interdependencies between innovative capital intensity and key labour market outcomes; a detailed discussion of how we address endogeneity within this simultaneous equation system is provided below. Specifically, we estimate the following three equations jointly:

$$\mathrm{hwage}_{igcjkt} = \alpha + \beta_1 \mathrm{hours}_{igcjkt} + \beta_2 \mathrm{innov\_k\_int}_{it} + \beta_3 (\mathrm{innov\_k\_int} \times \mathrm{ARI}_{bottom50\_ind09})_{it} + \beta_4 \mathrm{lmt}_{it} + \beta_5 \mathrm{markup}_{it} + \beta_6 \mathrm{ud}_{it} + \beta_7 \mathrm{sh\_w\_small\_firms}_{it} + \beta_8 \mathrm{sh\_w\_large\_firms}_{it} + \tau_t + \eta_{igcjk} + \varepsilon_{igcjkt} \quad (1)$$

$$\mathrm{hour}_{igcjkt} = \alpha + \gamma_1 \mathrm{hwage}_{igcjkt} + \gamma_2 \mathrm{innov\_k\_int}_{it} + \gamma_3 (\mathrm{innov\_k\_int} \text{ x } \mathrm{ARI}_{bottom50\_ind09})_{it} + \gamma_4 \mathrm{offshor}_{it} + \gamma_5 \mathrm{lmt}_{it} + \gamma_6 \mathrm{sh\_w\_small\_firms}_{it} + \gamma_7 \mathrm{sh\_w\_large\_firms}_{it} + \tau_t + \eta_{igcjk} + \varepsilon_{igcjkt} \tag{2}$$

$$\mathrm{innov\_k\_int}_{it} = \alpha + \lambda_1 \mathrm{RD}_{it} + \lambda_2 (\mathrm{RD} \text{ x } \mathrm{ARI}_{bottom50\_ind09})_{it} + \lambda_3 \mathrm{markup}_{it} + \lambda_4 \mathrm{sh\_w\_small\_firms}_{it} + \lambda_5 \mathrm{sh\_w\_large\_firms}_{it} + \lambda_6 \mathrm{non\_innov\_k\_int}_{it} + \tau_t + \eta_{igcjk} + \varepsilon_{igcjkt} \tag{3}$$

The subscripts in the model equations denote: industry (i), gender (g), age group (j), educational background (k), employment status (c), and year (t). For a detailed definition and description of all variables used in the analysis see Table 3.

The three simultaneous equations are estimated using panel data spanning the period 2009 to 2019. The years 2020 to 2023 are excluded due to the potentially confounding effects of the COVID-19 pandemic.

The model specification includes fixed effects at the cell level (i.e., industry × gender × age × education × employment status) as well as year fixed effects, allowing us to control for both unobserved heterogeneity and macroeconomic shocks over time.

In Equation (1), hourly wages are specified as the dependent variable, while working hours and innovative capital intensity are treated as endogenous regressors. The model also includes a set of exogenous controls to account for key labour market and firm-level determinants of wages. Labour market tightness is incorporated to capture cyclical and local demand conditions affecting wage-setting, consistent with the wage curve literature, which shows a negative relationship between wages and unemployment (Blanchflower and Oswald, 1994). Union density is included to reflect collective bargaining power, which has been shown to raise wages and compress wage dispersion (Freeman and Medoff, 1984). Market power is controlled for to account for deviations from perfect competition in labour markets, where firms with monopsony power can set wages below marginal productivity (Manning, 2003). Finally, the importance of small versus large firms is considered, as firm size is a well-documented determinant of wage differentials, with larger firms typically paying wage premia due to factors such as efficiency wages or rent-sharing (Brown and Medoff, 1989).

In Equation (2), annual hours worked are specified as the dependent variable, with wages and innovative capital intensity as endogenous regressors. The specification further includes offshoring intensity as an exogenous determinant, capturing the reallocation of tasks across borders and its impact on labour demand and working time, as emphasized in the task-based framework of globalisation (Grossman and Rossi-Hansberg, 2008). Labour market tightness is included to capture demand-side pressures in the labour market, as tighter conditions—proxied by a higher ratio of vacancies to job seekers—are expected to increase hours worked by strengthening firms' labour demand and inducing greater utilisation of the existing workforce, consistent with evidence on procyclical labour input adjustments (Bils, 1987). Finally, firm size is included as a control variable, reflecting systematic differences in work organisation and working time arrangements across firms, as larger and bettermanaged firms tend to adopt more structured practices that shape the allocation of hours (Bloom, Sadun and Van Reenen, 2012).

In Equation (3), innovative capital intensity is specified as the dependent variable, while R&D asset intensity is the main exogenous determinant, entered both directly and interacted with a low-ARI industry indicator to account for heterogeneous effects across sectors and to ensure the identification of the interaction terms in Equations (1) and (2). R&D asset intensity is expected to be positively associated with innovative investment, as firms with a stronger knowledge base and higher innovation capacity are more likely to adopt and complement digital technologies, consistent with evidence on the complementarities between intangible assets and ICT (Corrado et al., 2009). Market power is included as a control variable to capture firms' incentives and capacity to invest in productivity-enhancing technologies, as firms with greater markups may face weaker competitive pressure but possess more internal resources to finance innovation (De Loecker and Eeckhout, 2017). Firm size is controlled for to account for scale-related differences in technology adoption, as larger firms are more likely to invest in innovative forms of capital due to fixed costs, organizational capacity, and complementarities with managerial practices (Brynjolfsson and Hitt, 2000). Finally, non-innovative capital is included to control for broader capital deepening and technological substitution, as different forms of capital may complement or substitute for ICT/robots in the production process, influencing firms' digital investment decisions (Acemoglu and Restrepo, 2020).

For the purposes of our analysis, we define high-risk industries as those with an Automation Risk Index (ARI) above the median in 2009 (denoted as ARI_top_50_ind09), and low-risk industries as those with an ARI below the median in the same year (ARI_bottom_50_ind09). The use of industry-level ARI from the initial year—calculated as a weighted average of occupation-level ARI for 2024, using 2009 occupation shares (in hours worked) as weights—helps mitigate endogeneity concerns. Specifically, it reduces the risk of reverse causality between the adoption of automation technologies (which occurred after 2009) and changes in occupational structure.

The heterogeneity of the effects of innovative capital intensity on wages and hours depending on the level of automation risk is captured by the coefficients of the interaction terms (β_3 and γ_3) in Equations (1) and (2), respectively.

