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Automation and Human Capital Investment

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Abstract

Technological change has an ambiguous impact on labour market by creating demand for some skills and reducing demand of some others. Hence the relationship of demand for skills and the need for training is an empirical question. In this paper, I investigate association between types of technological change and decisions. I categorise several measures of automation on the basis of tasks (done at individual or occupation level) and technology (Software, Robot, AI) and compare their relationship with human capital investment. I find that the correlation between automation and training varies depending on the automation measure used, showing a decline with both individual- and occupation-level automation measures. However when relying on technology based measures of automation, workers exposed to older technologies (Robot, Software) receive less training with automation, while workers exposed to newer technologies (AI) receive more training with automation. The findings are consistent across workers of different age groups and skill levels.

Keywords: Automation, Artificial Intelligence, Robotization, On-the-job training, PIAAC, Human Capital Investment

JEL Classification: J23, J24, M53, O33, I26

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1 Introduction

Technological advancements have demonstrably yielded substantial economic growth and societal progress throughout history. To name a few, the current wave of automation, encompassing applications like automated customer service systems, industrial robots, computer-controlled machinery, and inventory management software, is significantly impacting both the labour force and the broader economy (Acemoglu et al. 2022). This prompts a critical inquiry: how can automation be effectively categorised to analyse its multifaceted effects? Furthermore, do different automation types exert homogeneous influences on economy and individuals?

Since the Industrial Revolution, automation has exerted a complex and multifaceted influence on the labour market. While routine tasks become susceptible to automation, leading to a decline in demand for associated jobs, this process often creates new employment opportunities requiring different skill-sets. This dynamic necessitates investment in human capital to equip the workforce with the necessary capabilities to thrive in a changing technological landscape. From an individual worker's perspective, acquiring skills in high-demand areas might seem like a rational response to the threat of automation. However, significant uncertainty surrounds the future returns on specific skills, and different automation metrics, focusing on varying aspects of job tasks, may yield disparate impacts on skill relevance. Furthermore, it's crucial to acknowledge that observed training choices may not solely reflect individual decisions. Firms often play a dominant role in training investments (Blundell et al. 2021), particularly when training involves direct costs. Therefore, observed training patterns may primarily reflect firm-level strategies for adapting to automation, rather than unconstrained individual choices. While it might appear, from an individual worker's perspective, that they are making choices about their skill development, it is essential to recognize that these choices are often constrained by the training opportunities offered by their employers. Analyses of employer training investments reveal declining real terms expenditure per worker in England between 2005 and 2011 (Davies et al. 2012), with further reductions reported subsequently (Winterbotham et al. 2014). Corroborating evidence from the Continual Vocational Training Survey indicates substantial cuts in UK training costs per employee over a similar period, suggesting a decline in training volume (Green et al. 2016). High-tech firms undergoing rapid technological change demonstrate two key training patterns: a greater reliance on in-house training, potentially due to the scarcity of external resources for specialized skills, and a concentration of company-provided training among highly educated workers (Lillard and Tan 1986).

This paper examines the relationship between workers' training incidence and occupational automation risk. A granular task-based assessment of automation risk, disaggregated by underlying technology, is employed to explore variations in observed training patterns. Using data from the Programme for the International Assessment of Adult Competencies (PIAAC) cycle 1 (2011-2018), the study investigates the association between automation risk and human capital investment, as reflected in training incidence. PIAAC offers a unique advantage for this analysis as it encompasses a comprehensive set of worker characteristics, including details on training undertaken within the past twelve months. Additionally, the dataset provides valuable insights into the specific tasks performed by workers within their occupations. This granular data on worker skill sets and recent skill development allows for a more nuanced examination of how automation risk, as it relates to the tasks performed, influences investment decisions. Using five measures of automation (Frey and Osborne (2017); Arntz et al. (2016); Webb (2019)), I investigate the relationship between specific automation measures and training decisions. I use the Technological Readiness from World Economic Forum, measured at country level, as measure for rate of adoption of technology in different countries. The contributions of the paper are threefold. First, it provides a classification and comparison between various measures of automation. Prior to this, multiple measures of automation have been used to understand the labour market (Frey and Osborne (2017); Arntz et al. (2016); Webb (2019)), but there has not been a comparison between the measures and their differential impacts. This paper classifies measures of automation in two ways: level at which tasks are executed, and exposure of tasks to a particular technology. All occupations can be divided into tasks which can be automated or not (Autor et al. (2003); Josten and Lordan (2019)). These tasks can be used to calculate the measure of automation. If the tasks done by the worker are observed and used to estimate the automation risk, it is termed as individual level automation measure. When the occupation of the worker is observed, the automation at occupation level can be estimated using the tasks associated with that occupation and this is termed as occupation level automation. As an additional classification, I use exposure to technology of tasks. Different types of technology have different impacts on the same task and hence the occupation. Robots automate manual tasks. Software automates routine information processing. AI automates routine information processing, identifying patterns in the information and makes suggestions or predictions based on this. These varying functionalities of automation technologies lead to differential impacts on workers performing seemingly similar tasks.

The second contribution is to quantify the relationship between automation and human capital investment. Nedelkoska and Quintini (2018) ask the same question with automation risk at individual level but not at occupation level. This paper examines the relationship between automation risk, measured at both the individual and occupational levels, and human capital investment. Individual workers within the same occupation might perform a variety of tasks, some more susceptible to automation than others. Looking at the occupational level allows to aggregate these individual tasks and understand the overall automation risk for that occupation. While focusing on the individual level initially seems appealing, it's important to acknowledge the potential endogeneity issue. This refers to the fact that the specific tasks a worker performs can be influenced by their existing human capital (skills and knowledge). A worker with a higher skill set might be assigned more complex tasks within the same occupation compared to someone with lower skills. This broader perspective captures the overall automation risk for an occupation, encompassing the variety of tasks performed by workers with different skill levels within that occupation. Thirdly, this paper explores the relationship between different automation technologies and human capital investment.

The analysis demonstrates that workers exposed to high automation risk, in general, are associated with lower investment in human capital. However, the level of investment varies depending on the specific technology driving the automation process. A positive relationship is observed between the prospect of AI-driven automation and increased human capital development. This observation may reflect a perception among workers that AI-driven automation is associated with a need for complementary skills or firms that is exposed to AI are investing more in their human capital development. Conversely, a negative correlation is observed between exposure to automation driven by robots and software and human capital investment decisions. This observation may be related to a perception that these technologies are associated with full job replacement, particularly for lower-skilled roles.

Furthermore, the findings reveal a positive association between a country's level of technological readiness and worker investment decisions in the face of automation. This suggests that a more technologically advanced environment is associated with increased human capital investment, even in the presence of automation risk.

The paper is organised as follows, section 2 provides the background information about types of automation, its measures and implications. Section 3 and 4 describes the data and empirical strategy used in the study. Section 5 explains the results followed by robustness checks and conclusion.

2 Background

2.1 Automation - Measures

The economic models examining the impact of automation and technological change are based on two main approaches: the factor-augmenting approach and the task-based approach. Each of these approaches offers a unique perspective on how automation and technological changes influence the economy, particularly in terms of labour markets, productivity, and income distribution.

The factor-augmenting approach, derived from the Solow-Swan growth model, posits that technological change uniformly increases the productivity of labour or capital without altering the structure of production or employment. It implies that automation and technological progress serve as a boost to the factors of production, making them more effective without necessarily changing the fundamental nature of the tasks performed. A seminal work that exemplifies this approach is Solow (1957) who laid the foundation for understanding how technology impacts growth through factor augmentation.

Contrary to the factor-augmenting view, the task-based approach (Autor et al. 2003), focuses on the tasks performed by workers and how technology substitutes or complements these tasks. This perspective is particularly relevant in the context of automation, as it considers the possibility that technology may directly substitute for tasks previously performed by humans, potentially leading to job displacement, while also creating new tasks that can complement human skills. The task-based approach provides a framework to analyse the nuanced effects of technological change on labour demand, skill requirements, and wage inequality.

The choice between these two approaches depends on the specific research question at hand. The factor-augmenting approach offers a broader framework for analysing the overall impact of automation on productivity and factor demand. The task-based approach, on the other hand, delves deeper into the specific mechanisms through which automation affects different skill sets and job structures. Both approaches contribute valuable insights into the complex relationship between automation and the labour market.

In the factor-augmenting technological change model, capital and labour are identified as the primary factors. Automation can be considered as form of capital-augmenting technological change that enhances capital productivity (Sachs and Kotlikoff (2012); Graetz and Michaels (2018); Nordhaus (2015)) . However, these models do not account for the shift in labour demand attributable to automation. Conversely, Bessen (2019) conceptualises automation as labour-augmenting technological change, thereby forecasting an increase in labour productivity as a consequence to automation. This perspective aligns with observations of a diminishing labour share, albeit without a corresponding decrease in labour demand.

The task-based approach to modelling automation views a job as an assemblage of individual tasks, some of them susceptible to automation and others not ((Acemoglu and Restrepo 2018b); Acemoglu and Restrepo (2020)). This perspective necessitates careful consideration of the level of granularity at which tasks are observed during empirical analysis. When the analysis focuses on the specific tasks performed by individual workers, the resulting measure is termed an "individual-level automation measure." This approach has been employed by Arntz et al. (2016) and Nedelkoska and Quintini (2018) to estimate automation. In these studies, a job where 70% of the tasks are classified as "automatable" is considered to be at high risk of automation. Using this methodology, Arntz et al. (2016) estimated that 9% of jobs in OECD countries fall into the highly automatable category, while Nedelkoska and Quintini (2018) arrived at a slightly higher estimate of 14%.

The task-based approach extends to measuring automation risk at the occupation level. In this approach, researchers analyse the tasks associated with a particular occupation to assess its overall susceptibility to automation. Frey and Osborne (2017) and Autor et al. (2003) exemplify this approach by utilising the Description of Occupational Titles (DOT) database to estimate automation risk for different occupations. Frey and Osborne (2017) predict that nearly half (47%) of jobs in the US are at risk of automation based on their analysis. In contrast, Autor et al. (2003) focus on the specific types of tasks susceptible to automation. Their research suggests that computers are more likely to substitute for manual tasks and those involving routine information processing. Conversely, computers tend to complement tasks requiring non-routine and complex information processing skills.

The individual-level approach captures the inherent heterogeneity within occupations. Jobs categorised within the same broad occupational group may involve a diverse set of tasks, and individual workers might specialise in different aspects of these tasks. This approach acknowledges this variation and provides a more nuanced understanding of how automation risk affects specific workers within an occupation. In contrast, the occupation-level approach aggregates the tasks associated with a particular occupation to arrive at an overall automation risk assessment. This approach offers the benefit of simplicity and facilitates comparisons across different occupations. However, by aggregating tasks, this approach overlooks the heterogeneity within occupations, potentially underestimating the risk for some workers and overestimating it for others. Automation is a firm's decision on jobs and hence occupation level automation should give an accurate measure of potential of an occupation getting automated, under the assumption all workers in the same job do the same tasks Webb (2019). This paper uses the framework of Nedelkoska and Quintini (2018) for individual level automation and Frey and Osborne (2017) for occupation level automation and use these measures to assess how they are correlated with training.

Additionally, to understand the somehow conflicting claims made about the impact of technological innovation on the labour market, it is important to distinguish between different components of technology. In particular, technology has been varying over the years and so does its impact on jobs. Robots automate manual tasks. Software technology automates routine information processing. Artificial intelligence (AI) does routine information processing and pattern recognition. It is unlikely that the impact of robots is the same as the impact of software on jobs since the tasks automated are different. Webb (2019) calculates the exposure to these three technologies of jobs, looking at patents related to the technologies and the tasks involved in the patent. The higher the number of patents for a particular technology to a task, the higher the exposure to, and thus the risk of, automation. I standardise exposure scores of the technologies, so that it's comparable with other measures[1].

2.2 Human Capital

Human capital encompasses the expertise, abilities, competencies, and other qualities possessed by individuals that enable them to contribute effectively in the production of goods, services, or ideas (Liu and Fraumeni 2020). It is an intangible asset fundamentally linked to the individual and not easily transferable to firms (assumption for this review, aligned with cited references). It can be further break down into three key components: innate abilities, knowledge acquired through formal education, and skills developed through work experience and training (Becker

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[1] The procedure followed to get these standardised exposure scores is described in Section 3

(2009); Blundell et al. (1999)).

The rise of automation presents both challenges and opportunities for the labour market. Automation can either substitute or complement tasks performed by workers (Autor et al. 2003). For tasks replaced by automation, workers may need to find new positions less susceptible to automation, potentially requiring investment in new skills through training. Conversely, when automation complements tasks, workers may need training to effectively utilise the new technology.

