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Digital skills and employment of older workers: A Japanese panel data analysis

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Abstract

This study investigates the 'digital divide' in the labour market for older adults in Japan. We focused on differences in employment status among older adults related to differences in their capability to use digital technology. The digital skills analysed in this study were limited to computer skills in spreadsheets, macros, and programming. We used longitudinal data from Japan which included questions about these digital skills.

We set two hypotheses. Initially, having digital skills is associated with a higher probability of employment at an advanced age, and second, acquiring digital skills is positively associated with a higher probability of employment at an advanced age in Japan. To estimate the treatment effects of having and acquiring each of the three digital skills, we used propensity score matching. The estimation results revealed that for men, the average treatment effects (ATEs) of having digital skills or acquiring them were not statistically significant. For women, the ATEs of having or acquiring digital skills were statistically significant in the estimation uncontrolled for education and occupation, whereas they were insignificant in the estimation that controlled for them. In other words, neither hypothesis was supported by our analyses. However, for women, digital skills combined with higher education and job experience contribute to maintaining jobs at an advanced age. The factors that explain the sex-related differences in the estimation results are not clear.

The results of the analyses indicated that digital skills related to computers are acquired through formal education or job-related training instead of individual learning. This suggests the importance of a recurrent education system in providing people from various backgrounds with the life-long opportunity to learn job-enhancing digital skills.

Keywords

Digital skills, spreadsheets, macros, programming, older adults, employment, longitudinal data

JEL classification

C23, J24, J26

1 Introduction

In many parts of the world, the population is ageing owing to improvements in life expectancies and a decline in fertility rates. As of 2022, the average proportion of people aged 65 or older in the total population of Organisation for Economic Co-operation and Development (OECD) countries is approximately 18% and is expected to continue growing (OECD 2022a). In Japan, where the population is ageing more rapidly than that in other countries, this proportion has approached 30%. Researchers have forecasted the negative effects of ageing on the size of the labour force, labour productivity, real GDP per capita growth, and fiscal sustainability.

To mitigate the adverse economic effects of ageing, the Japanese government raised the pension age for the Employee Pension Scheme to 65 and amended the Act on Stabilization of Employment of Elderly Persons[1] so that firms can take measures to secure the employment of elderly persons until they reach the age of 65. Consequently, workforce participation among people aged 65 or older has steadily increased. According to the Statistics Bureau of Japan (2025), the labour force participation rate for those aged 65–69 is 53.5%, which is higher than the corresponding OECD average of 29.8% (OECD 2025).

However, the older workforce is not always effectively leveraged. In Japan, businesses often do not employ individuals in their mid-60s owing to concerns about ‘skills and productivity issues’, as well as ‘health concerns’ (Japan Institute for Labour Policy and Training 2020). In 2024, the unemployment rate for men aged 65–69 in Japan was 3.1%, which is higher than the 2.7% for people of all ages, indicating the existence of skill mismatches between firms and older jobseekers (Statistics Bureau of Japan 2025). The insufficient digital skills of older adults could be one factor explaining unemployment and labour market mismatches. The OECD (2019) points out that older workers are less equipped to work effectively in the digital world and advocates training to enhance their workers’ skills.

The COVID-19 pandemic contributed to the spread of remote teleworking. This has brought the issue of the digital divide to the surface, as working from home requires the use of computers and software. Work style has changed, and digital devices have been used more frequently than before the pandemic. Accordingly, the effects of digital skills on older adults could have been more conspicuous than before, as many older adults did not receive information technology training when they were young.

Based on these facts, this study investigates whether there is a ‘digital divide’ caused by the levels of digital skills for older adults in Japan. We focused on differences in employment status among older adults related to differences in their capability to use digital technology. We used longitudinal data from the Japan Household Panel Survey (JHPS/KHPS), which includes questions about digital skills and employment status.

The rest of this paper is organised as follows: Section 2 discusses the preceding research, Section 3 sets the hypotheses, Section 4 explains the data and variables, Section 5 explains the sample and presents the descriptive statistics, Section 6 presents the econometric analyses, and Section 7 concludes the paper.