From an econometric perspective, our approach follows the empirical literature on labour demand estimation within a simultaneous equation framework. In this setting, simultaneity arises because wages and hours worked are jointly determined, implying that their respective equations are inherently correlated (Wooldridge, 2010, pp. 241–243). As a result, the correlation between the endogenous variables and the error terms in Equations (1) and (2) renders ordinary least squares (OLS) estimators inconsistent, making an instrumental variables (IV) strategy necessary.

In addition to this simultaneity, there is potential endogeneity involving our key regressor—ICT/robot capital intensity—and the dependent variables in both equations. For instance, omitted factors such as managerial ability may be correlated with both the adoption of ICT/robot technologies and hours worked

(Equation 2), as well as with wages (Equation 1). To address this concern, we specify a third equation in which innovative capital is expressed as a linear projection on a set of only exogenous variables (Wooldridge, 2010, p. 242), including R&D assets. This equation effectively mirrors the first stage of a standard IV procedure.

We therefore treat the system as fully simultaneous and estimate it using three-stage least squares (3SLS). Compared to a conventional IV approach, 3SLS offers efficiency gains by explicitly accounting for cross-equation error correlations. Specifically, the procedure first estimates each structural equation using two-stage least squares (2SLS), then uses the resulting residuals to construct an estimate of the covariance matrix of the disturbances. In the final stage, a generalised least squares (GLS) estimation is performed, combining this covariance structure with the instrumented regressors (Greene, 2018).

Regarding identification, and following Wooldridge (2010, pp. 242–243), we impose exclusion restrictions based on the economic interpretation of our variables. Union density is treated as wage shifters in Equation (1), offshoring serves as a labour demand shifter in Equation (2), and R&D assets act as the excluded instrument in Equation (3). Nonetheless, we acknowledge that the orthogonality conditions required for a fully causal interpretation may not be perfectly satisfied. Consequently, our results should not be interpreted as establishing a strictly causal relationship between recent automation technologies—captured by ICT/robot intensity (interacted with automation risk)—and wages or hours worked. Instead, in our baseline analysis, we compare OLS and 3SLS estimates to assess the extent of bias in the former and the degree to which 3SLS mitigates endogeneity concerns.

5. Results: Automation Risk, Innovative Capital and Labour Market Outcomes

5.1 Baseline model and components of innovative capital

Table 4 presents the estimation results of the model outlined in equations (1–3). The left panel (columns i-iii) reports the estimates of a simple OLS estimator, as a benchmark. The right panel (columns iv-vi) describes the results of 3SLS approach. A first piece of information coming from the comparison of two approaches is that the signs and significance of the coefficients in the three equations are consistent. The only exception is the sign of hours worked in the first equation, which is positive in the OLS estimates and negative in the 3SLS estimates, where the variable appears as the dependent variable in the second equation. This difference likely reflects the endogeneity of hours worked. In the OLS specification, hours worked may be correlated with unobserved individual characteristics such as ability or job quality, leading to an upward-biased estimate. By contrast, the 3SLS approach accounts for the simultaneous determination of hours worked and wages, as well as cross-equation error correlation, yielding a negative coefficient that can be interpreted as the structural effect. This suggests that, once endogeneity is addressed, longer working hours are associated with lower hourly wages, possibly reflecting lower productivity per hour or labor supply responses.

The other coefficients in the OLS and 3SLS model differ only in terms of magnitude. Such differences can again be interpreted as evidence of the bias due to possible endogeneity of the OLS estimates and of the violation of the hypothesis of independence of errors in the three equations. The Breusch–Pagan-type test, based on the estimated cross-equation covariance matrix from the 3SLS model, strongly rejects the null hypothesis of no cross-equation correlation ($p < 0.001$), indicating that the error terms are contemporaneously correlated. This supports the use of a system estimation approach, such as 3SLS, rather than estimating each equation separately. Hence, from now on, we will focus on the outcomes of the simultaneous equations estimates (columns 4 to 6 of Table 4).

Table 4: Baseline model: OLS FE and 3SLS (years 2009-2019, 94 JIP industries)

	OLS			3SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln(h_wage)	ln(hours)	ln(innov_k_int)	ln(h_wage)	ln(hours)	ln(innov_k_int)
ln(innov_k_int)	-0.039***	-1.008***		-0.150***	-0.719***	
	(0.006)	(0.038)		(0.005)	(0.017)	
ln(innov_k_int)*ARI_bottom_50_ind09	0.017**	0.249***		0.027***	0.047***	
	(0.008)	(0.042)		(0.003)	(0.011)	
ln(hours)	0.042***			-0.208***		
	(0.002)			(0.005)		
ud	-0.001			0.000*		
	(0.001)			(0.000)		
mark-up	-0.553***		0.392***	-0.263***		0.541***
	(0.017)		(0.027)	(0.009)		(0.011)
lmt	0.022***	0.203***		0.035***	0.091***	
	(0.003)	(0.026)		(0.002)	(0.007)	
sh_work_100-	-0.190***	-1.045***	-0.734***	-0.300***	-1.012***	-0.585***
	(0.027)	(0.339)	(0.023)	(0.010)	(0.041)	(0.011)
sh_work_300+	0.115***	4.591***	0.375***	0.337***	1.197***	0.347***
	(0.027)	(0.305)	(0.019)	(0.008)	(0.032)	(0.009)
ln(h_wage)		0.748***			-2.469***	
		(0.043)			(0.085)	
offshoring		-11.700***			-0.220***	
		(0.511)			(0.057)	
ln(RD_int)			0.344***			0.270***
			(0.015)			(0.007)
ln(RD_int)*ARI_bottom_50_ind09			-0.142***			-0.104***
			(0.015)			(0.007)
ln(non_ICT_k_int)			0.575***			0.649***
			(0.010)			(0.003)
Constant	2.778***	3.672***	-3.663***	0.053***	0.235***	0.218***
	(0.035)	(0.180)	(0.016)	(0.002)	(0.009)	(0.002)
RMSE	0.30772	1.4774	0.23124	0.194	0.711	0.177
F-test	491.08	443.23	88345.91			
F-test (p-value)	0.000	0.000	0.000			
Wald test (chi2)				5780	5754	123360
Wald test (p-value)				0.000	0.000	0.000
BP test (chi2)				54843		
BP test (p-value)				0.000		
R-squared / Pseudo R-squared	0.776	0.727	0.971	0.00190	0.00813	0.532
Observations	138,432	138,432	364,608	138,432	138,432	138,432

*Notes: Standard errors in parentheses; demographic group (dg) and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Breusch–Pagan-type test based on reg3 residual covariance matrix. As the conventional R-squared is not directly applicable to system estimation methods such as 3SLS, we report a goodness-of-fit measure (Pseudo R-squared) defined as the squared correlation between actual and fitted values for each equation.*

All coefficients on the control variables in the three equations have signs consistent with the literature discussed in Section 4.2. Specifically, higher union density, tighter labour markets and a larger share of large companies (over 300 employees) are associated with higher wages (column 4). This is consistent with the role of collective bargaining in raising wage floors and compressing dispersion, as well as with wage-setting models in which tighter labour markets increase workers' bargaining power (Suzuki, 2004). The positive effect of firm size reflects well-documented wage premia in larger firms, which may arise from efficiency wages, rent-sharing, or higher productivity (Tachibanaki, 1996; Morikawa, 2010).