Given the potential economic benefits of acquiring new skills, a key question emerges: how do workers and firms decide on human capital investment? Under the assumption of no credit constraints and transferable skills, the decision to invest in training may not solely depend on who finances it (firm vs. worker) but rather on the overall cost of the training itself. However, future wage expectations also play a crucial role. Workers are likely to be more willing to invest in skills today by accepting lower wages if they anticipate increased demand for those skills and higher future wages from firms (Acemoglu 1997). Similarly, firms are more incentivised to invest in innovation when they expect a future workforce with enhanced skills, creating a potential feedback loop between worker investment and firm innovation Lillard and Tan (1986).

Intuitively, the expected future wages of a worker depend on the demand for their skill-set. If automation is leading to the widespread adoption of new technologies across firms, there will be a rise in demand for the skills necessary to operate and maintain these technologies. When the anticipated future wages associated with specific skills are high, workers have a stronger incentive to invest in human capital by acquiring those skills.

Older workers nearing retirement might be less likely to invest in training due to a shorter time horizon to reap the benefits (Acemoglu and Autor 2011). They might prioritise remaining employed in their current role until retirement, even if automation disrupts some tasks, as the investment in new skills might not pay off within their remaining working years. Conversely, younger workers facing a longer career path have more to gain from acquiring skills that complement evolving technologies (Brynjolfsson and McAfee 2014). Their investment in training could lead to higher future wages and career advancement opportunities.

The cost-benefit analysis of training is likely to vary based on an individual's educational attainment. Workers with higher levels of education might possess better cognitive skills and learning strategies that facilitate the acquisition of new knowledge and skills (Hanushek and Kimko 2000). This can make them more adaptable to technological changes and potentially reduce the perceived time and effort required for training. Additionally, individuals with higher educational attainment might have greater access to resources like financial aid or employer-sponsored training programs, further reducing the cost barrier associated with skill development.

This study explore the relationship between different automation metrics (e.g., individual-level vs. occupation-level) and workers' training incidences.

3 Data

This section outlines the data sources and key variables employed in my analysis of human capital investment and automation risk.

3.1 Data Preparation

3.1.1 Individual level data

The primary data source for this study is the Programme for the International Assessment of Adult Competencies (PIAAC). PIAAC is a large-scale international survey designed to assess the skills and competencies of adults. While PIAAC has undergone multiple cycles of data collection, the first cycle (PIAAC 1) holds particular relevance for research on human capital and automation. PIAAC 1 data collection spanned over several years, with the initial round starting in 2011 and concluding around 2018. This time frame coincides with the early stages of heightened discussions and concerns surrounding automation and its potential impact on the workforce.

Training in PIAAC is primarily assessed through self-reported data collected via structured survey questions. Respondents are asked whether they have participated in training activities over the past 12 months, with further distinctions made between formal and non-formal education. Formal education refers to structured programs that lead to recognized qualifications, while non-formal education includes job-related training, workshops, and courses that do not necessarily result in formal certification. The survey also gathers information on various characteristics of training episodes, including their duration, purpose, funding source, and mode of delivery. PIAAC categorizes training as employer-sponsored or self-initiated, capturing differences in how training is accessed and financed. Additionally, respondents indicate the primary reasons for undertaking training, such as job requirements, career advancement, or personal interest. By incorporating these details, PIAAC provides a comprehensive framework for understanding adult participation in learning activities.

PIAAC also assesses adult skills in three primary domains: literacy, numeracy, and problem-solving in technology-rich environments. Literacy measures the ability to understand, evaluate, and engage with written texts, while numeracy assesses the capacity to interpret, use, and communicate mathematical information. The problem-solving domain evaluates the ability to use digital technologies to access, evaluate, and manage information. These competencies are measured through direct assessment tasks, administered via computer or paper-based formats, and results are reported on a continuous proficiency scale, enabling cross-country comparisons and in-depth analysis of skill distributions.

PIAAC collects demographic information about respondents, including age, education level, occupation and tasks in occupation including the usage of Internet and Communication Technology skills (ICT), and work experience. This data allows me to control for factors that may influence human capital investment decisions outside of automation risk. PIAAC surveys individuals on their participation in formal and informal training activities within the past twelve months. This data provides a direct measure of an individual's recent investment in human capital development. PIAAC captures information about the specific tasks performed by workers in their occupations. This data allows me to construct individual-level automation risk measures based on the susceptibility of these tasks to automation. However, it is important to acknowledge that PIAAC relies on self-reported data, which can introduce potential biases.

3.1.2 Crosswalks

This analysis integrates automation risk measures with data from the Programme for the International Assessment of Adult Competencies (PIAAC). However, a key challenge arises due to the differing occupational coding systems employed by PIAAC and the source of automation risk scores. PIAAC utilises the International Standard Classification of Occupations (ISCO), while automation risk scores are calculated within the framework of the Occupational Information Network (O*NET) and its Standard Occupational Classification (SOC) system.

To address this incompatibility and facilitate data integration, we leverage a crosswalk provided by the Bureau of Labor Statistics (BLS). This crosswalk acts as a mapping tool, enabling the association of automation risk scores derived from the O*NET/SOC framework with their corresponding ISCO codes used in PIAAC. It's important to acknowledge the nature of this crosswalk. Unlike a one-to-one mapping, the BLS crosswalk exhibits a many-to-many relationship between O*NET SOC and ISCO-2008 codes. This implies that a single O*NET SOC code can potentially map to multiple ISCO-2008 codes, and vice versa.

To navigate this many-to-many mapping challenge within the context of the empirical analysis, the following strategy is adopted: whenever an O*NET SOC code maps to multiple ISCO-2008 codes in the BLS crosswalk, the average automation risk score across all the corresponding O*NET SOC jobs is assigned to the relevant ISCO-2008 code in the PIAAC data.

By employing this approach, we effectively bridge the gap between the two occupational coding systems and ensure the successful integration of automation risk measures with PIAAC data for further analysis. This allows economists to examine the relationship between automation risk and various worker skills and competencies as measured by PIAAC.

3.1.3 Measures of Automation

Task automation is a binary decision, but the probability of automation is calculated by the tasks associated with the job (Autor et al. (2003); Acemoglu and Restrepo (2018a)). The idea is that every job consists of a number of tasks and some of these tasks can be perfectly automated and some cannot. When these tasks are observable the probability of a job getting automated can be calculated.

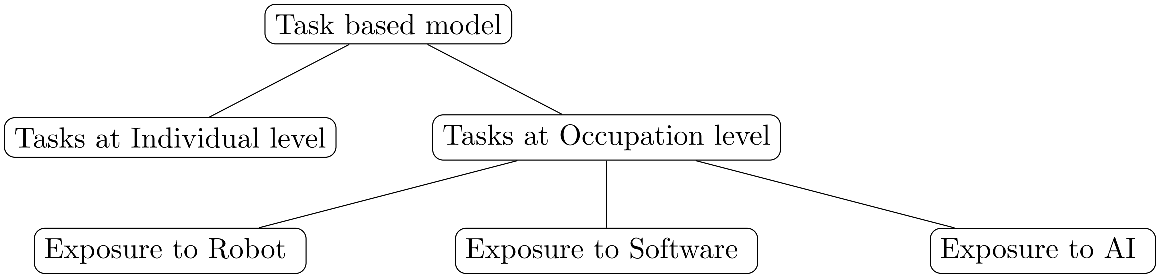

Figure 3.1: Hierarchy of measures of automation used in analysis of this paper

A worker carries out multiple tasks to "complete" his/her job. Similarly, every job has certain tasks associated with it. The tasks associated with a job can be measured at multiple dimensions: two such being individual or occupation level of tasks, and technology. The paper uses the terms individual level automation when the tasks done by worker are used to calculate the automation risk, and occupation level automation when tasks associated with a job are used (Figure 3.1). The paper uses the framework of Nedelkoska and Quintini (2018), for individual level automation and Frey and Osborne (2017), for occupation level automation. Webb (2019), calculates the exposure of robotization, software and AI to a particular job. This exposure to the three technologies is standardised and is matched on the occupation.[2]

Nedelkoska and Quintini (2018), present an individual-level approach that leverages PIAAC to construct individual-level automation risk measures. PIAAC surveys collect information from individual respondents about the tasks they perform in their jobs. This data typically involves respondents reporting the frequency and importance of various tasks associated with their occupations. Existing research classifies tasks based on their susceptibility to automation. Tasks requiring routine cognitive skills, manual dexterity, or following well-defined procedures are generally considered more susceptible to automation. Conversely, tasks requiring creativity, complex problem-solving, or social interaction are typically considered less susceptible. Using a logistic regression, the estimate the relationship between reported task characteristics and expert classifications of automation risk. This analysis allows them to develop a model that predicts the automation risk of a particular individual based on their tasks performed at job.

Frey and Osborne (2017), propose a methodology to assess automation potential of occupations using the Occupational Information Network (O*NET) database. O*NET offers both standardised variables quantifying skills (e.g. dexterity) and open-ended task descriptions. The authors address limitations of existing subjective or O*NET-based methods by combining them. First, researchers hand-labelled a subset of occupations as automatable or non-automatable based on O*NET task descriptions. Second, they identified key O*NET variables posing challenges to automation (e.g. creativity). A probabilistic classification algorithm was then developed to analyse the relationship between these variables and the hand-labelled data. This allowed the algorithm to predict the automation probability for all occupations in the dataset, leveraging O*NET

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[2] Table B.1 in appendix summarises the measures of automation used in the paper.

data to refine subjective expert judgements and providing a more nuanced understanding of automation risk across different occupations.

Webb (2019), proposes a method to quantify exposure to technology for different occupations. It utilises two key sources of information: patent text describing technological capabilities and job description text outlining worker tasks. By analysing these texts through natural language processing, the method identifies verb-noun pairs that represent specific actions within each domain (e.g., ”diagnose condition” in a doctor’s job description). The overlap between these pairs across patents and job descriptions is then measured. Essentially, the more patents related to a technology (AI, software and Robot) contain verb-noun pairs similar to those found in a specific occupation’s tasks, the higher the exposure score for that occupation to that technology. This score reflects the potential for automation by that technology, as it indicates how many tasks within the occupation could be replaced. By aggregating these task-level scores, the method calculates an overall exposure score for each occupation to a particular technology. This measure is forward looking - as the patent are not yet in use; while the previous measures where backward looking.

Table 3.1: Correlation of Measures of Automation

	AI	Software	Robotization	Individual	Occupation
AI	1				
Software	0.620 ***	1			
Robotization	0.121***	0.571***	1		
Individual				1	
Occupation				0.356***	1

* $p < 0.05$, ** $p < 0.01$, ** $p < 0.001$

Table 3.1 presents the correlations between various measures of automation employed in this study. Looking at the table, we see interesting patterns. There’s a strong positive correlation between AI and software exposure (0.620), which is unsurprising. Both technologies often work together, with AI performing tasks like pattern recognition that complement software’s routine information processing capabilities. Similarly, a strong positive correlation exists between software and robotization (0.571). While robots primarily handle physical tasks, they often rely on software for control and information processing, explaining this connection.

However, the correlation between individual and occupation-level automation measures is notably lower (0.356). This suggests that while an occupation might be susceptible to automation due to its inherent tasks, the specific tasks assigned to individual workers within that occupation can vary. This highlights the importance of considering both individual and occupational factors when assessing automation risk.

3.1.4 Technological Readiness

This section explores the potential moderating effect of a country's level of technological readiness on the relationship between automation risk and human capital investment. Technological readiness reflects a nation's capacity for adopting and integrating new technologies, particularly in relation to Information and Communication Technologies (ICT). As a key determinant of economic adaptability, it influences the extent to which automation risk translates into shifts in workforce skill requirements and training investments.

To quantify technological readiness, this analysis utilizes data from the World Economic Forum's Global Competitiveness Index (GCI). The GCI assesses countries across multiple dimensions, including:

- Speed of Technological Adoption: This metric evaluates how rapidly a country adopts emerging technologies, serving as an indicator of its overall capacity for technological advancement and economic transformation.
- ICT Use: This component measures the extent of ICT penetration and utilization within a country. It encompasses indicators such as the percentage of internet users, broadband subscriptions per capita, available internet bandwidth, and mobile phone penetration rates.

These variables collectively offer insight into the degree to which digital infrastructure supports economic and labour market adaptation.

For the purposes of this study, the technological readiness score is calculated as the average value for each country between 2008 and 2013. This approach ensures consistency in measurement across nations while accounting for potential year-to-year fluctuations in the GCI's specific assessment criteria. Since the methodology for computing technological readiness may vary slightly across GCI reports, a detailed breakdown of its composition for the relevant years is provided in a later section (see Table A.1 in the appendix for specific country values).

The technological readiness score operates on a scale ranging from 1 to 7, where higher values indicate a greater degree of technological integration and infrastructure development. The mean score across the countries included in this analysis is 4.95, with a standard deviation of 0.68. However, substantial cross-country variation is evident, reflecting differences in national policies, digital infrastructure, and economic conditions.