[1] According to Article 9 of this law, the employer must take any one of the following measures if the mandatory retirement age has been fixed under 65 years of age: re-employment until 65, raising mandatory retirement age, and abolition of mandatory retirement age.

2 Preceding research

Our analyses are based on preceding research about skill-biased technical change and its effects on labour demand. These studies trace back to research conducted since the 1990s, including Acemoglu (1998, 2002), Autor et al. (1998), DiNardo and Pishike (1997), and Berman et al. (1998); Berman and Machin (2000); and Card and DiNardo (2002). These studies have developed into analyses of the relationships between information and communication technology (ICT) skills and skill-biased labour demand, including Falk and Koebel (2004), O'Mahony and Peng (2008), Weiss (2008), Michaels et al. (2014), Ikenaga and Kambayashi (2016), and Kiyota and Maruyama (2017).

Since the COVID-19 pandemic, many academic papers have focused on digital literacy, employment, and income for people of all ages (Budnitz and Tranos 2021, Falck et al. 2021, Kurita et al. 2021, Pusteria and Renold 2022, Jahan and Zhou 2023, Pizzinelli and Shibata 2023, Gathmann et al. 2024). Since the pandemic, research on the digital skills of older adults has emphasised social inclusion or mental health instead of labour market issues (Aung et al. 2022, Li et al. 2022, Sixsmith et al. 2022, Zhang et al. 2022, Tirado-Morueta 2023, Chen et al. 2024, Lu 2024).

Among the scarce literature on digital skills and labour market outcomes for older adults, König and Seifert (2022) analysed data for 28 countries from the Survey of Health, Ageing, and Retirement in Europe (SHARE) and found that working from home during the COVID-19 pandemic pushed older adults to acquire digital skills. Lee et al. (2022), using data from the OECD's Programme for the International Assessment of Adult Competencies, observed that an individual's proficiency in ICT skills and their utilisation in jobs had a positive effect on the wages of workers aged 50–64 with a high level of education or in a skill-intensive occupation. Lakomỳ's (2023) estimation using the SHARE data led to a conclusion that changes in digital skills did not affect older adults' retirement intentions. Using Norwegian data, Solem et al. (2023) found that experiencing difficulties in utilising digital tools in the workplace is linked to a preference for quitting a job earlier than the average age of retirement. Yamashita et al. (2024), using PIACC data for the U.S., revealed that higher skill proficiency and full-time employment were positively associated with the frequent usage of digital skills. The fact that there have been few studies on the effects of digital skills on the employment of older adults motivated our research.

3 Hypotheses

The results from preceding research are mixed, in that some revealed the effects of digital skills on employment income, while others did not. However, we assume that in a country such as Japan, where the employment rates of older adults are already high, the problem of the digital divide could be apparent. Based on these findings, we propose the following hypotheses:

H1: Digital skills are associated with a higher probability of employment at an advanced age.
H2: Acquiring digital skills is positively associated with a higher probability of employment at advanced age.

4 The data

We used longitudinal data from Japan, the JHPS/KHPS. JHPS and KHPS are abbreviations for Japan Household

Panel Survey and Keio Household Panel Survey, respectively. Both datasets were collected by the Panel Data Research Centre of Keio University, Japan.[2] Longitudinal microdata encompass a wide array of topics including family life, activities, mental and physical health, cognitive functions, employment and pensions, work history, income and expenditure, accommodation, assets, and social support. An overview of JHPS/KHPS is presented in Table 1.

Table 1. Data used in this study

	JHPS/KHPS	Samples used in this research
Starting year	2009	2019
Number of respondents	4000 for JHPS and KHPS for the first wave, respectively	7447
Age of respondents	20 to 69 in the first wave	55 or more
Frequency	Yearly	2019–2022, yearly
Organisation that conducted the survey	Keio University	Keio University

We used the JHPS/KHPS from 2019 to 2022 because the surveys from 2004 to 2018 did not include questions about the respondents' digital skills.

Dependent variable

The dependent variable is a dummy variable for employment status: 'employed.' The definitions for being 'employed' is presented in Table 2.