By contrast, the presence of small firms (100 employees or less) and stronger market power decrease wages. The negative association with small firms is in line with their lower productivity levels and more limited capacity to pay wage premia (OECD, 2021). The negative coefficient on market power is consistent with monopsonistic labour market models, where firms with greater wage-setting power can pay wages below marginal productivity.

As regards hours worked (column 5), higher labour demand is positively associated with the presence of large companies and tighter labour markets. This supports the idea that, under stronger demand conditions, firms increase labour utilisation along the intensive margin, raising hours worked rather than (or in addition to) employment. Larger firms, with more structured production processes and management practices, are also more likely to adjust working time in response to demand fluctuations.

Hours worked are instead negatively associated with offshoring and the presence of small employers. The negative effect of offshoring is consistent with the task-based framework of globalisation, whereby the relocation of labour-intensive tasks abroad reduces domestic labour demand and therefore working time; evidence for Japan shows similar restructuring effects linked to international fragmentation (Head and Ries, 2002). Similarly, smaller firms may face more limited demand, financial constraints, or less flexible work organisation, leading to lower average hours worked.

Lastly, a higher innovative capital intensity goes along with market power, firm size, non-innovative capital intensity and investments in R&D activities. The positive association with R&D intensity confirms the complementarity between knowledge-based assets and the adoption of innovative technologies. The role of firm size reflects the presence of fixed costs and organisational capabilities required for technology adoption. The positive link with market power suggests that firms with higher markups have greater internal resources to finance innovation, despite potentially weaker competitive pressure. Finally, the positive association with non-innovative capital and robot intensity points to complementarities across different forms of capital deepening, consistent with the idea that digital technologies are adopted as part of broader investment strategies.

We now turn our attention to the endogenous variables of our model. The positive coefficient on hours worked in the wage equation suggests that industries characterised by stronger labour demand exhibit both greater labour utilisation and higher wages. This is consistent with procyclical adjustments in labour input, whereby tighter labour markets and a higher prevalence of large firms—both associated with longer working hours in Equation (2)—also contribute to upward pressure on wages (Bils, 1985; Solon et al., 1994). At the same time, the system estimates indicate a negative relationship between wages and hours worked in the hours equation, pointing to a simultaneous determination of the two variables. This pattern is consistent with labour supply responses or cost considerations, whereby higher wages reduce the demand for hours or induce adjustments along the intensive margin. Additionally, the positive association between hours and wages in the wage equation may reflect persistent industry-level heterogeneity, with more productive industries simultaneously paying higher wages and operating with longer working hours, in line with evidence on firm and industry wage premia (Brown and Medoff, 1989; Card et al., 2018).

As regards the core of our analysis, innovative capital intensity exhibits a statistically significant negative relationship with working hours, indicating that investments in digital technologies and robotics act as substitutes for labour. Innovative capital intensity is also negatively associated with wages, suggesting a potential decline in the bargaining power of workers who remain employed following the adoption of such technologies. This contrasts with the descriptive (simple correlation) evidence described in Figure 2 (left panel), which highlighted a weak positive correlation between innovative capital intensity and wages. Apart from the obvious explanation of controlling for other drivers of wages, that enable a correct identification of the effect of capital, the two results are not in contrast if we consider the moderating effect of the risk of automation, which is the core of our analysis. We indeed find that in industries with low automation risk—defined as those with a median ARI or lower in 2009—the negative association of innovative capital with labour market outcomes are attenuated. These results suggest that lower exposure to automation risk offers a protective buffer against the adverse impacts of technological capital intensity on both wages and hours worked. The results are confirmed if we define low automation risk more narrowly, i.e. industries in the lowest quartile or decile of the ARI distribution in 2009 - ARI_bottom_25_ind09 and ARI_bottom_25_ind09 (see Table A1 in the Appendix). The moderating effect of ARI on wages, in particular, increases the narrower the definition of low automation industries; the size of the coefficients of the main effect of innovative capital and the cross term indicate that in sectors with the lowest risk of labour/technology capital substitution, higher innovative capital intensity is associated with higher wages. As lower ARI is also associated with higher wages (see left panel of Diagram 1), this reconciles the apparent inconsistency: in industries with a higher share of workers sheltered by the risk of substitution, wages are higher, and a higher innovative capital intensity reinforces their bargaining position and capacity to appropriate higher returns.

By contrast, in the high–automation-risk industries reported in Table 2—such as traditional services (e.g. road transportation, mail, and hospitality) and traditional manufacturing (e.g. textiles)—the adoption of automation technologies may be driven by workforce ageing (Acemoglu and Restrepo, 2022b). This process not only reduces working hours but also weakens the bargaining power of remaining incumbent workers, ultimately lowering their wages (Acemoglu and Restrepo, 2022a).

When the analysis is replicated for the individual components of innovative capital intensity (Table 5), the moderating role of automation risk is consistently observed across all capital types. Across all specifications, the baseline estimates show a negative association between innovative capital and wages or between innovative capital and hours worked in high–automation-risk industries. This supports the view that technological investment tends to substitute for labour, putting downward pressure on labour market outcomes. These findings are consistent with the broader literature on the recent wave of automation driven by AI and robotics, despite differences in estimated magnitudes across studies (Frey and Osborne, 2017; Arntz et al., 2016, 2017; Acemoglu and Restrepo, 2020, 2022a; Morikawa, 2017).