For example, countries such as the Netherlands (5.96), Denmark (5.92), and the United Kingdom (5.77) exhibit high levels of technological readiness, suggesting robust digital infrastructure and widespread ICT adoption. Conversely, countries like the Russian Federation (3.59) and Turkey (3.84) report lower scores, indicating comparatively weaker technological integration. These disparities are crucial in understanding how automation risk and workforce training decisions might vary across different national contexts.

By incorporating this measure of technological readiness into the analysis, we can explore how differences in a country's technological landscape are associated with variations in the relationship between automation risk and human capital investment. Specifically, this approach enables an assessment of whether workers in countries with higher levels of technological readiness tend to report different patterns of skill acquisition in response to automation risk compared to those in countries with lower levels of ICT infrastructure and digital adoption.

By combining data from these diverse sources, I am able to create a comprehensive dataset that allows me to investigate the relationship between automation risk, worker characteristics, human capital investment decisions, and the moderating influence of technological readiness.

3.2 Descriptive Statistics

The final dataset integrates individual-level worker information encompassing demographics, human capital investment decisions, and corresponding automation risk measures. This data is structured such that each worker's human capital investment decision is linked to their occupational category, and both are further linked to the automation risk associated with that occupation. Additionally, the dataset includes individual-level information on the specific tasks workers perform within their occupations and individual level automation risk.

Table 3.2 shows, in PIAAC nearly half (46.5%) of the workers participated in some form of training. Interestingly, computer usage at work is quite prevalent, with 64% of workers reporting using computers. In the sample On average, workers reported that approximately a quarter (26%) of their tasks involved were exposed to with AI advancements. This exposure, however, exhibited substantial variation as evidenced by the standard deviation of 0.15. Software use for tasks was present for 17% of workers on average, with a relatively low standard deviation, suggesting more consistency in software usage. Notably, robot interaction was reported by 16% of workers on average, but with a very high standard deviation of 0.18, pointing to significant variation in robot integration across different job roles. Overall, the individual automation risk based on job tasks averaged 0.480, but it's important to note that this risk varied considerably across the sample.

In terms of broader demographics, the sample displayed a relatively high level of technological readiness on average, with a score of 4.949 and a low standard deviation. This suggests a generally tech-savvy group. Additionally, the sample included roughly equal proportions of men and women (around 50% each). Finally, the average educational attainment within the sample was 13 years, with a low standard deviation, indicating a relatively consistent level of education among the participants.

Software Risk and Age: Software risk exhibits a positive correlation with age. This could be explained by the growing prevalence of software across various occupations as workers gain experience and potentially move into roles that rely more heavily on software tools.

Table 3.2: Summary Statistics

	Observations	Mean	SD
Human Capital Investment	100116	0.46	0.50
AI exposure (Occupation)	72,261	0.26	0.15
Software exposure (Occupation)	72,261	0.17	0.10
Robotization (Occupation)	72,261	0.16	0.18
Automation - Individual	88,512	0.48	0.20
Automation-Occupation	69,384	0.52	0.35
Experience with computer in job	89,288	0.64	0.48
Age	100116	40.27	13.30
Average Readiness of Country	100125	4.95	0.68
Numerical Score (standardised)	100099	-0.00	1.00
Years of education	99,397	12.79	3.08
Female	100114	0.50	0.50

The table contains the summary of main variables used in the analysis.

3.2.1 Age Profile

Figure 3.2 shows the relationship between automation risk and worker age, revealing a more nuanced picture than initially apparent. While both individual and occupation-level automation risk tend to be higher for younger workers, a closer look at specific automation technologies uncovers some interesting variations.

Individual and Occupation Level Measure of Automation: Younger workers, particularly those in their 20s, appear to face a higher risk of automation compared to their older counterparts above 30. This observation could be partially explained by the typical career trajectory. Younger workers often enter the workforce with less experience and specialised skills, potentially leading to an initial concentration in routine, manual tasks that are more susceptible to automation. As workers gain experience and potentially pursue further education, they may transition into occupations less vulnerable to automation.

Robotization Risk and Age: A U-shaped pattern emerges for robotization risk. Young workers face a higher risk compared to middle-aged workers, potentially due to their concentration in jobs involving manual tasks that are prime targets for robots. However, the risk rises again for older workers, possibly reflecting the increasing adoption of robots in tasks requiring some experience or physical capabilities that younger workers might lack.

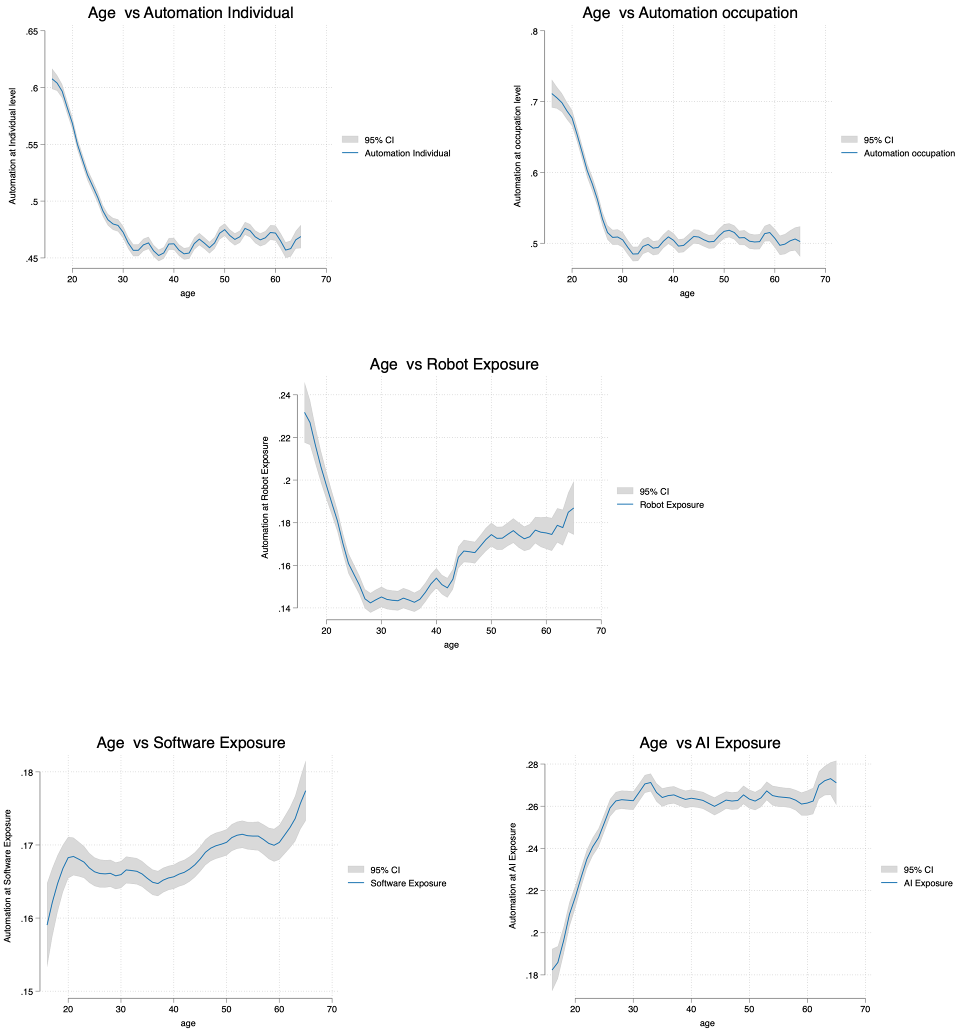


Figure 3.2: Descriptive for Age Profile. Plot 3.2a shows the smoothed curve of individual-level automation risk; Plot 3.2b shows the smoothed curve of occupation-level automation risk; Plot 3.2c shows the smoothed curve of standardised exposure to robot technology; Plot 3.2d shows the smoothed curve of standardised exposure to software technology; Plot 3.2e shows the smoothed curve of standardised exposure to AI technology

AI Risk and Age: AI risk displays a sharp increase with age, followed by a plateau for middle-aged and older workers. This suggests that while AI adoption might initially be limited for younger workers, it rises significantly in middle age, potentially reflecting the increasing complexity of tasks and the demand for problem-solving skills that AI can complement.

3.2.2 Wage Profile

Figure 3.3 depicts the relationship between wage earned by workers (in deciles) and automation risk. The results suggest that jobs offering lower wages tend to exhibit a higher likelihood of automation. This aligns with the notion that routine, manual tasks are often compensated at lower wages and are therefore prime targets for automation technologies.

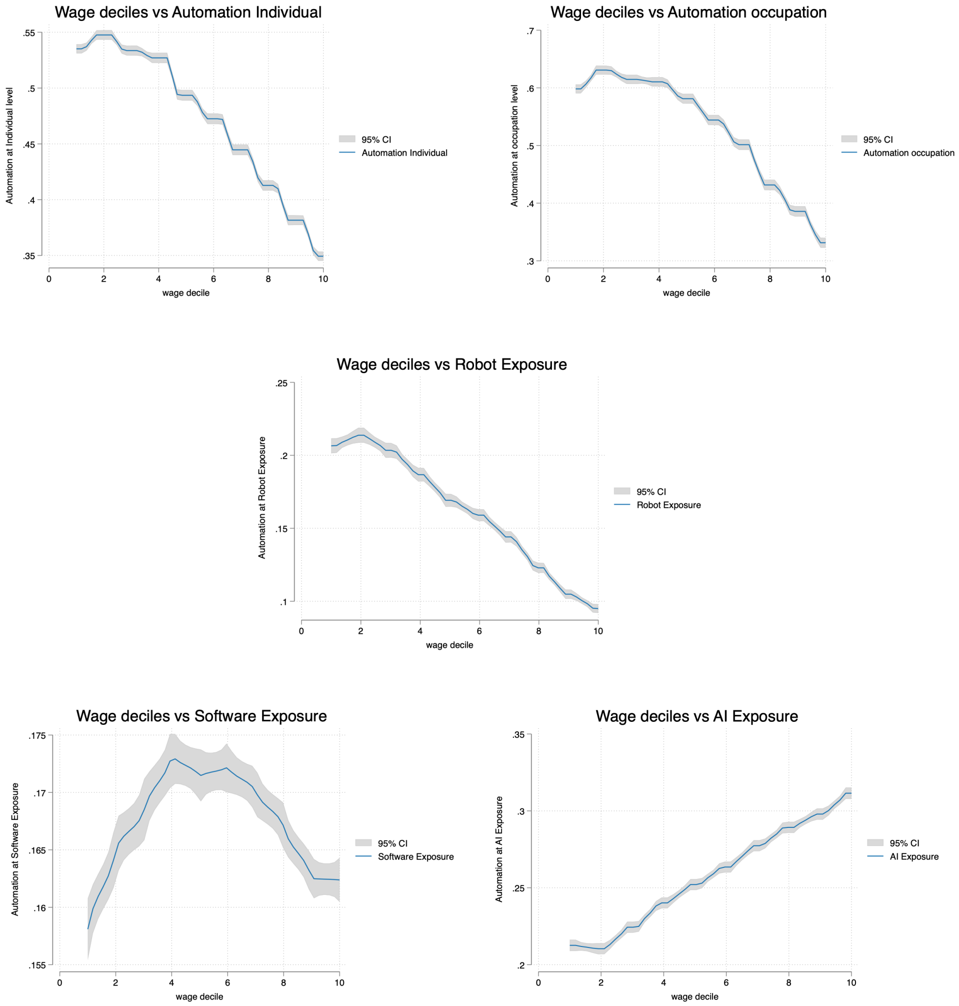


Figure 3.3: Descriptive for Wage Profile. Plot 3.3a shows the smoothed curve of individual-level automation risk ; Plot 3.3b shows the smoothed curve of occupation-level automation risk ; Plot 3.3c shows the smoothed curve of standardised exposure to robot technology; Plot 3.3d shows the smoothed curve of standardised exposure to software technology; Plot 3.3e shows the smoothed curve of standardised exposure to AI technology

Interestingly, software risk exhibits a different pattern. The analysis suggests that jobs in the middle-wage range might face a higher risk of automation due to software adoption. This could be attributed to the increasing pervasiveness of software tools across various occupations. As tasks become more reliant on software for data analysis, automation, and routine processes, jobs in this wage bracket might become more susceptible to displacement. These findings potentially support the argument made by Michaels et al. (2014) regarding the polarising effects of information and communication technologies (ICT) on the labour market.

AI risk, however, paints a contrasting picture. The results indicate that high-wage jobs face the highest risk of automation due to AI, corroborating the results by Webb (2019). This suggests that AI might be displacing jobs requiring higher levels of skills and experience. This finding aligns with the notion that AI excels at tasks involving complex problem-solving, pattern recognition, and data analysis, often associated with high-skilled, high-wage occupations. By automating these tasks, AI could potentially substitute for some of the skills traditionally performed by such workers.