Table 2. Dependent variables

Variable	Definition
Employed (outcome variable)	1 = if the respondent is employed or self-employed 0 = if otherwise (off work, looking for a job, mainly engaged in studying or homemaking)

Independent variables

Treatment variables

[2] The KHPS and the JHPS were merged into a single longitudinal data JHPS/KHPS in 2014, as the questions are almost the same. The English website for the JHPS/KHPS is as follows: https://www.pdrc.keio.ac.jp/en/paneldata/datasets/jhpskhps/

The JHPS/KHPS contains questions about digital skills based on the following question: To what extent can you perform the following tasks?

a. Using spreadsheets (such as Excel).
b. Using macro functions for the spreadsheets.
c. Data analysis using software programmes or programming.

Based on this question, we set three dummy variables: Spreadsheets, Macro, and Program as demonstrated in Table 3. That is, each of them is set to 1 if the respondents selects either 'able to utilise them without difficulty' or 'able to utilise them to some extent' and set to 0 if otherwise.

Table 3. Dummy variables for digital skills

Response options	Spreadsheets	Macro	Program
1. Able to utilise them without difficulty	1	1	1
2. Able to utilise them to some extent	1	1	1
3. Almost impossible to utilise them	0	0	0
4. Not able to utilise them at all	0	0	0
5. Not sure/Don't know	0	0	0

We use the lags of Spreadsheets(t-1), Macro(t-1), and Program(t-1) as treatment variables in the analyses in the following section. We also used the following variables for the acquisition of digital skills within one year: Acq_spreadsheets, Acq_macro, and Acq_program. Acq_spreadsheets are set to 1 if the respondent who was not able to employ spreadsheets in the previous period is able to apply them in the current year, as presented in Table 4. The dummy variables Acq_macro and Acq_program are defined similarly.

Table 4. Dummy variable for acquiring skills for spreadsheets

Spreadsheets (t-1)	Spreadsheets (t)	Acq_spreadsheets (t)
0	0	0
0	1	1
1	0	0
1	1	0

We also use treatment or control variables from the JHPS/KHPS, as defined in Table 5. The dummy variable Clerical(t-1) was set to 1 if the respondent had a clerical job in the previous period. Similarly, the dummy variable

Professional(t-1) is for a professional job in the previous period. We used these variables because respondents with clerical or professional jobs are more likely to use digital skills in their jobs (OECD 2022b, Lennon et al. 2023). The variable K6, abbreviated as the Kessler 6-Item Psychological Distress Scale, is the score for mental disorders based on six questions[3]. Respondents were asked for how long they felt a sense of 1) nervousness, 2) restlessness, 3) uneasiness, 4) depression, 5) spiritless, and 6) worthlessness on a 4-point scale ranging from 0 (hardly ever) to 3 (all the time). The six items were summed to create a scale ranging from 0 to 24. Higher scores represent a greater extent of mental distress. The cutoff score for the K6 was set to 15 in this study.

Table 5. Control variables – JHPS/KHPS

Variables	Definitions
Age(t-1)	Respondent's age
Married(t-1)	Dummy variable = 1 if the respondent is married, Dummy variable = 0 if otherwise
Health	Reference: not good or poor
Health_ex(t-1)	Dummy variable = 1 if the respondent's self-rated health is either 'excellent' or 'very good', Dummy variable = 0 if otherwise
Health_good(t-1)	Dummy variable = 1 if the respondent's self-rated health is either 'good' or 'fair', Dummy variable = 0 if otherwise
Univ(t-1)	Dummy variable = 1 if the respondent's highest education is university or higher, Dummy variable = 0 if otherwise
K6(t-1)	K6 = 1 if the total of the respondent's score for K6 mental disorder score is 15 or more, Dummy variable = 0 if otherwise
Clerical(t-1)	Dummy variable = 1 if the respondent had a clerical job in the previous period, Dummy variable = 0 if otherwise.
Professional (t-1)	Dummy variable = 1 if the respondent had a professional job in the previous period, Dummy variable = 0 if otherwise

[3] Preceding research based on Japanese data has found that poor working conditions such as long hours of work deteriorate workers' mental health (Kuroda and Yamamoto 2016, Sato et al. 2020). However, ill mental health is found to significantly reduce probability of employment (Frijiters et al. 2014, Bryan et al. 2022). In other words, there is a bi-directional causality between employment status and mental health. Nonetheless, in our analysis, we assume the causality from mental health to employment instead of the reverse relationship.