Table 5: Components of innovative capital, ARI and labour market outcomes (summary)

	ln(h_wage) innov k	ln(hours) innov k	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(h_wage) robot	ln(hours) robot
ln(innov_k_int)	-0.150***	-0.719***								
	(0.005)	(0.017)								
ln(innov_k_int)*ARI_bottom_50_ind09	0.027***	0.047***								
	(0.003)	(0.011)								
ln(software_int)			-0.085***	-0.407***						
			(0.006)	(0.025)						
ln(software_int)*ARI_bottom_50_ind09			0.083***	0.047**						
			(0.006)	(0.023)						
ln(comp_equip_int)					-0.059***	-0.240***				
					(0.004)	(0.014)				
ln(comp_equip_int)*ARI_bottom_50_ind09					0.037***	0.053***				
					(0.003)	(0.014)				
ln(comm_equip_int)							-0.069***	-0.426***		
							(0.003)	(0.012)		
ln(comm_equip_int)*ARI_bottom_50_ind09							0.018***	0.053***		
							(0.001)	(0.006)		
ln(robot_int)									-0.084***	-0.220***
									(0.004)	(0.019)
ln(robot_int)*ARI_bottom_50_ind09									0.027***	-0.027*
									(0.004)	(0.016)

Notes: Standard errors in parentheses; cell and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Complete tables of results are available in the appendix

However, the interaction term with low automation risk (ARI_bottom_50_ind09) is positive and statistically significant across all components, indicating that these adverse effects are attenuated in industries less exposed to automation. Overall, this supports the view that the influence of technology depends on the task composition of jobs. In low–automation-risk industries, AI and robots can complement workers on certain tasks, boosting productivity and encouraging hiring. Even when they substitute for labour in some tasks, the resulting productivity gains can be large enough to increase demand for non-automated tasks, partially offsetting losses in employment, hours worked, and wages (Acemoglu and Restrepo, 2019; Acemoglu et al., 2022b).

More in detail, the magnitude of both the baseline and moderating effects varies across types of capital. The negative association with hours worked is particularly strong for software and communication equipment, suggesting that these technologies are especially effective in reducing labour input through task automation. At the same time, the relatively large interaction terms indicate that industries with lower automation risk are better able to absorb these technologies without substantial reductions in labour utilisation for the reasons explained above.

The moderating effect is especially pronounced for software intensity—the component most closely associated with AI-related technologies. In this case, the interaction term fully offsets, and even reverses, the negative baseline effect on wages. This is consistent with the "reinstatement effect," whereby new technologies create or enhance tasks in which labour has a comparative advantage (Acemoglu and Restrepo, 2019; Acemoglu et al., 2022b), and with recent evidence showing that AI can act as both a substitute and a complement to labour depending on task characteristics (Brynjolfsson et al., 2025; Eloundou et al., 2024).

For other forms of capital, such as computer equipment, communication equipment, and robots, the protective effect of low automation risk is present but generally weaker. In these cases, the interaction term mitigates but does not fully offset the negative baseline effect, suggesting that these technologies remain more directly substitutive for labour even in relatively sheltered industries (Acemoglu and Restrepo, 2020).

5.2 Heterogeneity across workers' characteristics: education, gender and age

By providing a more detailed breakdown across education groups, we show that highly educated workers are more likely to complement the new wave of automation technologies in certain tasks and are less affected by reductions in wages and hours worked. Table 6 presents the results of our analysis on the effects of innovative capital intensity and automation risk (ARI) across different education groups. Consistent with previous findings, the baseline effect of innovative capital on both wages and hours worked is negative across all groups, but its magnitude is significantly smaller for highly educated workers (i.e., those with a university degree or higher). This pattern is consistent with the task-based framework, whereby more educated workers are disproportionately employed to complement AI- and robot-suitable tasks (Acemoglu and Restrepo, 2019; Acemoglu et al., 2022b; Morikawa, 2017).

The interaction term with low automation risk is indeed positive across all education groups, indicating that the adverse effects of innovative capital are systematically attenuated in industries less exposed to automation. However, the magnitude of this moderating effect is stronger for highly educated workers, particularly on the wage dimension. In this group, low automation risk offsets a larger share of the negative association between innovative capital intensity and wages (around 24%), compared to approximately 16% (on average) for workers with lower levels of education.

By contrast, workers with lower levels of education are more exposed to the labour-substituting effects of innovative capital, experiencing greater declines in both wages and hours worked. This reflects their higher concentration in tasks that are more susceptible to automation by AI and robotics, a pattern also documented for Japan (Ikenaga and Kambayashi, 2016). Overall, these findings reinforce the view that the labour market effects of technological change are highly heterogeneous and depend critically on the interaction between technology, task composition, and worker characteristics. In particular, they suggest that AI and digital technologies may amplify existing inequalities, disproportionately benefiting higher-skilled workers while exposing lower-skilled workers to stronger negative effects (Acemoglu et al., 2022; Freire, 2025).

Table 6: Innovative capital, ARI and labour market outcomes by workers' level of education (summary)

	ln(h_wage) primary	ln(hours) primary	ln(h_wage) secondary	ln(hours) secondary	ln(h_wage) jun coll	ln(hours) jun coll	ln(h_wage) college	ln(hours) college
ln(innov_k_int)	-0.161***	-0.918***	-0.151***	-0.678***	-0.168***	-0.673***	-0.144***	-0.619***
	(0.009)	(0.038)	(0.008)	(0.027)	(0.009)	(0.032)	(0.010)	(0.027)
ln(innov_k_int)*ARI_bottom_50_ind09	0.013**	0.015	0.034***	0.071***	0.029***	0.048**	0.034***	0.038**
	(0.005)	(0.024)	(0.004)	(0.018)	(0.005)	(0.021)	(0.005)	(0.018)

*Notes: Standard errors in parentheses; cell and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Complete tables of results are available in the appendix*

Table 7 reports the results by gender, providing further evidence of heterogeneity in the effects of innovative capital intensity and automation risk. As in the baseline specification, innovative capital has a negative effect on both wages and hours worked for both men and women, confirming its labour-substituting nature. The magnitude of these effects is broadly similar across genders.

More striking differences emerge, however, when considering the moderating role of automation risk. The interaction term with low automation risk is positive and statistically significant for men, for both wages and hours worked, indicating that the adverse effects of innovative capital are substantially attenuated in less exposed industries. By contrast, for women, the moderating effect is weaker—insignificant for wages and only marginally significant for hours—suggesting a more limited protective role. This pattern is consistent with gender differences in occupational and task composition. Women are more likely to be employed in occupations that combine non-routine and routine tasks, some of which remain exposed to automation, and may have more limited access to technology-complementary roles (Autor et al., 2003; Cortes et al., 2017; Dekle, 2020). As a result, they benefit less from the complementarity between innovative capital and non-automatable tasks.

Overall, the findings indicate that the gains from technological change are unevenly distributed across genders. While low automation risk mitigates the negative effects of innovative capital for male workers, female workers appear to capture a smaller share of these benefits, in line with recent evidence on gender-differentiated impacts of automation and digitalisation (Acemoglu and Restrepo, 2022; ILO, 2021; Brussevich et al., 2019).