Combining these findings suggests a potential skill polarisation effect driven by automation. While routine, manual tasks associated with lower wages are susceptible to automation, AI seems to be targeting high-wage jobs requiring advanced skills. This might lead to a hollowing out of the middle-wage jobs as software automates routine tasks, potentially exacerbating income inequality.

3.2.3 Education Profile

Figure 3.4 and figure 3.5 explore the relationship between education levels and automation risk, highlighting the importance of human capital investment in the face of automation.

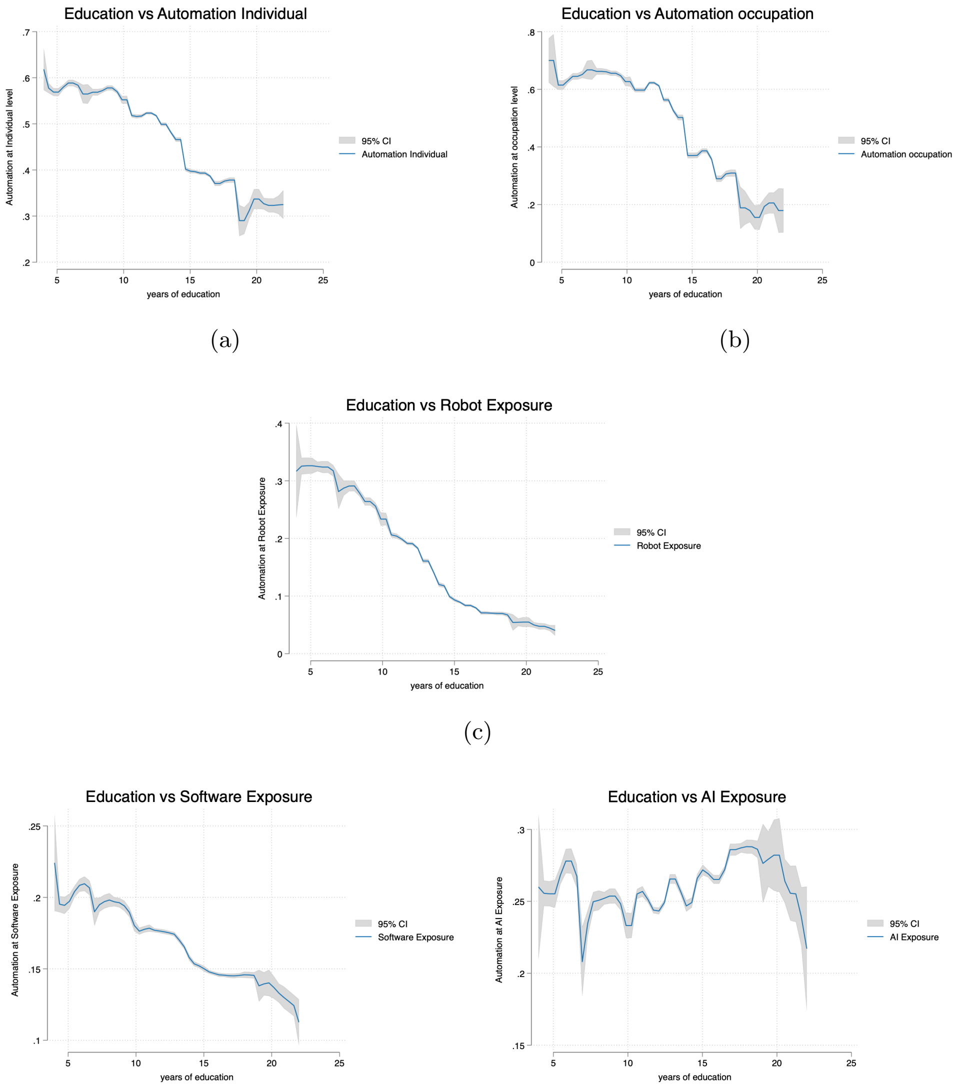
Individual and Occupation Level Measure of Automation: The analysis reveals a clear negative correlation between education and automation risk, both at the individual and occupational levels. Workers with fewer years of formal education, typically those with a high school diploma or less, face a significantly higher risk of automation compared to their more educated counterparts. This aligns with the notion that automation technologies often target routine, manual tasks which require less complex skill sets (Figure 3.5).

Robotization Risk and Education: Similar to the overall trend, robot automation risk exhibits a positive correlation with lower education levels. Jobs requiring less education often involve routine manual tasks that are prime targets for robotization.

Software Risk and Education: Software risk appears to decrease with increasing education. This could be because software tools are increasingly integrated across various occupations. Workers with higher levels of education might be better equipped to leverage and adapt to software-driven workflows, potentially reducing their risk of displacement.

AI Risk and Education: AI risk displays a more complex relationship with education. While the risk generally increases with education levels, it appears to plateau for highly educated workers. This aligns with some existing research by Webb (2019) suggesting that AI might contribute to a reduction in income inequality between the very high earners and the rest of the population. The explanation could lie in the fact that AI excels at tasks requiring advanced skills currently performed by highly educated workers. However, AI adoption itself might create new high-skill job opportunities, mitigating the risk of displacement for the most educated segment of the workforce.

In short the data shows a multifaceted relationship between automation and worker character-



(a) (b)

(c)

(d) (e)

Figure 3.4: Descriptive for Education Profile. Plot 3.4a shows the smoothed curve of individual-level automation risk ; Plot 3.4b shows the smoothed curve of occupation-level automation risk ; Plot 3.4c shows the smoothed curve of standardised exposure to robot technology; Plot 3.4d shows the smoothed curve of standardised exposure to software technology; Plot 3.4e shows the smoothed curve of standardised exposure to AI technology

istics. Younger workers and those with lower education face a higher risk of automation due to their concentration in routine tasks susceptible to automation technologies. However, the impact of specific automation technologies varies. Robotization risk exhibits a U-shaped pattern, impacting younger and older workers more. Software adoption seems to disproportionately affect middle-wage jobs, potentially supporting the argument of ICT-induced skill polarization. Conversely, AI targets high-wage, high-skilled jobs, potentially exacerbating income inequality. Education emerges as a critical factor in mitigating automation risk. Workers with higher

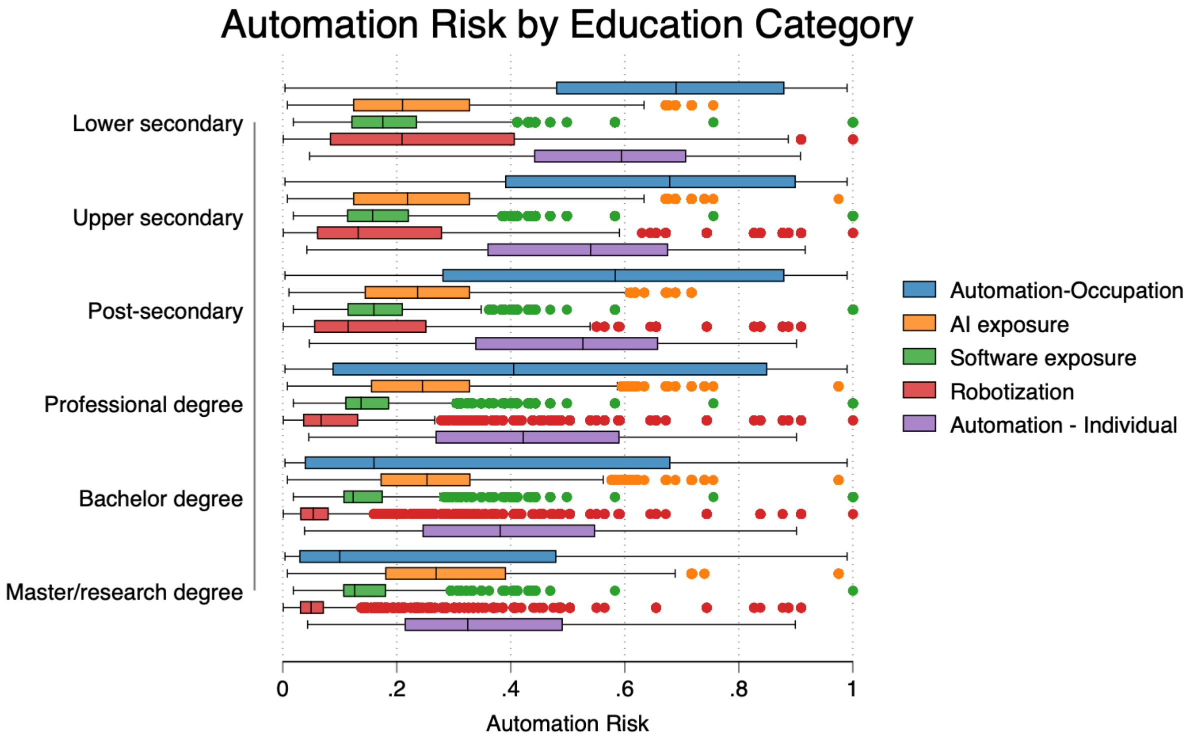


Figure 3.5: Box plot of Automation risk with educational categories

education possess skill sets that are more adaptable and less susceptible to automation across different technologies. These findings suggest that automation might have a polarising effect on the labour market, highlighting the importance of education and skill development strategies as crucial tools for navigating the changing technological landscape.

3.2.4 Training and automation

Figure 3.6 depicts the relationship between the incidence of training received by workers and various measures of automation risk. The curves associated with each automation measure exhibit a generally negative slope, indicating that workers facing lower levels of automation risk are more likely to have received training. This suggests a potential association between training and skills that might mitigate the threat of automation. However, it's important to acknowledge the widening confidence intervals around higher automation values. This implies a degree of uncertainty in the relationship for highly automated occupations. While the overall trend suggests a negative association, we cannot definitively rule out the possibility of a different relationship existing for these high-risk jobs due to the larger margin of error in the estimates. The following section delves deeper into the validity of this observed relationship by employing appropriate statistical techniques to account for potential confounding factors.

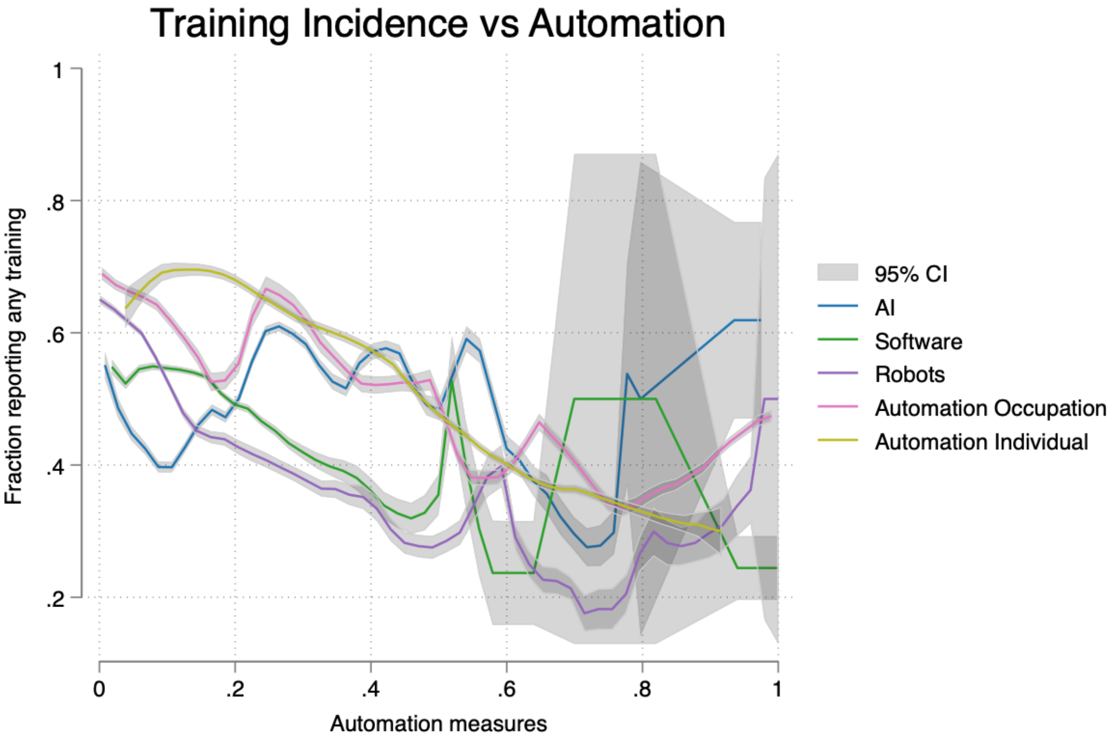


Figure 3.6: Training Incidence vs Automation

4 Empirical Strategy

For the purpose of this analysis, I consider automation as being primarily shaped by strategic decisions at the firm level. This approach emphasizes the role of job types rather than focusing on granular task-based analysis, enabling an investigation of broader patterns within the workforce. Following the framework outlined by Acemoglu (1997) regarding training and technological change, workers may engage in human capital investment if they perceive potential benefits, such as higher expected future earnings. This process could involve acquiring new skills or enhancing existing ones to adapt to an evolving labour market influenced by automation.