Non-labour(t-1)	Dummy variable = 1 if the respondent receives non-labour incomes, including pension, either public or private, dividends or rents; Dummy variable = 0 if otherwise

5 Samples and descriptive statistics

We used samples aged 55 or older with no missing variables. The numbers of samples for the JHPS/KHPS were 3449 and 3757 for men and women, respectively. Descriptive statistics for men and women are presented in Appendices 1-1 and 1-2, respectively.

Among men, the proportions of respondents with digital skills (in the previous period) were 47.0%, 25.2%, and 9.0% for spreadsheets, macro, and programming, respectively. The corresponding figures for women were 20.8%, 7.2%, and 2.4%, respectively. That is, the skills in spreadsheets, macro, and programming tended to be higher for men than for women. However, the proportion of respondents who acquired these digital skills within one year was not significantly different between men and women. For men, the proportions were 4.7%, 5.8%, and 2.7%, whereas for women, the proportions were 4.1%, 2.8%, and 1.2% for spreadsheets, macro, and programming, respectively.

The occupational distribution also differed between men and women. The proportion of respondents with clerical jobs in the previous period was 11.7% for women and 5.9% for men. The proportions of men and women in professional occupations were 10.7% and 7.5%, respectively.

The correlation coefficients between the control variables were calculated and are listed in Table 6. A positive correlation was observed between clerical jobs and digital skills, specifically spreadsheet skills. The correlation coefficient between clerical jobs and spreadsheet skills was +0.229, higher than that between professional jobs and spreadsheet skills (+0.165). In contrast, a negative correlation (-0.276) was observed between age and clerical jobs, indicating that people are more likely to quit clerical jobs as they get older. The dummy variable for university or higher education was also positively associated with spreadsheet skills (+0.306) and macros (+0.203).

(Insert Table 6 here).

6 Estimation

Logit estimation

We estimated the treatment effects of having digital skills and acquiring digital skills using propensity score matching. The propensity scores are calculated by estimating the logit models, where the dependent variables for each are *Spreadsheets(t-1), Macro(t-1), Program(t-1), Acq_spread, Acq_macro, and Acq_pr*. The results of the logit models for estimating *Spreadsheets(t-1)* are shown in Tables 7 and 8.

Table 7 indicates that the skills in spreadsheets were higher for respondents with university or higher education and those with clerical or professional jobs in the previous period for both men and women. The same applies to the macroscopic skills. Programming skills were higher for those with university or higher education or those who had professional jobs, whereas not for those who had clerical jobs in the previous period. However, the effects of variables for age, health factors, and non-labour income are mixed, depending on gender and skill type.

Table 8 indicates that, for men, skill acquisition in spreadsheets, macros, and programming was not affected by education or occupation in the previous period. Only for women, the probability of acquiring macro or programming skills is higher for those who had clerical jobs.

(Insert Tables 7 and 8 here).

Propensity score matching

Based on the propensity scores obtained from the logit estimations, samples with each of the three digital skills were matched with those without. Subsequently, we estimated the average treatment effects (ATEs) for the three skill types. Similarly, the samples that acquired each of the three digital skills within a year were matched with those that did not acquire each of them. Finally, we estimated the ATEs for the three types of skill acquisition.

We estimated the ATEs instead of the average treatment effects on the treated (ATTs) because we are interested in the degree to which the probability of employment can be raised when older adults have or have acquired digital skills[4].

We estimated both the 'full model', in which all control variables were discussed in the previous section, and the 'partial model', which excludes the variables for higher education and previous jobs. The estimation results for the 'full model' and 'partial model' are listed in Table 9.