Table 7: Innovative capital, ARI and labour market outcomes by workers' gender (summary)

VARIABLES	ln(h_wage) male	ln(hours) male	ln(h_wage) female	ln(hours) female
ln(innov_cap_int)	-0.134***	-0.691***	-0.152***	-0.736***
	(0.006)	(0.023)	(0.007)	(0.025)
ln(innov_cap_int)*ARI_bottom_50_ind09	0.045***	0.113***	0.006	-0.027*
	(0.003)	(0.015)	(0.004)	(0.016)

*Notes: Standard errors in parentheses; cell and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Complete tables of results are available in the appendix*

Table 8 reports the results by age group, further highlighting heterogeneity in the effects of innovative capital intensity and automation risk. As in the previous specifications, innovative capital has a negative effect on both wages and hours worked across all age groups, confirming its labour-substituting nature. However, the magnitude of these effects increases with age, with older workers (55+) experiencing the strongest negative association, particularly for wages.

Table 8: Innovative capital, ARI and labour market outcomes by workers' age class (summary)

VARIABLES	ln(h_wage) 15-34 yo	ln(hours) 15-34 yo	ln(h_wage) 35-54 yo	ln(hours) 35-54 yo	ln(h_wage) over 55 yo	ln(hours) over 55 yo
ln(innov_cap_int)	-0.116***	-0.664***	-0.137***	-0.686***	-0.212***	-0.752***
	(0.006)	(0.026)	(0.007)	(0.027)	(0.011)	(0.033)
ln(innov_cap_int)*ARI_bottom_50_ind09	0.020***	0.040**	0.019***	0.047***	0.043***	0.027
	(0.004)	(0.017)	(0.004)	(0.018)	(0.005)	(0.021)

*Notes: Standard errors in parentheses; cell and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Complete tables of results are available in the appendix*

Differences also emerge in the moderating role of automation risk. The interaction term with low automation risk is positive and statistically significant for younger (15–34) and prime-age (35–54) workers, indicating that the adverse effects of innovative capital are attenuated in less exposed industries. For older workers, the moderating effect remains positive but is weaker and less precisely estimated for hours worked, suggesting a more limited protective role.

This pattern is consistent with age-related differences in adaptability and task composition. Younger and prime-age workers are more likely to possess skills that complement new technologies and to adjust more easily to changing task requirements, while older workers may be more concentrated in occupations and tasks that are more vulnerable to automation and less easily reallocated (Acemoglu and Restrepo, 2022; Autor et al., 2003; Hamaaki et al., 2012). In addition, differences in training, mobility, and technological adoption may further limit older workers' ability to benefit from the complementarity between innovative capital and non-automatable tasks (Chen and Liu, 2025).

Overall, these findings suggest that the labour market effects of technological change vary systematically over the life cycle. While low automation risk mitigates the negative effects of innovative capital for younger and prime-age workers, older workers appear more exposed to its adverse impacts, reinforcing the uneven distribution of gains and losses associated with technological change.

6. Conclusions

This paper set out to investigate how the diffusion of artificial intelligence (AI) and robotics—proxied by innovative capital intensity—interacts with the structure of labour markets to shape wages and working time in Japan. To this end, we introduced a novel dataset, the Automation Risk Index (ARI), which provides a granular, ability-based measure of exposure to automation at the occupational and industry level. This dataset provides, to our knowledge, the first comprehensive measure of automation risk for the Japanese economy, enabling a detailed assessment of how different segments of the labour market are exposed to technological substitution. Building on this contribution, we developed an empirical framework that jointly models wages, hours worked, and innovative capital intensity, explicitly accounting for endogeneity and cross-equation interdependence through a system estimation approach. The analysis was conducted using detailed industry-level panel data for the period 2009–2019, enriched with information on worker heterogeneity across education, gender, and age groups.

While a large body of literature has examined the impact of automation on employment and wages, relatively little empirical work has explored how exposure to automation moderates the relationship between capital deepening and labour outcomes, particularly outside the U.S. context. By providing new evidence for Japan—an economy characterised by rapid population ageing and strong incentives for automation—this paper contributes to filling this gap and offers insights that are relevant for other advanced economies facing similar structural challenges.

The empirical results yield several key findings. First, innovative capital intensity—encompassing software, ICT equipment, and robots—is associated with a reduction in both hours worked and wages, supporting the view that technological capital has, on average, a labour-substituting effect. This result is consistent with the displacement channel emphasised in the task-based literature, whereby capital increasingly performs tasks previously carried out by labour. However, this average effect masks substantial heterogeneity across industries and worker groups.

A second key finding is the role of automation risk as a crucial moderating factor. The negative association between innovative capital and labour market outcomes is significantly weaker in industries characterised by lower exposure to automation. In these contexts, workers appear to retain a stronger position in the production process, allowing them to better capture the gains from technological progress. This result provides empirical support to the idea that the impact of AI and robotics depends critically on the task composition of production and the extent to which tasks remain difficult to automate. It also helps reconcile the coexistence of labour-displacing and productivity-enhancing effects of technological change observed in the descriptive evidence.

Third, the analysis highlights important differences across types of capital. While all components of innovative capital display labour-substituting tendencies, the moderating effect of automation risk is particularly strong for software—the component most closely linked to AI-related technologies. In low-risk industries, the adoption of software capital not only mitigates negative effects but may even be associated with higher wages, pointing to the presence of complementarities between AI and non-automatable tasks. By contrast, more traditional forms of capital, such as robots and computer equipment, remain more directly substitutive, even in relatively sheltered sectors.

Finally, the results reveal a pronounced heterogeneity across worker characteristics. Highly educated workers experience smaller negative effects from innovative capital and benefit more from the protective role of low automation risk, consistent with the notion of task complementarity. Gender differences also emerge, with male workers benefiting more from the mitigating effect of low automation risk, while female workers appear to capture a smaller share of the gains, possibly reflecting occupational segregation and differential access to technology-complementary roles. Age patterns further reinforce this heterogeneity: younger and prime-age workers are better able to adapt to technological change and benefit from lower automation risk, whereas older workers remain more exposed to its adverse effects. Taken together, these findings suggest that the diffusion of AI and digital technologies may amplify existing inequalities in the labour market along multiple dimensions.

These results speak directly to the broader debate on the labour market effects of AI and automation. Rather than supporting a purely pessimistic or optimistic view, our findings point to a more nuanced perspective in which technological change generates both substitution and complementarity effects, with outcomes depending on the interaction between technology, tasks, and worker characteristics. In this respect, the evidence is consistent with recent contributions emphasising the coexistence of displacement and reinstatement mechanisms, as well as the importance of institutional and structural factors in shaping the distribution of gains from innovation.