The implementation of automation technologies is associated with changes in skill requirements, as firms integrating automation may rely on a workforce that possesses the necessary competencies to operate effectively within a technologically advanced environment. In this context, worker skills may be relevant to the extent that they align with the evolving demands of firms. Technological readiness at the national level may also be relevant in shaping the environment in which automation is adopted. Factors such as digital infrastructure, ICT penetration, and the overall technological capacity of a country could influence the extent to which firms integrate automation into their production processes. A higher level of technological readiness might be associated with fewer barriers to automation adoption, potentially influencing the pace at which firms implement these technologies. Additionally, the characteristics of a country's workforce, particularly its skill composition, could be related to firms' ability to adopt new technologies. The availability of skilled workers may influence the feasibility of automation adoption, as firms operating in environments with a high-skilled workforce may find it more straightforward to integrate new technologies. Understanding the interplay between worker skills, human capital investment, and automation provides insight into how different labour markets engage with technological change.

In this study, I employ a three-level multilevel model to estimate the probability of human capital investment, taking into account automation risk at both the individual and occupational levels while accounting for variation across countries. This approach is motivated by the need to properly account for the hierarchical nature of the data and to ensure that variance components at different levels are appropriately estimated. Hierarchical Linear Modelling (HLM) or multi level modelling is a statistical approach specifically designed to analyse data with nested structures, allowing for the explicit modelling of hierarchical dependencies (Raudenbush and Bryk (2002) Snijders and Bosker (2012)). This methodology is particularly appropriate when data are organized at multiple levels, such as individuals nested within occupations, which are in turn nested within countries. Traditional regression techniques assume independence of observations, which is violated in hierarchical data structures, potentially leading to incorrect statistical inferences (Gelman and Hill 2007). Multilevel models address this issue by incorporating random effects that account for between-group variation, allowing for more accurate parameter estimation.

The general form of the hierarchical model can be expressed as follows:

$$HCI_{ijk} = \beta_0 + \beta_1 \mathit{Auto\_Individual}_{ijk} + \beta_2 \mathit{Auto\_occupation}_{jk} + \sum_m \beta_m \mathrm{X}_{ijk} + u_j + u_{kj} + r_{ijk}, \quad (1)$$

where:

- HCI_{ijk} - human capital investment for individual i, in occupation k, within country j.
- $\mathit{Auto\_Individual}_{ijk}$ captures automation risk at the task level for the individual.
- $\mathit{Auto\_occupation}_{jk}$ captures automation risk at the occupational level.
- u_j denotes the country-level random effect, accounting for variation in training propensity across countries.
- u_{jk} represents the occupation-level random effect nested within countries.
- r_{ijk} is the individual-level residual.

A key assumption in this multilevel model is that the random effects at each level are normally distributed with a mean of zero:

$$u_{0j} \sim N(0, \tau_j^2), \quad u_{0k(j)} \sim N(0, \tau_k^2), \quad r_{ijk} \sim N(0, \sigma^2). \tag{2}$$

This model structure allows us to estimate the probability of an individual engaging in training, considering the average occupational automation risk within a given country. By incorporating random effects at both the country and occupation levels, we explicitly model the variation in training behaviour that arises due to structural factors beyond individual characteristics. This approach is particularly important in labour market studies, where macro-level factors such as national policies and industrial composition influence individual-level decisions (Goldstein, 2011). A key assumption in multilevel modelling is that the random effects at each level are normally distributed with a mean of zero. This assumption ensures that unobserved heterogeneity at higher levels does not introduce systematic bias into the estimation of fixed effects. Additionally, it assumes that the within-group residuals are independent and homoskedastic Raudenbush and Bryk (2002). These assumptions allow us to disentangle individual, occupational, and national influences on human capital investment.

Multilevel models offer several advantages over traditional regression techniques. First, they allow for the estimation of variance components, providing insights into how much variation in training participation is attributable to differences at the country and occupational levels. Second, they enable the inclusion of cross-level interactions, which makes it possible to explore how country-level factors (such as technological readiness) moderate the relationship between automation risk and training investment. Finally, by appropriately modelling the data hierarchy, multilevel models enhance the precision and validity of statistical inferences, making them particularly suited for policy-relevant research. To account for unobserved heterogeneity specific to country,the standard error are clustered around the country.

The concept of human capital investment in this study focuses on the training decisions made by individual workers i. This is done by a binary variable, denoted by hci_i. The variable takes a value of 1 if the worker participated in any form of training during the year preceding the survey, encompassing on-the-job training, seminars/workshops, private lessons, or open/distance education. Conversely, a value of 0 indicates no training participation. Measure of automation used are individual level, occupation level and exposure to robot, software, and AI. To account for the national context of automation adoption, the analysis incorporates a measure of technological readiness. This variable is observed at the country level where the worker resides and reflects the nation's overall capacity for technological integration and utilisation of information and communication technologies. PIAAC provides three measures of skill for each worker based on the individual's performance on tasks that assess their ability to perform in literacy, numeracy and problem solving.

The following covariates aim to isolate the specific effects of human capital investment and skill development on automation risk.

- Age: Age is categorised into distinct groups reflecting typical career stages: "school age (16-19)," "entry age (20-29)," "prime age (30-44)," "prime age 2 (45-54)," and "exit age (55-65)." This allows us to capture the potential variation in automation risk faced by workers at different points in their careers.
- Type of Employment: The analysis focuses on workers with an active employment status. This category is further subdivided into "full-time employed," "part-time employed," "student," "apprenticeship," and "unemployed." This distinction is crucial as employment type might influence training opportunities and automation exposure.
- Education: The International Standard Classification of Education (ISCED)-7 is used to categorise worker education levels. This classification system provides a standardised framework for comparing educational attainment across different countries.
- ICT Skills at Work: The analysis also considers whether workers utilise information and communication technology (ICT) skills in their current jobs. This variable helps us understand how digital literacy and comfort with technology might influence training decisions and automation risk.
- Industry: The International Standard Industrial Classification (ISIC) at the one-digit level categories the industry in which workers are employed. This allows us to account for potential industry-specific trends in automation adoption and skill demands.

All covariates are included as categorical variables. This allows the model to capture non-linear relationships between these factors and automation risk. For instance, the impact of age on automation risk might not be linear, with younger and older workers potentially facing higher risks compared to those in their prime working years.

Incorporating these covariates allows us to conduct a rigorous analysis that isolates the specific effects of human capital investment and skill development on automation risk, while controlling for potential confounding factors related to worker demographics, employment status, industry context, and unobserved heterogeneity.

5 Results

5.1 Do workers in automatable jobs invest in their human capital?

This section delves into the empirical results of the study, focusing on how automation risk influences workers' decisions to invest in human capital. Table 5.1 presents the estimated coefficients of the model detailed in equation (1) for the automation measure.

The regression results suggest that automation at the individual level is significantly associated with a reduction in training incidence (-0.217), implying that individuals in more automated environments may receive less training. Similarly, automation at the occupational level also shows a negative association (-0.0792). These findings align with Lillard and Tan (1986) who argue that employer-provided training is influenced by perceived returns on investment and Nedelkoska and Quintini (2018). In heavily automated jobs, firms may perceive diminishing returns on training, leading to lower training incidence. This echoes the concerns raised by Harris (1999), who noted that technological advancements can reduce firms' incentives to invest in upskilling employees when task automation is feasible. At the same time, the positive coefficient for "Average Readiness of Country" (0.0990) indicates that national-level readiness mitigates the negative impact of automation. In countries with strong institutional support for workforce training, automation exposure may be less likely to discourage human capital investment, as public policies and employer initiatives can help mitigate potential displacement risks.

The data show that training incidence is highest among young workers, particularly in the 20–29 age cohort (0.186), with a gradual decline as age increases. This trend supports Lillard and Tan (1986), who find that firms prioritize training for younger employees due to their longer expected tenure, making investment in human capital more economically viable. Education emerges as a significant predictor of training incidence, worker with tertiary degrees (bachelor's: 0.121; master's: 0.115) being associated with a higher likelihood of training participation. This supports Green et al. (2016), who argue that higher educational attainment facilitates continuous learning and workforce adaptability.

The regression estimates suggest that problem-solving skills are a strong predictor of training incidence (0.0288), while numerical and literacy skills show no statistically significant effect. Their framework suggests that firms are more likely to train individuals with higher cognitive flexibility, which is consistent with the observed positive association. Furthermore, ICT skills at work significantly predict training incidence (0.139), reinforcing the notion from Blundell et al. (1996) that digital skills are increasingly becoming prerequisites for workplace learning and career progression in automated environments.

Firm size is another key determinant of training incidence. Employees in larger firms (e.g., firms with more than 1000 employees: 0.132) are more likely to receive training, consistent with Harris (1999), who highlight that large firms have greater resources to invest in workforce development compared to small enterprises. In contrast, employment status plays a major role, as part-time workers (-0.0379), students (-0.0781), and retirees (-0.194) have significantly lower training incidence compared to full time workers. These findings align with Harris (1999), who suggests that precarious or non-traditional employment reduces employer incentives for training investment. The second regression table highlights industry-specific variations, with financial and insurance activities (0.133), mining (0.105), and human health (0.0715) showing higher training incidence. Conversely, industries such as accommodation and food services and manufacturing exhibit lower(non significant) training rates. This is in line with Blundell et al. (1996), who emphasize that knowledge-intensive industries are more likely to engage in workforce development due to higher skill requirements and technological dynamism. The low training incidence in traditional sectors, such as manufacturing, is also consistent with Lillard and Tan (1986), who note that industries with high turnover rates are less likely to invest in training.

Table 5.1: Training incidence for automation at level of tasks done

	hci	
Automation - Individual	-0.217***	(0.018)
Automation-Occupation	-0.079***	(0.010)
Average Readiness of Country	0.099***	(0.027)
Numerical Score (standardized)	-0.005	(0.009)
Literacy score (standardized)	0.009	(0.009)
Problem solving score (standardized)	0.029***	(0.008)
Skill use work - ICT - Experience with computer in job	0.139***	(0.011)
Age cohorts(16-19)	0.000	(.)
Age cohorts(20-29)	0.186***	(0.033)
Age cohorts(30-44)	0.152***	(0.038)
Age cohorts(45-54)	0.157***	(0.039)
Age cohorts(55-65)	0.139***	(0.042)
Firm size - 1 to 10 people	0.000	(.)
Firm size - 11 to 50 people	0.048***	(0.009)
Firm size - 51 to 250 people	0.086***	(0.009)
Firm size - 251 to 1000 people	0.119***	(0.014)
Firm size - More than 1000 people	0.132***	(0.021)
Lower secondary or less (ISCED 1,2, 3C short or less)	0.000	(.)
Upper secondary (ISCED 3A-B, C long)	0.056***	(0.011)
Post-secondary, non-tertiary (ISCED 4A-B-C)	0.070***	(0.021)
Tertiary – professional degree (ISCED 5B)	0.117***	(0.012)
Tertiary – bachelor degree (ISCED 5A)	0.121***	(0.018)
Tertiary – master/research degree (ISCED 5A/6)	0.115***	(0.013)
female=0	0.000	(.)
female=1	-0.002	(0.005)
Full-time employed (self-employed, employee)	0.000	(.)
Part-time employed (self-employed, employee)	-0.038***	(0.011)
Unemployed	-0.033	(0.025)
Pupil, student	-0.078**	(0.038)
Apprentice, internship	-0.091**	(0.045)
In retirement or early retirement	-0.194***	(0.030)
Permanently disabled	-0.033	(0.059)
In compulsory military or community service	-0.128	(0.135)
Fulfilling domestic tasks or looking after children/family	-0.183***	(0.029)
Other	-0.050	(0.032)
The private sector	0.000	(.)
The public sector	0.053***	(0.015)
A non-profit organisation	0.080***	(0.014)
Constant	-0.184	(0.139)
var(_cons[cntryid])	0.006***	(0.002)
var(_cons[cntryid>isco08_c])	0.005***	(0.001)
var(e.hci)	0.188***	(0.005)
Observations	36740	

Standard errors in parentheses

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

Table 5.2: Coefficients for Industry

	hci	
Agriculture, forestry and fishing	0.000	(.)
Mining and quarrying	0.105***	(0.040)
Manufacturing	-0.005	(0.026)
Electricity, gas, steam and air conditioning supply	0.089**	(0.044)
Water supply; sewerage, waste management and remediation activities	0.040	(0.041)
Construction	-0.011	(0.029)
Wholesale and retail trade; repair of motor vehicles and motorcycles	-0.008	(0.025)
Transportation and storage	0.017	(0.028)
Accommodation and food service activities	-0.033	(0.022)
Information and communication	0.012	(0.021)
Financial and insurance activities	0.133***	(0.024)
Real estate activities	0.011	(0.030)
Professional, scientific and technical activities	0.026	(0.026)
Administrative and support service activities	0.031	(0.025)
Public administration and defence; compulsory social security	0.049*	(0.028)
Education	0.060**	(0.027)
Human health and social work activities	0.072***	(0.025)
Arts, entertainment and recreation	0.036	(0.027)
Other service activities	0.060**	(0.028)
Activities of households as employers	-0.103*	(0.056)
Activities of extraterritorial organizations and bodies	0.124**	(0.055)
Observations	36740	

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

5.2 Do workers in automatable (technology level measurement) jobs invest in their human capital?

The results suggest a differing relationship between automation technologies and workers' likelihood of participating in training and skill development. Specifically, exposure to robotization and software technologies is associated with a lower likelihood of investing in human capital, while exposure to AI shows a positive relationship with training participation.