Table 9 Average treatment effects of having or acquiring digital skills on employment

	Full model		Partial model without education and previous occupation	
	Men ATT	Women ATT	Men ATT	Women ATT
Spreadsheets	-0.054***	-0.021	-0.039***	0.111***
	(-3.21)	(-0.74)	(-2.61)	(4.15)
Macro	-0.023	0.034	0.001	0.135***
	(-1.11)	(0.78)	(0.03)	(2.84)
Program	-0.001	0.011	-0.004	0.133***
	(-0.02)	(0.14)	(-0.13)	(2.87)
Acq_spreadsheets	0.001	0.028	0.032	0.038
	(0.04)	(0.62)	(0.78)	(0.82)

[4] We conducted an overidentification test to assess covariate balance. The null hypothesis, which suggested that the treatment model balanced the covariates, was rejected. Nevertheless, as illustrated in the appendices (Appendix 3 for the 'Spreadsheets'), our model enhanced the level of covariate balance, as indicated by weighted standardised differences approaching 0 and weighted variance ratios approaching 1.

Acq_macro	-0.032	0.060	-0.037	0.101**
	(-0.99)	(1.16)	(-1.11)	(2.17)
Acq_program	0.009	0.066	0.000	0.100*
	(0.19)	(1.34)	(0.00)	(1.94)
Number of observations	3347	3483	3347	3483

Source: Author's estimation based on JHPS/KHPS 2019−2022.

The figures in parentheses are the z-values.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 9 presents that the ATEs of having or acquiring digital skills were not statistically significant for men. In contrast, for women, the ATEs of having digital skills were statistically significant in the partial model but insignificant in the full model controlled for education and previous occupation. It means that the 'pure' effects of digital skills are not detected, as the digital skills are inseparably linked with the educational level and occupation held in the previous period.

As mentioned in Section 3, we set two hypotheses. Neither H1 nor H2 were supported by our analyses. Nevertheless, we observe that digital skills, when combined with higher education and previous jobs utilising digital skills, have a positive effect on acquiring or retaining jobs at an advanced age.

Further analysis

We performed a similar analysis using a sample of respondents aged 54 or younger from the JHPS/KHPS. The estimated ATEs were insignificant for both the 'full' and 'partial' samples. In other words, the effects of digital skills on employment status are specific to people aged 55 or older. We also estimated the ATEs of digital skills on the probability of keeping a job from the $(t\text{-}1)^{th}$ to the t^{th} period instead of employment status in the t^{th} period. The estimated treatment effects of the digital skills were not fundamentally different.

7 Concluding remarks

This study estimated the effects of digital skills on employment outcomes in older adults based on longitudinal data. The originality of this study lies in the fact that digital skills are limited to computer skills, including spreadsheets, macros, and programming. To estimate the treatment effects of computer skills, we applied a propensity score matching method based on logit estimations.

The logit model estimation results indicated that skills in spreadsheets, macros, and programming were higher for those with university or higher education or those previously engaged in clerical or professional jobs for both genders. Nonetheless, the acquisition of digital skills within a year is affected neither by education nor by previous occupations. It was positively affected by clerical jobs in the previous period for women only.

We then estimated the propensity score-matching model based on logit estimation. These results do not support the hypotheses that having or acquiring digital skills is associated with a higher probability of employment at an advanced age in Japan. For men, the treatment effects of digital skills were not observed in either the controlled or uncontrolled models. For women, the effects of digital skills were observed in the model uncontrolled for the effects of higher education and previous occupation, but not in the model controlled for them. In other words, the combination of digital skills, higher education, and occupational experience increases the probability of employment for women.

Our results pertaining to the gender-related differences in the effects of digital skills are in line with O'Mahony and Peng (2008) and Lakomỳ (2023), which highlighted that men are less likely to receive digital trainings at the advanced age than women. However, our research differs in that the linkages between gender, education, and occupation related to digital skills, particularly computer usage, are clarified.

One of our findings is that digital skills tend to be acquired through formal education or job experience instead of through individual learning. This suggests the importance of a recurrent education system for providing people with limited education or those without experience in jobs that utilise digital skills.

Limitations

The econometric analysis in this study is preliminary in that the propensity score matching method we used was not for longitudinal data. That is, the characteristics of the longitudinal data were not fully utilised. We will continue this research by using a more advanced method for longitudinal data. We also added variables such as family structure, financial transfers among family members, and respondents' detailed health factors in future analyses. The factors explaining sex differences in the estimated results have not been clarified. Thus, this remains a topic for future studies. This study's scope is also limited because digital skills are limited to computer skills in spreadsheets, macros, and programming. However, their digital skills were more diverse. Broadening the scope of digital skills is a challenge for future research.