From a policy perspective, the results underscore the importance of addressing heterogeneity in exposure to automation. Policies aimed at strengthening workers' adaptability—such as investments in education, lifelong learning, and reskilling—are likely to play a key role in enabling a broader share of the workforce to benefit from technological change. At the same time, measures that support the diffusion of complementary skills and facilitate transitions across occupations may help mitigate the adverse effects on more vulnerable groups, particularly older and less-educated workers. In Japan, these challenges are particularly salient given the combined pressures of demographic decline and rapid technological adoption.

The paper is not without limitations. While the use of a simultaneous equations framework improves identification, the results should not be interpreted as fully causal, as the validity of the exclusion restrictions cannot be tested directly. In addition, the ARI, while offering a novel and detailed measure of automation risk, relies in part on expert assessments, which may be subject to uncertainty. Future research could extend this work by incorporating firm-level data, exploring dynamic adjustments over longer time horizons, or refining measures of AI exposure as technologies continue to evolve.

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Appendix

Table A1: Robustness check, baseline model: bottom 25% and bottom 10% ARI industries (3SLS, years 2009-2019, 94 JIP industries)

	ARI bottom 25			ARI bottom 10		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(h_wage)	ln(hours)	ln(innov_k_int)	ln(h_wage)	ln(hours)	ln(innov_k_int)
ln(innov_k_int)	-0.231***	-0.821***		-0.117***	-0.750***	
	(0.005)	(0.012)		(0.005)	(0.012)	
ln(innov_k_int)*ARI_bottom_25_ind09	0.116***	0.272***				
	(0.003)	(0.011)				
ln(innov_k_int)*ARI_bottom_10_ind09				0.145***	0.232***	
				(0.003)	(0.015)	
ln(hours)	-0.277***			-0.135***		
	(0.006)			(0.007)		
ud	0.001***			0.002***		
	(0.000)			(0.000)		
mark-up	-0.240***		0.508***	-0.377***		0.505***
	(0.009)		(0.010)	(0.009)		(0.010)
lmt	0.037***	0.083***		0.036***	0.045***	
	(0.002)	(0.007)		(0.002)	(0.007)	
sh_work_100-	-0.324***	-0.913***	-0.679***	-0.247***	-0.764***	-0.569***
	(0.011)	(0.039)	(0.011)	(0.010)	(0.038)	(0.010)
sh_work_300+	0.377***	1.100***	0.427***	0.273***	0.990***	0.343***
	(0.010)	(0.030)	(0.009)	(0.009)	(0.030)	(0.008)
ln(h_wage)		-2.081***			-1.206***	
		(0.065)			(0.063)	
offshoring		-0.212***			-0.821***	
		(0.052)			(0.062)	
ln(RD_int)			0.127***			0.130***
			(0.004)			(0.004)
ln(RD_int)*ARI_bottom_25_ind09			0.191***			
			(0.005)			
ln(RD_int)*ARI_bottom_10_ind09						0.274***
						(0.006)
ln(non_ICT_k_int)			0.644***			0.641***
			(0.003)			(0.003)
Constant	0.073***	0.248***	0.220***	0.045***	0.205***	0.222***
	(0.002)	(0.008)	(0.002)	(0.002)	(0.008)	(0.002)
RMSE	0.223	0.684	0.176	0.167	0.637	0.176
chi2	5942	6355	124862	6915	6043	126080
P>chi2 Eq.1	0.000	0.000	0.000	0.000	0.000	0.000
BP chi2	72342			23967		
BP p-value	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo-R2	0.00189	0.0113	0.524	0.00748	0.0180	0.522
Observations	138,432	138,432	138,432	138,432	138,432	138,432

*Notes: Standard errors in parentheses; demographic group (dg) and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Breusch–Pagan-type test based on reg3 residual covariance matrix. As the conventional R-squared is not directly applicable to system estimation methods such as 3SLS, we report a goodness-of-fit measure (Pseudo R-squared) defined as the squared correlation between actual and fitted values for each equation.*

Table A2: Components of innovative capital, ARI and labour market outcomes (3SLS, years 2009-2019, 94 JIP industries)

VARIABLES	(1) software	(2) software	(3) software	(4) comp_equip	(5) comp_equip	(6) comp_equip	(7) comm equip	(8) comm equip	(9) comm equip	(10) robot	(11) robot	(12) robot
ln(software_k_int)	-0.084***	-0.408***										
	(0.006)	(0.025)										
ln(software_k_int)*ARI_bottom_50_ind09	0.082***	0.048**										
	(0.006)	(0.023)										
ln(comp_equip_k_int)				-0.059***	-0.240***							
				(0.004)	(0.014)							
ln(comp_equip_k_int)*ARI_bottom_50_ind09				0.037***	0.053***							
				(0.003)	(0.014)							
ln(comm_equip_k_int)							-0.069***	-0.426***				
							(0.003)	(0.012)				
ln(comm_equip_k_int)*ARI_bottom_50_ind09							0.018***	0.053***				
							(0.001)	(0.006)				
ln(robot_k_int)										-0.084***	-0.220***	
										(0.004)	(0.019)	
ln(robot_k_int)*ARI_bottom_50_ind09										0.027***	-0.027*	
										(0.004)	(0.016)	
ln(hours)	-0.022***			-0.137***			-0.142***			-0.140***		
	(0.005)			(0.004)			(0.004)			(0.004)		
ud	0.001***			0.000***			0.001***			0.001***		
	(0.000)			(0.000)			(0.000)			(0.000)		
mark-up	-0.409***		0.846***	-0.447***		-0.424***	-0.398***		-0.277***	-0.231***		
	(0.010)		(0.016)	(0.009)		(0.023)	(0.009)		(0.020)	(0.010)		
lmt	0.033***	0.049***		0.033***	0.040***		0.036***	0.075***		0.071***	0.107***	
	(0.002)	(0.007)		(0.002)	(0.007)		(0.002)	(0.007)		(0.002)	(0.013)	
sh_work_100-	-0.213***	-0.487***	-0.612***	-0.219***	-0.284***	-0.062***	-0.209***	-0.393***	-0.051**	-0.252***	-0.909***	0.256***
	(0.009)	(0.040)	(0.016)	(0.009)	(0.039)	(0.023)	(0.009)	(0.040)	(0.020)	(0.010)	(0.049)	(0.033)
sh_work_300+	0.187***	0.920***	0.536***	0.292***	0.833***	0.299***	0.273***	0.884***	0.124***	0.354***	1.310***	
	(0.008)	(0.031)	(0.013)	(0.008)	(0.031)	(0.018)	(0.008)	(0.031)	(0.016)	(0.008)	(0.039)	
ln(h_wage)		-0.575***			-0.508***			-1.384***			-1.648***	-0.509***
		(0.082)			(0.079)			(0.080)			(0.108)	(0.033)
offshoring		-1.119***			-1.113***			-0.807***			-0.672***	0.701***
		(0.066)			(0.064)			(0.065)			(0.085)	(0.024)
ln(RD_int)			0.218***			0.520***			0.570***			0.256***
			(0.010)			(0.015)			(0.013)			(0.019)
ln(RD_int)*ARI_bottom_50_ind09			0.127***			-0.410***			-0.400***			-0.293***
			(0.011)			(0.015)			(0.013)			(0.019)
ln(non_ICT_k_int)			0.443***			0.734***			0.661***			0.708***
			(0.005)			(0.007)			(0.006)			(0.013)
Constant	0.028***	0.079***	0.202***	0.016***	0.011	0.061***	0.043***	0.211***	0.409***	0.044***	0.047***	0.103***
	(0.002)	(0.009)	(0.003)	(0.002)	(0.008)	(0.004)	(0.002)	(0.009)	(0.003)	(0.003)	(0.012)	(0.005)
RMSE	0.149	0.621	0.272	0.169	0.623	0.383	0.171	0.656	0.334	0.167	0.657	0.468
Wald test (chi2)	5541	4695	40143	5898	3462	24703	5720	4176	63356	6220	2941	13215
Wald test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BP test (chi2)	1410			11621			20521			22459		
BP test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R-squared /Pseudo R-squared	0.0222	0.0164	0.291	0.00419	0.00785	0.219	0.00272	0.00534	0.544	0.00585	0.00456	0.252
Observations	138,432	138,432	138,432	138,432	138,432	138,432	138,432	138,432	138,432	107,085	107,085	107,085