Workers exposed to robots demonstrate a significant negative association with training incidence (-0.139), suggesting that their engagement in skill development may be relatively lower. A possible explanation for this pattern aligns with findings from Lillard and Tan (1986), who argue that workers' decisions to invest in human capital are influenced by both perceived costs and expected returns on training. In the case of robotization, workers with lower education levels may find the learning curve for interacting with automated systems steep, leading them to forgo training. Additionally, as suggested byGreen et al. (2016), firms facing technological transitions may reduce training investments in workers performing routine tasks, particularly if automation replaces rather than complements their roles. These dynamics could contribute to lower participation in training among employees in highly automated environments.

A similar pattern is observed with software exposure, which exhibits a negative association with training incidence (-0.104). While software-based automation may not replace workers as directly as robotics, its role in streamlining tasks can still influence skill development decisions. Blundell et al. (1996) emphasize that firm-level investment in training often depends on perceived future productivity gains, and if software technologies are seen as mature or static, firms may reduce their investment in workforce training. Workers, particularly those in middle-wage occupations, may also perceive a lower return on training in older software applications, reinforcing the observed association.

In contrast, exposure to AI shows a positive and significant relationship with training incidence (0.102). Workers with higher education levels may be more inclined to engage in training to develop AI-related competencies, as these skills offer long-term career benefits. The concept of an "early mover advantage," is relevant here, as workers who acquire AI skills early may benefit from increased job security and wage premiums as AI adoption expands across industries. Furthermore, firms investing in AI technology may be more likely to provide training opportunities for their employees, recognizing the need for workforce adaptation to leverage AI-driven efficiencies.

These results contribute to the broader discussion on how different types of automation influence workforce training decisions. While automation through robotics and software may be associated with lower training incidence, AI appears to encourage skill development, particularly among highly educated workers. The findings align with previous research on human capital investment in technological transitions and suggest that the impact of automation on training participation varies depending on the type of technology and the broader institutional context.

This section explores how exposure to different types of automation technologies influences human capital investment presented in Table 5.3.The analysis indicates a negative correlation between workers' exposure to robots and software technology—classified here as "older" automation technologies—and their likelihood of investing in human capital. As shown in Figures 3.4 and 3.3, workers with low education and low wages who are exposed to robots exhibit the strongest reluctance to invest in skill development. Two key factors likely contribute to this trend. First, their limited educational background may make acquiring the skills needed to interact with robots seem overwhelming, requiring an effort they perceive as disproportionate to the benefits. Second, firms themselves may be transitioning away from older automation technologies, reducing incentives for training. A similar, though potentially weaker, pattern is observed among low-education workers exposed to software technology. While their middle-wage status may provide slightly more financial flexibility for training, the perceived low return on investment in skills related to older software technologies likely discourages participation in further skill development.

In contrast, the findings for AI technology reveal a different trend. Workers—particularly those with high education and high wages—are more inclined to invest in human capital when exposed to AI. This can be attributed to two primary reasons. First, individuals with a strong educational foundation are better equipped to acquire and apply new AI-related skills. Second, the relative novelty of AI creates an "early mover advantage," where workers who upskill early may benefit from higher future earnings as AI becomes more deeply integrated into the workplace. Additionally, firms adopting AI may be actively investing in workforce training to facilitate the transition to newer technologies.

The inclusion of covariates in the specification that disaggregates the effects of different types of technologies reveals a trend consistent with the general automation model. The negative association observed for robotization and software exposure, along with the positive association for AI exposure, mirrors the overall automation pattern. This suggests that while the specific impact of each technology varies, the broader relationship between automation and training incidence remains stable across different technological contexts.

Table 5.3: Training incidence for automation at level of technology

	hci		hci		hci	
Robotization	-0.139***	(0.022)				
Average Readiness of Country	0.106***	(0.026)	0.106***	(0.026)	0.106***	(0.026)
Numerical Score (standardized)	-0.003	(0.009)	-0.002	(0.009)	-0.003	(0.009)
Literacy score (standardized)	0.008	(0.009)	0.008	(0.009)	0.009	(0.009)
Problem solving score (standardized)	0.030***	(0.007)	0.030***	(0.007)	0.030***	(0.007)
Age cohorts(16-19)	0.000	(.)	0.000	(.)	0.000	(.)
Age cohorts(20-29)	0.192***	(0.033)	0.191***	(0.033)	0.190***	(0.034)
Age cohorts(30-44)	0.167***	(0.038)	0.168***	(0.038)	0.165***	(0.038)
Age cohorts(45-54)	0.173***	(0.039)	0.174***	(0.039)	0.172***	(0.039)
Age cohorts(55-65)	0.152***	(0.042)	0.154***	(0.042)	0.152***	(0.042)
Firm size - 1 to 10 people	0.000	(.)	0.000	(.)	0.000	(.)
Firm size - 11 to 50 people	0.049***	(0.009)	0.049***	(0.009)	0.048***	(0.009)
Firm size - 51 to 250 people	0.087***	(0.010)	0.087***	(0.010)	0.086***	(0.010)
Firm size - 251 to 1000 people	0.120***	(0.014)	0.120***	(0.014)	0.117***	(0.014)
Firm size - More than 1000 people	0.136***	(0.021)	0.137***	(0.021)	0.134***	(0.021)
Lower secondary or less (ISCED 1,2, 3C short or less)	0.000	(.)	0.000	(.)	0.000	(.)
Upper secondary (ISCED 3A-B, C long)	0.059***	(0.011)	0.061***	(0.011)	0.061***	(0.011)
Post-secondary, non-tertiary (ISCED 4A-B-C)	0.075***	(0.021)	0.078***	(0.021)	0.078***	(0.021)
Tertiary – professional degree (ISCED 5B)	0.129***	(0.012)	0.134***	(0.013)	0.133***	(0.013)
Tertiary – bachelor degree (ISCED 5A)	0.138***	(0.018)	0.144***	(0.018)	0.143***	(0.019)
Tertiary – master/research degree (ISCED 5A/6)	0.140***	(0.013)	0.146***	(0.014)	0.145***	(0.014)
female=0	0.000	(.)	0.000	(.)	0.000	(.)
female=1	-0.016***	(0.006)	-0.014**	(0.006)	-0.008	(0.006)
Full-time employed (self-employed, employee)	0.000	(.)	0.000	(.)	0.000	(.)
Part-time employed (self-employed, employee)	-0.046***	(0.012)	-0.047***	(0.012)	-0.046***	(0.012)
Unemployed	-0.038	(0.026)	-0.041	(0.025)	-0.042*	(0.025)
Pupil, student	-0.086**	(0.040)	-0.086**	(0.040)	-0.085**	(0.040)
Apprentice, internship	-0.107**	(0.044)	-0.108**	(0.044)	-0.107**	(0.044)
In retirement or early retirement	-0.196***	(0.032)	-0.197***	(0.032)	-0.196***	(0.033)
Permanently disabled	-0.032	(0.063)	-0.031	(0.064)	-0.030	(0.064)
In compulsory military or community service	-0.121	(0.135)	-0.119	(0.135)	-0.119	(0.134)
Fulfilling domestic tasks or looking after children/family	-0.185***	(0.027)	-0.185***	(0.028)	-0.184***	(0.028)
Other	-0.054*	(0.031)	-0.055*	(0.031)	-0.052*	(0.031)
The private sector	0.000	(.)	0.000	(.)	0.000	(.)
The public sector	0.053***	(0.015)	0.053***	(0.015)	0.053***	(0.015)
A non-profit organisation	0.086***	(0.015)	0.086***	(0.015)	0.087***	(0.016)
Software exposure			-0.104**	(0.043)		
AI exposure					0.102***	(0.018)
Constant	-0.355***	(0.133)	-0.375***	(0.135)	-0.449***	(0.136)
var(_cons[cntryid])	0.006***	(0.002)	0.006***	(0.002)	0.006***	(0.002)
var(_cons[cntryid>isco08_c])	0.006***	(0.001)	0.007***	(0.001)	0.006***	(0.001)
var(e.hci)	0.189***	(0.005)	0.189***	(0.005)	0.189***	(0.005)
Controls	Yes		Yes		Yes	
Observations	36740		36740		36740	

Standard errors in parentheses

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

Table 5.4: Coefficients for Industry

	hci		hci		hci	
Agriculture, forestry and fishing	0.000	(.)	0.000	(.)	0.000	(.)
Mining and quarrying	0.112***	(0.040)	0.109***	(0.039)	0.129***	(0.039)
Manufacturing	-0.023	(0.026)	-0.019	(0.027)	0.002	(0.025)
Electricity, gas, steam and air conditioning supply	0.077*	(0.047)	0.083*	(0.047)	0.106**	(0.046)
Water supply; sewerage, waste management and remediation activities	0.031	(0.042)	0.033	(0.043)	0.055	(0.042)
Construction	-0.013	(0.029)	-0.012	(0.030)	0.011	(0.029)
Wholesale and retail trade; repair of motor vehicles and motorcycles	-0.025	(0.025)	-0.019	(0.026)	0.014	(0.024)
Transportation and storage	0.000	(0.029)	0.002	(0.030)	0.030	(0.027)
Accommodation and food service activities	-0.045**	(0.022)	-0.050**	(0.024)	-0.007	(0.022)
Information and communication	0.006	(0.021)	0.012	(0.022)	0.039**	(0.019)
Financial and insurance activities	0.107***	(0.025)	0.115***	(0.027)	0.149***	(0.024)
Real estate activities	-0.001	(0.029)	0.001	(0.031)	0.034	(0.031)
Professional, scientific and technical activities	0.010	(0.025)	0.017	(0.027)	0.044*	(0.025)
Administrative and support service activities	0.024	(0.025)	0.023	(0.027)	0.052**	(0.025)
Public administration and defence; compulsory social security	0.041	(0.028)	0.047	(0.031)	0.079***	(0.029)
Education	0.078***	(0.027)	0.083***	(0.028)	0.119***	(0.027)
Human health and social work activities	0.077***	(0.025)	0.081***	(0.027)	0.116***	(0.026)
Arts, entertainment and recreation	0.031	(0.027)	0.037	(0.027)	0.072***	(0.027)
Other service activities	0.057**	(0.025)	0.063**	(0.027)	0.099***	(0.027)
Activities of households as employers	-0.073	(0.055)	-0.087	(0.056)	-0.046	(0.055)
Activities of extraterritorial organizations and bodies	0.128**	(0.052)	0.136**	(0.053)	0.168***	(0.054)
Controls	Yes		Yes		Yes	
Observations	36740		36740		36740	

Standard errors in parentheses

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

6 Robustness Checks

This section presents a series of robustness checks conducted to assess the stability of the empirical model and to explore potential heterogeneity in the relationship between automation risk and human capital investment.

Linear Probability model with Fixed effects

As an initial robustness check, I employed a linear probability model with fixed effects and observed trends consistent with those from the hierarchical linear model.

Age Groups

The first robustness check investigates the model's stability across different age groups. The sample is divided into three sub-samples: "entry age (16-29)," "prime age (30-44)," and "late age (44-65)." The model (equation (1)) is estimated for each sub-sample, including all control variables. The estimated coefficients are then plotted in Figure C.1. The lack of significant variation in the coefficients across age groups suggests that the model is robust to age-related effects.

Skill Levels

The second robustness check explores the potential relationship between worker skill level and automation risk. The sample is further divided into three sub-samples based on skill level: low, middle, and high (determined by a numerical score). The linear probability model (equation (1)) is again estimated for each sub-sample, with all control variables included. The estimated coefficients are presented in Figure C.4. Similar to the age analysis, the absence of significant variation across skill levels suggests that the model's core findings hold true for workers with varying skill sets.