Statements and Declarations

Declaration of competing interests: The authors declare no competing interests relevant to the content of this paper.

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Table 6. Correlation among covariates, both men and women

	Spreadsheets(t-1)	Macro(t-1)	Program(t-1)	Acq_spreadsheets	Acq_macro	Acq_program	Age(t-1)	Married(t-1)	Health_ex(t-1)	Health_good(t-1)	Univ(t-1)	K6(t-1)	Clerical(t-1)	Professional(t-1)	Non-labour(t-1)
Spreadsheets(t-1)	1.000														
Macro(t-1)	0.623	1.000													
Program(t-1)	0.357	0.518	1.000												
Acq_spreadsheets	-0.160	-0.087	-0.049	1.000											
Acq_macro	0.121	-0.095	-0.025	0.399	1.000										
Acq_program	0.059	0.061	-0.034	0.368	0.479	1.000									
Age(t-1)	-0.276	-0.195	-0.117	0.019	-0.016	0.024	1.000								
Married(t-1)	0.088	0.041	0.038	-0.005	0.011	0.000	-0.104	1.000							
Health_ex(t-1)	0.051	0.052	0.027	0.004	0.019	0.006	-0.019	-0.007	1.000						
Health_good(t-1)	0.093	0.071	0.036	0.002	-0.007	-0.006	-0.029	0.014	-0.199	1.000					
Univ(t-1)	0.307	0.204	0.137	0.006	0.031	-0.013	-0.101	0.077	0.048	0.092	1.000				
K6(t-1)	-0.036	-0.017	-0.016	0.004	0.015	0.010	-0.039	-0.039	-0.048	-0.063	-0.006	1.000			
Clerical(t-1)	0.229	0.122	0.042	0.009	0.026	-0.001	-0.208	0.011	0.037	0.046	0.069	0.004	1.000		
Professional(t-1)	0.165	0.168	0.162	0.007	0.026	0.033	-0.204	0.027	0.039	0.050	0.168	-0.014	-0.098	1.000	
Non-labour(t-1)	-0.138	-0.110	-0.080	-0.017	-0.011	0.009	0.494	-0.002	-0.008	0.007	-0.040	-0.031	-0.107	-0.092	1.000

Source: Author's estimation based on the JHPS/KHPS 2019−2022

Table 7. Estimation results for the digital skills based on a logit model

Dependent variable: Spreadsheets(t-1)

	Men			Women		
	Coefficient	z-value		Coefficient	z-value	
Age(t-1)	-0.002	-0.39		-0.028	-5.71	***
Married(t-1)	0.418	4.59	***	-0.074	-0.85	
Health_ex(t-1)	-0.060	-0.54		0.305	2.91	***
Health_good(t-1)	0.225	2.35	**	0.200	2.38	**
Univ(t-1)	1.337	14.81	***	0.777	9.09	***
K6 (t-1)	-0.077	-0.57		-0.218	-1.71	*
Clerical (t-1)	1.585	8.47	***	1.677	17.03	***
Professional (t-1)	1.112	8.96	***	0.313	3.35	***
Non-labour (t-1)	0.093	1.13		0.165	2.20	**
Year dummies	Yes			Yes		
Intercept	-0.283	-1.15		0.274	1.27	
Pseudo R^2	0.144			0.118		
Number of observations	3347			3483		

Dependent variable: Macro(t-1)

	Men			Women		
	Coefficient	z-value		Coefficient	z-value	
Age(t-1)	0.015	2.93	***	-0.016	-2.84	***

Married(t-1)	0.270	3.23	***	-0.065	-0.64	
Health_ex(t-1)	0.098	0.97		0.192	1.61	
Health_good(t-1)	0.107	1.27		0.084	0.84	
Univ(t-1)	0.519	6.71	***	0.365	3.86	***
K6 (t-1)	-0.106	-0.84		-0.420	-2.52	**
Clerical (t-1)	0.346	3.01	***	0.947	9.37	***
Professional (t-1)	0.706	7.60	***	0.362	3.16	***
Non-labour (t-1)	0.033	0.45		0.259	2.99	***
Year dummies	Yes			Yes		
Intercept	-1.740	-7.66	***	-1.428	-5.64	***
Psuedo R^2	0.040			0.047		
N of observations	3347			3483		