Notes: Standard errors in parentheses; demographic group (dg) and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Breusch–Pagan-type test based on reg3 residual covariance matrix. As the conventional R-squared is not directly applicable to system estimation methods such as 3SLS, we report a goodness-of-fit measure (Pseudo R-squared) defined as the squared correlation between actual and fitted values for each equation.

Table A3: Innovative capital, ARI and labour market outcomes by workers' level of education (3SLS, years 2009-2019, 94 JIP industries)

	(1) primary	(2) primary	(3) primary	(4) secondary	(5) secondary	(6) secondary	(7) jun coll	(8) jun coll	(9) jun coll	(10) univ	(11) univ	(12) univ
ln(innov_k_int)	-0.161***	-0.918***		-0.151***	-0.678***		-0.168***	-0.673***		-0.144***	-0.619***	
	(0.009)	(0.038)		(0.008)	(0.027)		(0.009)	(0.032)		(0.010)	(0.027)	
ln(innov_k_int)*ARI_bottom_50_ind09	0.013**	0.015		0.034***	0.071***		0.029***	0.048**		0.034***	0.038**	
	(0.005)	(0.024)		(0.004)	(0.018)		(0.005)	(0.021)		(0.005)	(0.018)	
ln(hours)	-0.165***			-0.217***			-0.256***			-0.238***		
	(0.008)			(0.008)			(0.010)			(0.011)		
ud	0.000			0.000			0.000			0.000		
	(0.000)			(0.000)			(0.000)			(0.000)		
mark-up	-0.238***		0.534***	-0.225***		0.554***	-0.234***		0.552***	-0.319***		0.544***
	(0.019)		(0.021)	(0.016)		(0.021)	(0.019)		(0.021)	(0.020)		(0.021)
lmt	0.033***	0.090***		0.039***	0.111***		0.037***	0.105***		0.033***	0.065***	
	(0.003)	(0.016)		(0.003)	(0.012)		(0.003)	(0.014)		(0.003)	(0.012)	
sh_work_100-	-0.316***	-1.271***	-0.593***	-0.271***	-0.881***	-0.582***	-0.294***	-0.888***	-0.583***	-0.318***	-0.989***	-0.584***
	(0.020)	(0.091)	(0.021)	(0.016)	(0.066)	(0.021)	(0.020)	(0.081)	(0.021)	(0.021)	(0.066)	(0.021)
sh_work_300+	0.308***	1.296***	0.362***	0.337***	1.219***	0.342***	0.356***	1.133***	0.341***	0.367***	1.108***	0.344***
	(0.017)	(0.070)	(0.017)	(0.015)	(0.050)	(0.017)	(0.017)	(0.063)	(0.017)	(0.018)	(0.053)	(0.017)
ln(h_wage)		-2.899***			-2.630***			-2.572***			-1.775***	
		(0.186)			(0.138)			(0.158)			(0.142)	
offshoring		-0.748***			-0.099			0.100			-0.113	
		(0.125)			(0.090)			(0.104)			(0.103)	
ln(RD_int)			0.265***			0.266***			0.267***			0.278***
			(0.013)			(0.013)			(0.013)			(0.014)
ln(RD_int)*ARI_bottom_50_ind09			-0.104***			-0.096***			-0.104***			-0.104***
			(0.014)			(0.014)			(0.014)			(0.014)
ln(non_ICT_k_int)			0.656***			0.645***			0.650***			0.643***
			(0.006)			(0.006)			(0.006)			(0.006)
Constant	0.040***	0.174***	0.218***	0.041***	0.163***	0.219***	0.096***	0.376***	0.218***	0.055***	0.241***	0.218***
	(0.004)	(0.020)	(0.003)	(0.004)	(0.015)	(0.003)	(0.005)	(0.018)	(0.003)	(0.005)	(0.014)	(0.003)
RMSE	0.193	0.801	0.177	0.165	0.583	0.177	0.212	0.707	0.177	0.192	0.574	0.178
Wald test (chi2)	1564	3290	30881	2039	2213	31111	1384	1659	31009	1279	3040	30444
Wald test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BP test (chi2)	13244			14075			16889			10428		
BP test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R-squared /Pseudo R-squared	0.00260	0.00869	0.533	0.00163	0.00685	0.531	0.00162	0.00701	0.531	0.00136	0.00867	0.531
Observations	34,481	34,481	34,481	34,973	34,973	34,973	34,743	34,743	34,743	34,235	34,235	34,235

*Notes: Standard errors in parentheses; demographic group (dg) and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Breusch–Pagan-type test based on reg3 residual covariance matrix. As the conventional R-squared is not directly applicable to system estimation methods such as 3SLS, we report a goodness-of-fit measure (Pseudo R-squared) defined as the squared correlation between actual and fitted values for each equation.*