Technological Context

The third robustness check examines the influence of a country's technological readiness on the relationship between automation risk and human capital investment. The sample is split into two sub-samples categorised as "low" and "high" technological readiness. The model (equation (1)) is estimated for each sub-sample, including all control variables. The results are presented in Figure C.6. Once again, the lack of significant variation in the coefficients across technological readiness categories suggests that the model's core findings are robust.

7 Conclusion

The findings of this study offer several important implications for understanding the relationship between automation and workforce skills development. The task-based framework used in the analysis, which differentiates automation risk by task level (individual and occupational) and technology type (robots, software, AI), provides valuable insights into how different forms of automation affect training incidence. The evidence suggests that automation exposure, particularly to older technologies like robots and software, is associated with a reduction in workforce training, whereas AI exposure appears to encourage investment in human capital.

A key implication is that automation may not be associated with uniform impact on workforce skill development. The negative association between training incidence and exposure to robots and software indicates that workers in these environments may face structural barriers to skill acquisition. As discussed by Lillard and Tan (1986), firms may be reluctant to invest in training for employees performing tasks that can be easily automated. Similarly, Harris (1999) argues that technological advancements can reduce firms' incentives to upskill workers, particularly in industries where automation replaces rather than complements human labour. This suggests that certain workers—especially those in routine-intensive jobs—may experience a decline in skill acquisition opportunities, potentially exacerbating labour market inequalities.

At the same time, the analysis highlights the role of national-level readiness in mitigating the negative effects of automation on training. The positive coefficient for "Average Readiness of Country" suggests that strong institutional frameworks and skill development programs at the national level can help counterbalance the decline in training associated with automation. Countries that invest in robust training and education systems may be better equipped to support workers in navigating technological disruptions, reducing the risk of skill obsolescence.

The role of cognitive skills in training participation also carries significant implications. The positive relationship between problem-solving skills and training incidence suggests that workers with strong cognitive abilities are more likely to engage in continuous learning. This finding supports Blundell et al. (1996), who argue that general cognitive flexibility is a key determinant of labour market adaptability. Furthermore, the strong association between ICT skill use and training participation suggests that digital literacy is increasingly becoming a prerequisite for workforce development in an automated economy. These insights underscore the need for educational systems and training programs to prioritize problem-solving and digital skills, equipping workers with the tools necessary to remain competitive in evolving labour markets.

Another important implication is the observed variation in training participation across age groups and firm sizes. The finding that younger workers, particularly those aged 20–29, have higher training participation rates suggests that firms prioritize skill development for employees with longer expected tenure. This is consistent with Lillard and Tan (1986), who argue that employer-provided training is more prevalent for younger workers due to the higher anticipated return on investment. Similarly, the positive relationship between firm size and training incidence indicates that larger firms, which typically have greater financial resources, are more likely to invest in workforce training. These findings suggest that policies aimed at promoting lifelong learning should address the training needs of older workers and employees in small firms, who may otherwise be at risk of skill stagnation.

The industry-level differences in training incidence also offer important policy insights. The higher training rates observed in knowledge-intensive industries, such as financial services and healthcare, suggest that these sectors recognize the value of continuous skill development. In contrast, industries with high turnover rates, such as accommodation and food services, exhibit lower training participation. Policymakers seeking to promote workforce resilience in the face of automation should consider targeted interventions for industries where training investments are relatively low.

The contrasting effects of AI exposure compared to older technologies like robots and software highlight an important dynamic in the future of work. While exposure to older automation technologies appears to discourage skill development—possibly due to perceived displacement risks or firms' reluctance to train workers for tasks likely to be automated—AI exposure is associated with increased training participation. Workers with higher education levels may recognize the long-term benefits of AI-related skills, while firms adopting AI may actively invest in workforce training to maximize productivity gains. The concept of an "early mover advantage, is particularly relevant here, as workers who acquire AI skills early may benefit from increased job security and wage premiums as AI adoption expands.

These findings underscore the importance of designing policies that support skill development in an era of rapid technological change. Given that exposure to older technologies like robots and software may lead to skill disinvestment, particularly for low-skilled workers, policymakers should focus on creating targeted reskilling programs that enable these workers to transition into roles where skill development remains viable. Simultaneously, the positive association between AI exposure and training participation suggests that governments and firms should proactively invest in AI-related skill development initiatives, particularly for highly educated workers who are best positioned to leverage these opportunities.

A key takeaway from this analysis is that automation does not necessarily lead to uniform skill displacement, but rather reshapes the incentives for human capital investment in complex ways. Policymakers should focus on fostering an environment that encourages lifelong learning and skill adaptability, particularly for workers at risk of being left behind by technological transitions. Strengthening national training systems, promoting digital and problem-solving skills, and incentivise firms to invest in workforce development will be crucial in ensuring that workers can successfully navigate the evolving landscape of automation.

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Appendices

Chapter 1

A Technological Readiness of Country

Table A.1: Technological Readiness of Country

Country	Average Technological Readiness
Chile	4.2091848
Cyprus	4.4422276
Czech Republic	4.6664072
Denmark	5.9231854
France	5.3708978
Greece	4.0110327
Israel	5.1520253
Italy	4.4683339
Japan	5.2320118
Korea	5.4453039
Lithuania	4.5546428
Netherlands	5.9647298
New Zealand	5.1503289
Norway	5.797392
Poland	4.0738839
Russian Federation	3.593848
Slovak Republic	4.3824565
Slovenia	4.6518828
Spain	4.8309266
Turkey	3.8414383
United Kingdom	5.7712285

Source : World Economic Forum

B Measures of Automation

Table B.1: Measures of Automation

	Individual- Nedelkoska and Quintini (2018)	**Occupation - Frey and Osborne (2017)**	**AI- Webb (2019)**	**Software - Webb (2019)**	**Robot - Webb (2019)**
Data	PIAAC	Survey data, Description of Occupational Title	Patent data, O*NET Description of Tasks and Skills	Patent data, O*NET Description of Tasks and Skills	Patent data, O*NET Description of Tasks and Skills
Method	Logistic Regression	Machine Learning	Natural Language Processing	Natural Language Processing	Natural Language Processing
Level	Individual	Occupation(O*NET SOC)	Occupation(O*NET SOC)	Occupation(O*NET SOC)	Occupation(O*NET SOC)
High	Shop sales assistants, Service station attendants, Heavy truck and lorry drivers, Gardeners, horticultural and nursery growers	Data entry clerks, Contact centre salespersons, Chemical products plant and machine operators, Clearing and forwarding agents, Repair of electronic and optical equipment	Radiologists, Optometrists and ophthalmic opticians, Astronomers, Bleaching, dyeing and fabric cleaning machine operators	Hand packers, Parking lot attendants	Riggers and cable splicers, Building caretakers, Window cleaners, Livestock farm labourers, Materials movers in factories
Low	Teaching professionals, Other language teachers Manufacturing supervisors, Real estate agents and property managers	Hotel Managers, Dietitians and nutritionists, Education methods specialists, Audiologists and speech therapists, Social welfare managers	University and higher education teachers, Kitchen helpers, Fashion and other models	University and higher education teachers, Actors, barbers, podiatrists, and postal service mail carriers	Clergy, Performance artists, Translators, interpreters and other linguists, payroll clerks, Survey and market research interviewers

The table summarises the measures of automation used in the paper

C Robustness Checks

C.0.1 Age

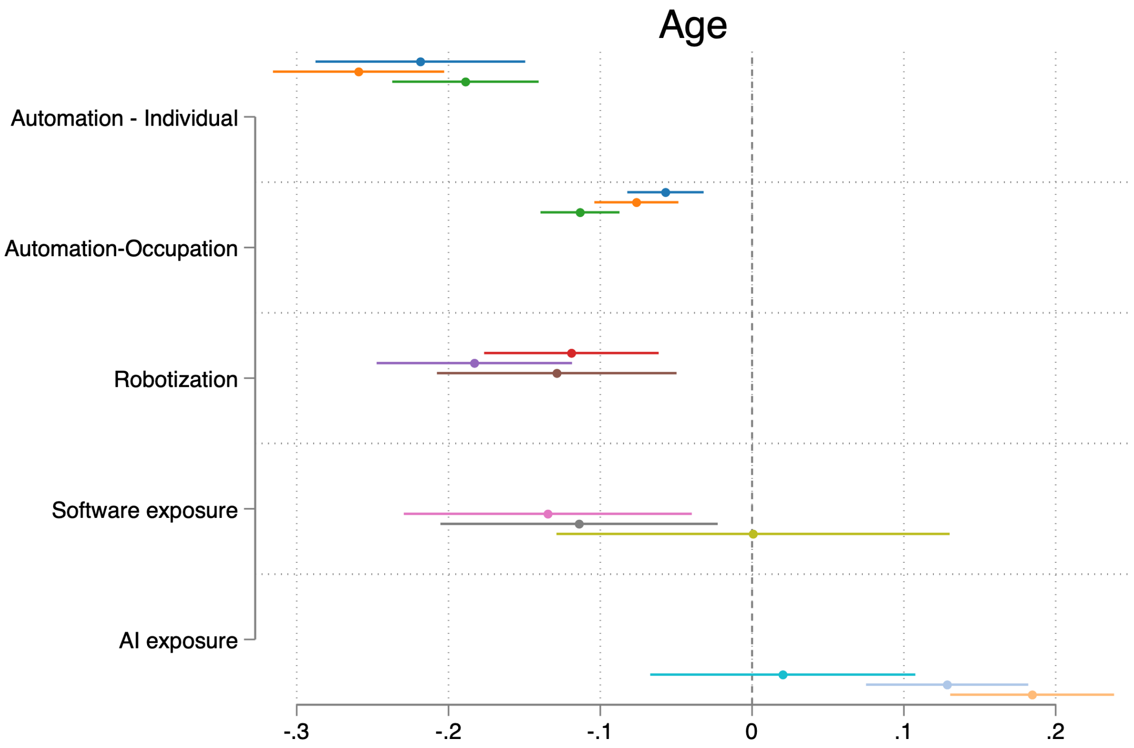

Figure C.1: HCI variation with age . Entry Age(<30 - top), Prime Age (30-45 middle), Late Age (>45 bottom)

C.0.2 Skill

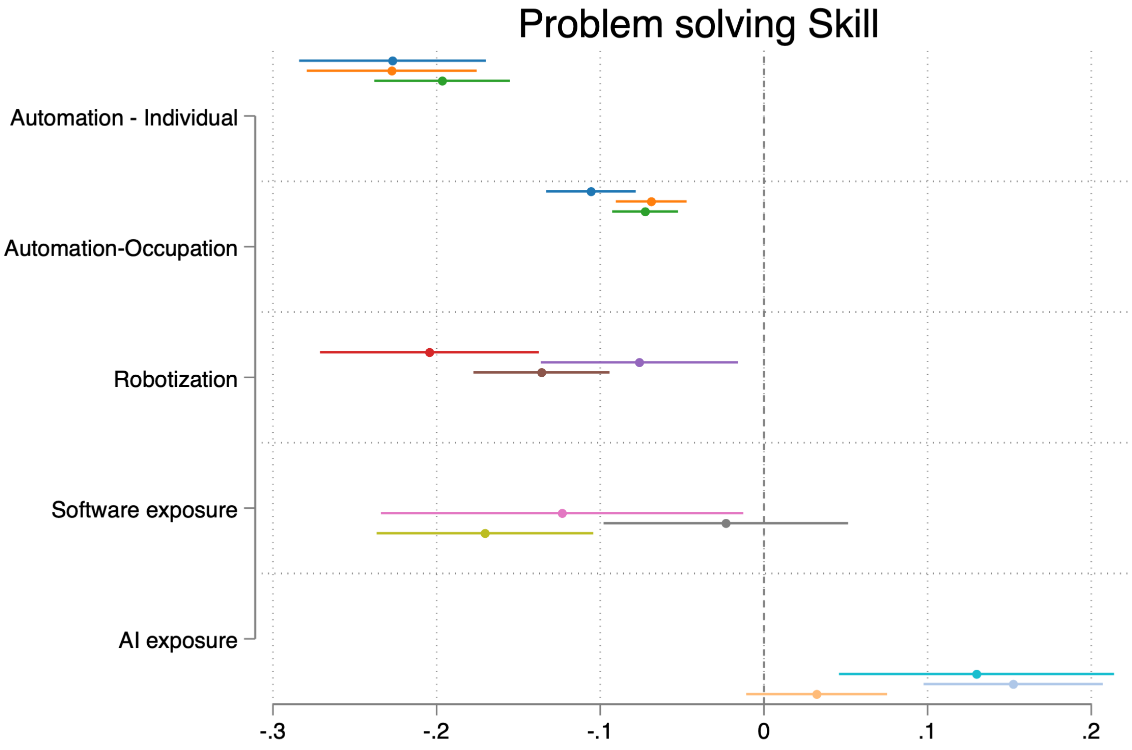

Figure C.2: variation with skill. Lower Skill(top), Middle Skill (middle), High Skill (bottom)