Dependent variable: Program(t-1)

	Men			Women		
	Coefficient	z-value		Coefficient	z-value	
Age(t-1)	-0.003	-0.46		-0.023	-2.47	**
Married(t-1)	0.061	0.55		-0.299	-1.81	*
Health_ex(t-1)	-0.048	-0.37		0.300	1.58	
Health_good(t-1)	-0.309	-2.68	***	-0.048	-0.28	
Univ(t-1)	0.491	4.70	***	0.263	1.68	*
K6 (t-1)	-0.158	-0.91		-0.067	-0.26	
Clerical (t-1)	0.000	0.00		0.792	4.62	***
Professional (t-1)	1.188	10.85	***	0.488	2.58	***
Non-labour (t-1)	0.060	0.61		0.264	1.81	*
Year dummies	Yes			Yes		
Intercept	-2.059	-6.97	***	-2.246	-5.44	***
Pseudo R^2	0.063			0.039		
N of observations	3347			3483		

Source: Author’s estimation using KHPS/JHPS 2019-2022.

***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level.

Table 8. Estimation results for the acquisition of digital skills based on a logit model

Dependent variable: Acq_spread

	Men	Women

	Coefficient	z-value		Coefficient	z-value	
Age(t-1)	-0.030	-2.99	***	-0.017	-1.90	*
Married(t-1)	-0.021	-0.12		-0.022	-0.14	
Health_ex(t-1)	-0.199	-0.93		-0.171	-0.85	
Health_good(t-1)	-0.159	-0.90		0.067	0.44	
Univ(t-1)	-0.282	-1.72	*	0.075	0.48	
K6 (t-1)	0.077	0.32		0.155	0.71	
Clerical (t-1)	-0.636	-2.04	**	-0.255	-1.41	
Professional (t-1)	-0.219	-1.05		0.032	0.19	
Non-labour (t-1)	-0.013	-0.08		-0.005	-0.03	
Year dummies	Yes			Yes		
Intercept	-1.495	-3.38	***	-1.865	-4.78	***
Pseudo R^2	0.018			0.012		
N of observations	3347			3483		

Dependent variable: Acq_macro

	Men			Women		
	Coefficient	z-value		Coefficient	z-value	
Age(t-1)	-0.010	-1.23		-0.028	-3.26	***
Married(t-1)	0.119	0.84		-0.106	-0.70	
Health_ex(t-1)	-0.040	-0.24		0.078	0.43	
Health_good(t-1)	-0.091	-0.64		-0.016	-0.11	
Univ(t-1)	0.128	0.99		0.086	0.59	
K6 (t-1)	-0.291	-1.29		0.121	0.57	
Clerical (t-1)	-0.149	-0.73		0.423	2.71	***
Professional (t-1)	-0.113	-0.70		0.055	0.31	
Non-labour (t-1)	0.011	0.09		0.288	2.17	**
Year dummies	Yes			Yes		
Intercept	-2.063	-5.57	***	-1.339	-3.61	***
Pseudo R^2	0.004			0.031		
N of observations	3347			3483		

Dependent variable: Acq_program

	Men			Women		

	Coefficient	z-value		Coefficient	z-value	
Age(t-1)	-0.038	-3.66	***	-0.046	-3.60	***
Married(t-1)	0.273	1.50		-0.057	-0.26	
Health_ex(t-1)	-0.212	-1.02		0.086	0.35	
Health_good(t-1)	-0.562	-2.88	***	-0.703	-2.79	***
Univ(t-1)	0.080	0.48		-0.065	-0.30	
K6 (t-1)	-0.509	-1.69	*	0.160	0.53	
Clerical (t-1)	-0.620	-1.98	*	0.757	3.45	***
Professional (t-1)	-0.069	-0.34		-0.067	-0.24	
Non-labour (t-1)	-0.004	-0.02		0.468	2.40	**
Year dummies	-0.032	-0.17		0.193	0.81	
Intercept	-1.248	-2.74	***	-1.894	-3.51	***
Pseudo R^2	0.020			0.049		
N of observations	3347			3483		

Source: Author's estimation using KHPS/JHPS 2019-2022.