Table A4: Innovative capital, ARI and labour market outcomes by workers' gender (3SLS, years 2009-2019, 94 JIP industries)

	(1) male	(2) male	(3) male	(4) female	(5) female	(6) female
ln(innov_k_int)	-0.134***	-0.691***		-0.152***	-0.736***	
	(0.006)	(0.023)		(0.007)	(0.025)	
ln(innov_k_int)*ARI_bottom_50_ind09	0.045***	0.113***		0.006	-0.027*	
	(0.003)	(0.015)		(0.004)	(0.016)	
ln(hours)	-0.166***			-0.220***		
	(0.006)			(0.006)		
ud	0.001***			0.000		
	(0.000)			(0.000)		
mark-up	-0.270***		0.530***	-0.269***		0.551***
	(0.012)		(0.015)	(0.014)		(0.015)
lmt	0.030***	0.060***		0.040***	0.118***	
	(0.002)	(0.010)		(0.002)	(0.011)	
sh_work_100-	-0.258***	-0.752***	-0.583***	-0.335***	-1.222***	-0.587***
	(0.012)	(0.057)	(0.015)	(0.015)	(0.060)	(0.015)
sh_work_300+	0.305***	0.940***	0.340***	0.360***	1.383***	0.355***
	(0.010)	(0.047)	(0.012)	(0.013)	(0.045)	(0.012)
ln(h_wage)		-1.959***			-2.757***	
		(0.133)			(0.109)	
offshoring		-0.403***			-0.178**	
		(0.081)			(0.084)	
ln(RD_int)			0.270***			0.270***
			(0.009)			(0.010)
ln(RD_int)*ARI_bottom_50_ind09			-0.104***			-0.104***
			(0.010)			(0.010)
ln(non_ICT_k_int)			0.652***			0.646***
			(0.005)			(0.005)
Constant	0.049***	0.236***	0.218***	0.051***	0.227***	0.219***
	(0.003)	(0.012)	(0.002)	(0.003)	(0.013)	(0.002)
RMSE	0.168	0.648	0.178	0.207	0.760	0.176
Wald test (chi2)	2915	2233	61949	3218	3764	61396
Wald test (p-value)	0	0	0	0	0	0
BP test (chi2)	23497			28155		
BP test (p-value)	0	0	0	0	0	0
R-squared / Pseudo R-squared	0.00250	0.00930	0.532	0.00181	0.00794	0.532
Observations	69,870	69,870	69,870	68,562	68,562	68,562

*Notes: Standard errors in parentheses; demographic group (dg) and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Breusch–Pagan-type test based on reg3 residual covariance matrix. As the conventional R-squared is not directly applicable to system estimation methods such as 3SLS, we report a goodness-of-fit measure (Pseudo R-squared) defined as the squared correlation between actual and fitted values for each equation.*

Table A5: Innovative capital, ARI and labour market outcomes by workers' age class (3SLS, years 2009-2019, 94 JIP industries)

	(1) 15-34	(2) 15-34	(3) 15-34	(4) 35-54	(5) 35-54	(6) 35-54	(7) over 55	(8) over 55	(9) over 55
ln(innov_k_int)	-0.116***	-0.664***		-0.137***	-0.686***		-0.212***	-0.752***	
	(0.006)	(0.026)		(0.007)	(0.027)		(0.011)	(0.033)	
ln(innov_k_int)*ARI_bottom_50_ind09	0.020***	0.040**		0.019***	0.047***		0.043***	0.027	
	(0.004)	(0.017)		(0.004)	(0.018)		(0.005)	(0.021)	
ln(hours)	-0.195***			-0.221***			-0.229***		
	(0.006)			(0.006)			(0.013)		
ud	-0.000*			-0.000			0.001***		
	(0.000)			(0.000)			(0.000)		
mark-up	-0.249***		0.546***	-0.219***		0.551***	-0.311***		0.530***
	(0.014)		(0.019)	(0.015)		(0.018)	(0.020)		(0.018)
lmt	0.032***	0.085***		0.041***	0.137***		0.033***	0.054***	
	(0.002)	(0.011)		(0.003)	(0.012)		(0.003)	(0.013)	
sh_work_100-	-0.231***	-0.904***	-0.595***	-0.342***	-1.276***	-0.587***	-0.329***	-0.775***	-0.574***
	(0.014)	(0.062)	(0.018)	(0.015)	(0.068)	(0.018)	(0.020)	(0.080)	(0.018)
sh_work_300+	0.307***	1.204***	0.356***	0.346***	1.301***	0.349***	0.370***	1.045***	0.337***
	(0.012)	(0.049)	(0.015)	(0.013)	(0.053)	(0.015)	(0.018)	(0.061)	(0.015)
ln(h_wage)		-2.691***			-3.108***			-1.561***	
		(0.138)			(0.130)			(0.161)	
offshoring		-0.473***			-0.128			0.031	
		(0.089)			(0.088)			(0.110)	
ln(RD_int)			0.275***			0.266***			0.271***
			(0.012)			(0.012)			(0.012)
ln(RD_int)*ARI_bottom_50_ind09			-0.104***			-0.099***			-0.110***
			(0.012)			(0.012)			(0.012)
ln(non_ICT_k_int)			0.649***			0.649***			0.648***
			(0.006)			(0.006)			(0.006)
Constant	0.033***	0.166***	0.218***	0.055***	0.248***	0.218***	0.076***	0.289***	0.219***
	(0.003)	(0.014)	(0.003)	(0.003)	(0.015)	(0.003)	(0.005)	(0.017)	(0.003)
RMSE	0.166	0.647	0.177	0.183	0.708	0.177	0.233	0.718	0.177
Wald test (chi2)	3054	2828	40589	2716	2336	41820	1349	1810	40951
Wald test (p-value)	0	0	0	0	0	0	0	0	0
BP test (chi2)	18567			21942			16734		
BP test (p-value)	0	0	0	0	0	0	0	0	0
R-squared / Pseudo R-squared	0.00218	0.00707	0.532	0.00194	0.00562	0.531	0.00136	0.0133	0.533
Observations	45,126	45,126	45,126	46,648	46,648	46,648	46,658	46,658	46,658

*Notes: Standard errors in parentheses; demographic group (dg) and time fixed effects included. p<0.01, ** p<0.05, * p<0.1. Breusch–Pagan-type test based on reg3 residual covariance matrix. As the conventional R-squared is not directly applicable to system estimation methods such as 3SLS, we report a goodness-of-fit measure (Pseudo R-squared) defined as the squared correlation between actual and fitted values for each equation.*