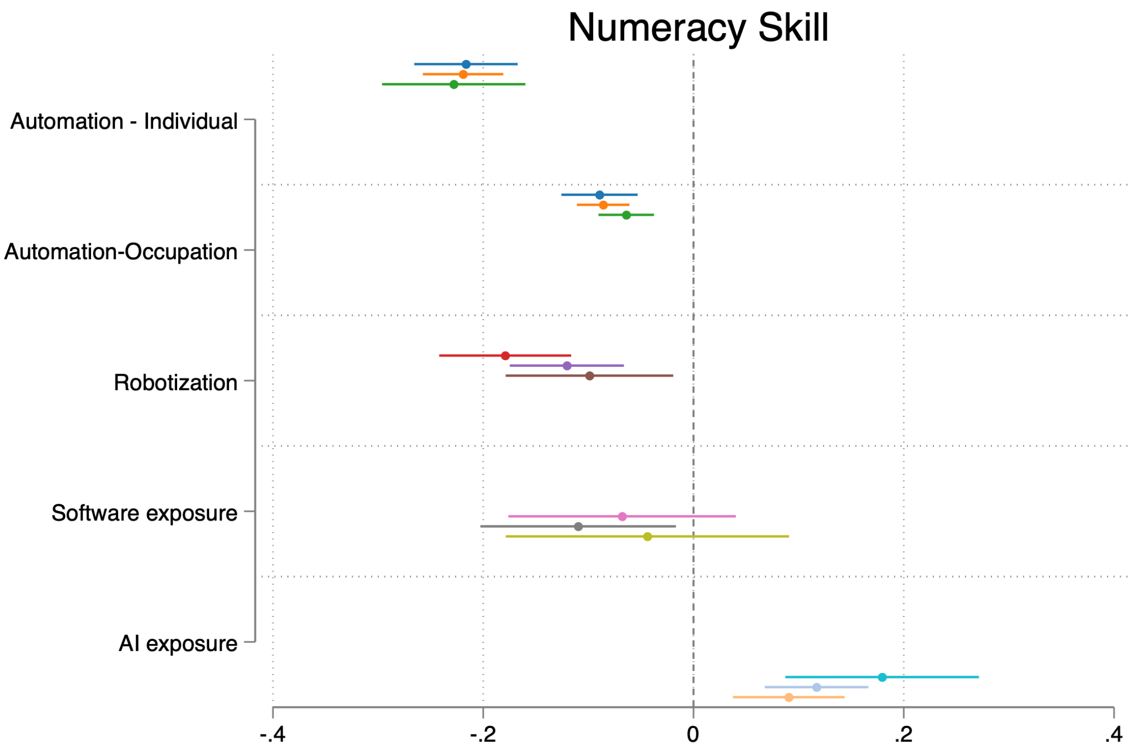

Figure C.3: variation with skill. Lower Skill(top), Middle Skill (middle), High Skill (bottom)

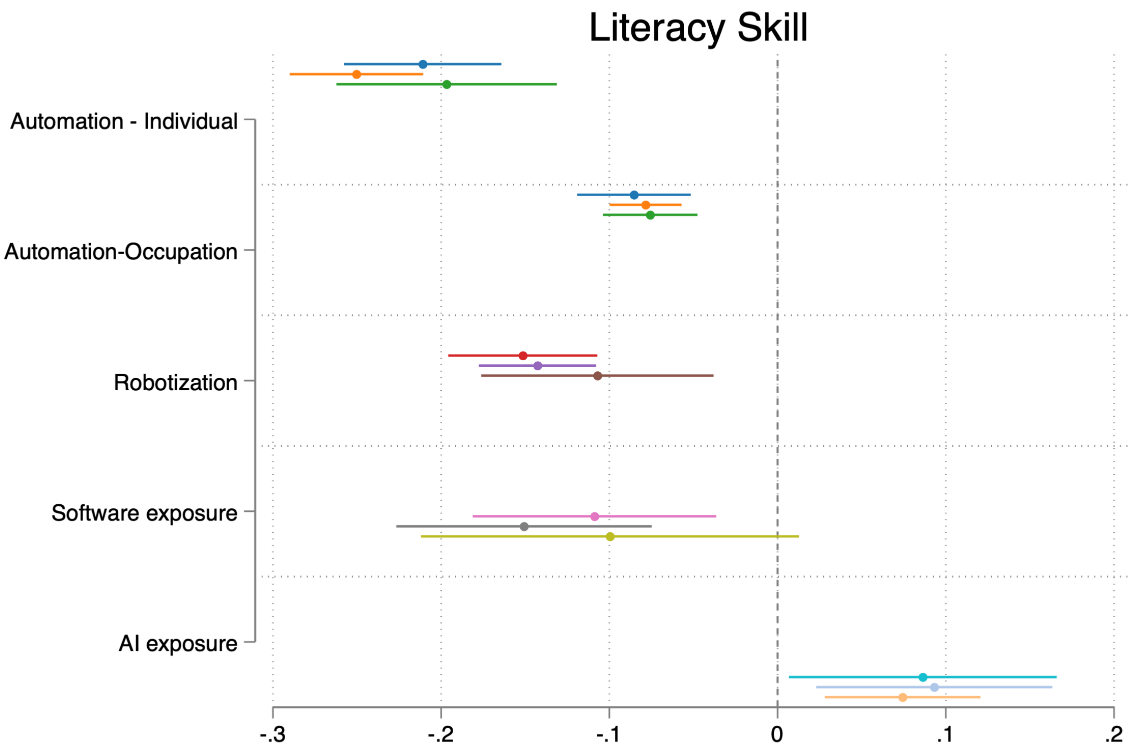

Figure C.4: variation with skill. Lower Skill(top), Middle Skill (middle), High Skill (bottom)

C.0.3 Technological Readiness

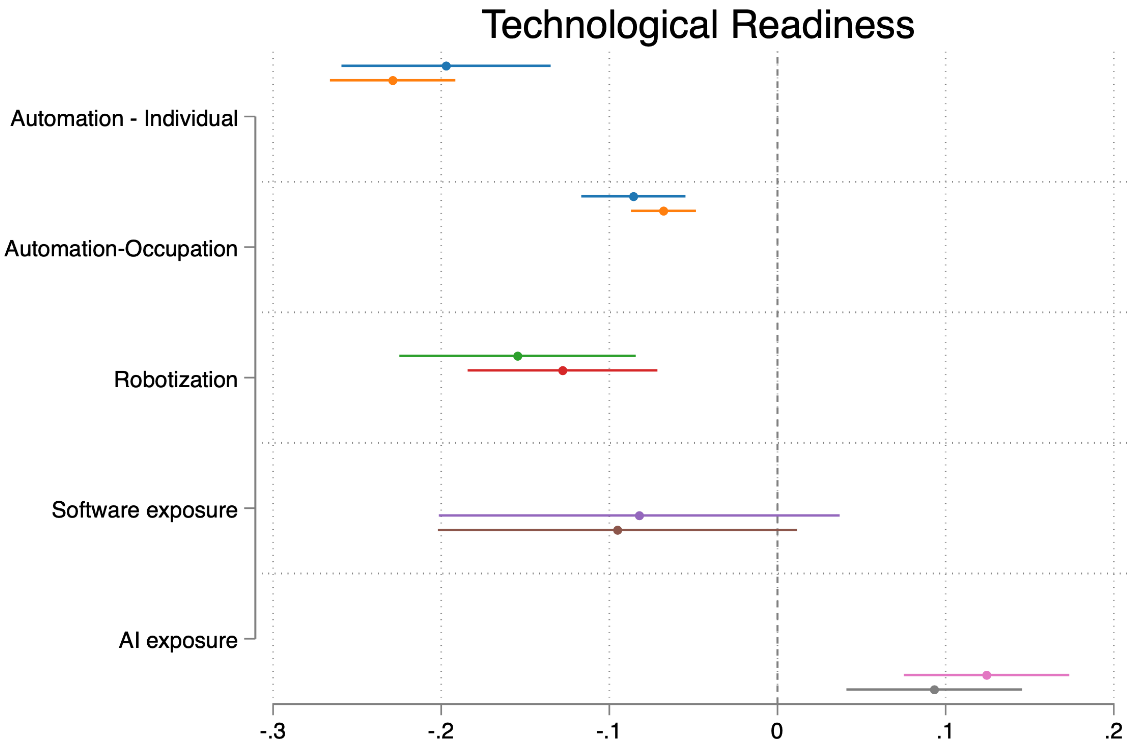

Figure C.5: HCI variation with Technological Readiness. Low Technological Readiness (bottom) and High Technological Readiness (top)

C.0.4 Education

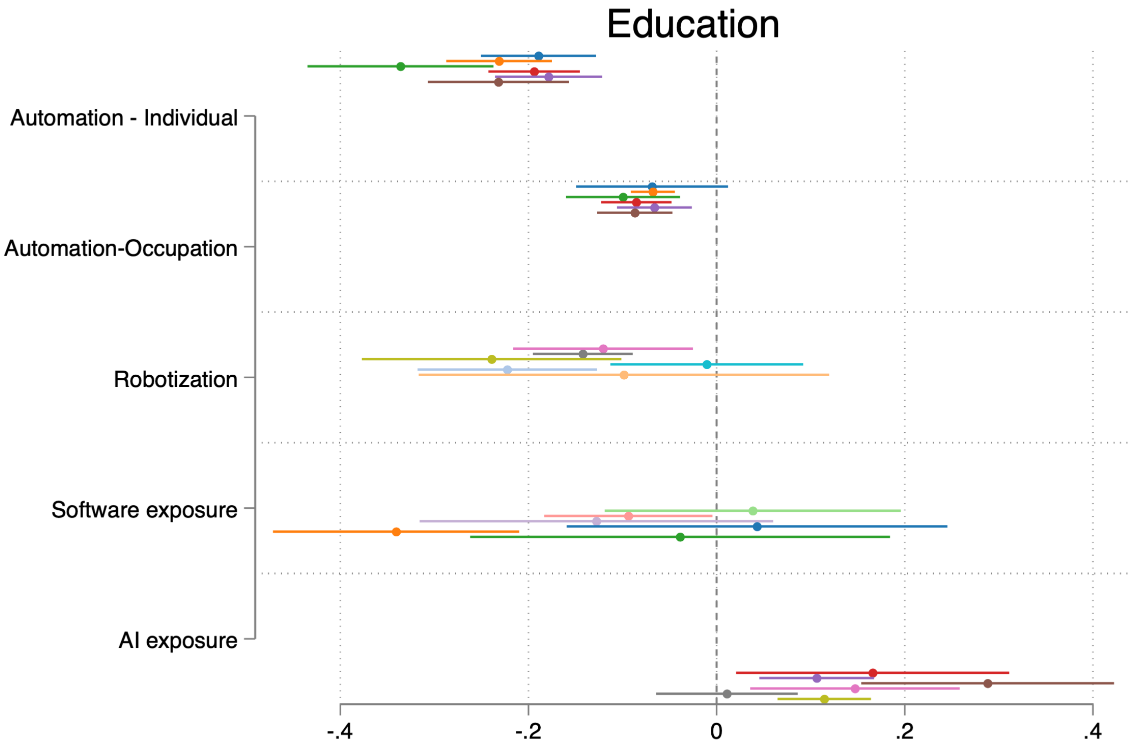

Figure C.6: HCI variation with different educational categories

D Relation with Last Job

In the whole sample, 18% of individuals have changed the job. These workers either moved to a new job or are unemployed or out of the labor force. The paper now descriptively analyses the job switch due to automation.

In order to achieve this the whole sample is first divided into two. Sample 1 contained individuals who had a job once, but now either moved to a new job or are unemployed or out of the labor force. Sample 2 contains workers who are currently employed, which is also the primary sample of the empirical analysis in the paper. Mean of automation of previous job is calculated for sample 1 and mean of automation of current job is calculated for sample 2. Table D.1 presents the results of this calculation.

Table D.1: Relation with Last Job

Type of Automation Measure	Mean Automation of Last Job	Mean Automation of Current Job
Individual	NA	NA
Occupation	.6188	.5236
Robot	.2074	.1620
Software	.1560	.1523
AI	.2313	.2600

Calculation for individual level automation is not feasible since tasks done during current work is observed. Risk of automation reduced by 15% for occupation level measure without disentangling the technology. Risk of automation reduced by 22% and 3% for exposure to robots and software. Meanwhile exposure to AI increased by 12%. Table D.1 suggests that demand for automatable jobs are decreasing in general. Even when we look at the technology level automation measure, demand for jobs with high exposure to robot and software is decreasing. On the contrary, demand for jobs with higher exposure to AI is increasing. This could be because AI is newer technology when compared to software and robot, and prospectus of a newer technology will be higher than an older technology.

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