***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level.

Appendix 1 Descriptive statistics, JHPS/KHPS, men

Variable	Mean	Standard deviation	Minimum	Maximum
Employed	0.620	0.485	0	1
Spreadsheets(t-1)	0.471	0.499	0	1
Macro(t-1)	0.263	0.440	0	1
Program(t-1)	0.103	0.304	0	1
Acq_spread	0.059	0.236	0	1
Acq_macro	0.069	0.253	0	1
Acq_program	0.039	0.194	0	1
Age(t-1)	67.368	8.383	55	92
Married(t-1)	0.822	0.382	0	1
Health_ex(t-1)	0.101	0.301	0	1
Health_good(t-1)	0.267	0.442	0	1
Univ(t-1)	0.378	0.485	0	1
K6(t-1)	0.038	0.191	0	1
Clerical(t-1)	0.058	0.234	0	1
Professional(t-1)	0.108	0.310	0	1
Non-labour(t-1)	0.784	0.412	0	1

Year2020	0.350	0.477	0	1
Year2021	0.332	0.471	0	1
Year2022	0.318	0.466	0	1

Appendix 2. Descriptive statistics, JHPS/KHPS, women

Variable	Mean	Standard deviation	Minimum	Maximum
Employed	0.487	0.500	0	1
Spreadsheets(t-1)	0.202	0.402	0	1
Macro(t-1)	0.076	0.265	0	1
Program(t-1)	0.027	0.161	0	1
Acq_spread	0.054	0.227	0	1
Acq_macro	0.040	0.196	0	1
Acq_program	0.025	0.156	0	1
Age(t-1)	67.387	8.534	55	91
Married(t-1)	0.681	0.466	0	1
Health_ex(t-1)	0.096	0.295	0	1
Health_good(t-1)	0.267	0.442	0	1
Univ(t-1)	0.111	0.314	0	1
K6(t-1)	0.052	0.222	0	1
Clerical(t-1)	0.116	0.320	0	1
Professional(t-1)	0.075	0.264	0	1
Non-labour(t-1)	0.821	0.384	0	1
Year2020	0.349	0.477	0	1
Year2021	0.332	0.471	0	1
Year2022	0.319	0.466	0	1

Appendix 3 Results of covariate test for the treatment variable 'Spreadsheets'

Men	Standardised differences		Variance ratio	
	Raw	Matched	Raw	Matched
Age(t-1)	-0.672	-0.014	0.771	1.012
Married(t-1)	0.230	0.013	0.670	0.976
Health_ex(t-1)	0.061	0.070	1.176	1.235
Health_good(t-1)	0.215	-0.010	1.253	0.989
Univ(t-1)	0.521	-0.002	1.292	0.999
K6(t-1)	-0.070	0.018	0.708	1.094

Clerical(t-1)	0.379	-0.060	5.920	0.803
Professional(t-1)	0.407	0.055	3.117	1.160
Non-labour(t-1)	-0.295	0.003	1.506	0.996

	Raw	Matched
Number of observations	3,512	7,024
Treated observations	1,655	3,512
Control observations	1,857	3,512

Women	Standardised differences		Variance ratio	
	Raw	Matched	Raw	Matched
Age(t-1)	-0.700	-0.074	0.705	0.836
Married(t-1)	-0.050	0.089	1.039	0.922
Health_ex(t-1)	0.173	-0.053	1.544	0.856
Health_good(t-1)	0.211	-0.059	1.212	0.935
Univ(t-1)	0.474	0.044	2.632	1.112
K6(t-1)	-0.047	0.156	0.823	1.688
Clerical(t-1)	0.758	0.008	4.086	1.020
Professional(t-1)	0.212	-0.027	1.847	0.914
Non-labour(t-1)	-0.262	-0.019	1.463	1.031

	Raw	Matched
Number of observations	3,826	7,652
Treated observations	773	3,826
Control observations	3,053	3,826