A dual-focus approach to gender disparities in the labor market: How different are advanced Asian economies?

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Abstract

Gender disparities in the labor market are much more complicated than we think. Meanwhile, research that comprehensively deals with the multiple dimensions of this challenge is largely absent in the literature. This study aims to fill this gap. Using a dual-focus approach, this study investigates gender disparities in advanced Asian economies—Japan, Korea, and Singapore—in relation to multidimensional human capital components. In this approach we focus on both qualitative (wage) and quantitative (employability) aspects of labor market outcomes, particularly, from a skill-based perspective. Relying on PIAAC dataset, we document that while cognitive skills positively associated with wages and employability, significant gender gaps persist across age groups and skills levels. Singapore exhibits smaller gaps, whereas Japan and Korea display wider disparities. Applying Gelbach decomposition suggests that not only accumulated human capital components such as schooling, experience and cognitive skills, but also human capital use components play a fundamental role in reducing the gender gaps in the labor market. If women have the same opportunity to use their accumulated human capital as men do, the gender gap would be much smaller than what it is. This research provides valuable insights for policymakers aiming to enhance gender equity and improve labor market outcomes for women.

Keywords: Gender wage and employability gap, cognitive skills, Gelbach Decomposition, Dual-focus approach, multidimensional human capital.

JEL codes: *J31, J24, J16, I20, D63.*

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1. Introduction

Gender disparity is a persistent and well-known issue in many countries. Despite efforts to reduce the disparity, it remains a significant challenge globally that has attracted much scholarly attention. Various theories attempt to explain wage disparity, with human capital (HC) being one of the essential drivers of wage inequality (Polachek, 2006; O'Neill and O'Neill, 2006; Bertrand, 2011). In addition, scholars attribute a large part of gender disparity in employment and wages to the gender gap in human capital. Literature has primarily focused on a single or several human capital domains, with formal education such as years of schooling as the most canonical measure of human capital (Blau and Kahn, 2017; Author and Wasserman, 2013; Goldin et al., 2006; Schultz, 1995). However, according to Hampf et al. (2017) a key challenge for the work on the role of human capital in gender disparity in the modern economies considered its measurement.

The existing empirical literature has mainly relied on quantity-based measures of human capital, such as educational attainment, which is typically measured by the number of years of schooling completed. Although these measures are correlated with human capital and have been demonstrated to be economically significant, they may not be entirely accurate indicators of effective human capital. For instance, the quality of education can vary both over time and across different countries. Therefore, measuring an individual's stock of human capital by years of schooling is problematic in cross-country comparisons as it assumes each school year contributes equally to human capital accumulation regardless of the education system's quality (Hanushek and Woessmann, 2008, 2015). This assumption can be challenged, and educational attainment measures only reflect human capital at the end of formal schooling, which may not reflect the quality of education and ongoing skill adaptation, and long life learning.

According to Hampf et al. (2017) human capital can be defined as workers skills that make them more productive while performing their tasks. When there was no direct measure of skills available, schooling has been utilized as a proxy for the skill level of workers in the labor market. However, the concave relationship between schooling and earnings (Colclough et al., 2010) and gendered job preferences (Lips, 2013) reduces the explanatory power of formal education (Cha and Weeden, 2014) in gender disparity. A different way to measure human capital is to directly assess the skills of adults. Fortunately, a new comprehensive evaluation of adult population skills, called the Programme for the International Assessment of Adult Competencies (PIAAC) that has been conducted by the Organization for Economic Cooperation and Development (OECD) gives us the opportunity to assess a wider variety of skills directly.

Despite a tremendous number of studies examining the impact of human capital on gender disparities, the presence of direct measure of skills in the analysis of gender disparity is quite limited, especially from a dual-focus approach. Advanced Asian economies including Japan, Korea and Singapore, have achieved remarkable economic success in recent decades. However, gender disparities are still prevalent in these countries. The objective of this study is to compare the wage, and employability returns to cognitive skills across Japan, Korea, and Singapore, and to compare the underlying factors that contribute to the gender wage gap with those that influence the gender employability gap in these countries. The study also aims to assess how these factors differ both within each country and across the three countries, providing a comprehensive analysis of gender disparities in both wage earnings and employability.

This research is motivated by the need to better understand the distinct and overlapping factors that drive gender disparities in wages and employability in advanced Asian economies, with a particular focus on the dual impact of cognitive skills. While the gender wage gap and the gender employability gap are both critical indicators of inequality in the labor market, they may be influenced by different factors, including cognitive skills, and to varying degrees across different countries. Cognitive skills are increasingly recognized as crucial determinants of labor market success, yet their role in either narrowing or widening gender gaps in wages and employability remains underexplored, especially in a comparative context across advanced Asian economies. By comparing these gaps and the influence of cognitive skills within and between Japan, Korea, and Singapore, the study seeks to identify specific areas where gender disparities are most pronounced. The insights gained from this analysis aim to inform more effective, targeted policy interventions to reduce these disparities in the labor market.

The remainder of the study is structured as follows. Section 2 provides a brief review of the related literature, followed by a detailed description of the research model and empirical strategy in Section 3. Section 4 presents an overview of the PIAAC data and descriptive statistics. The main findings are presented in Section 5, while Section 6 delves with the mechanisms. Finally, Section 7 concludes.

2. Literature review

There is a vast literature documenting the returns to skills and its effect on gender wage gap. However, much of this literature uses formal educational attainment or years of schooling as a proxy for skills (e.g., Card 1999, Harmon et al. 2003, Psacharopoulos and Patrinos 2004, Hekman et al. 2006, Oreopoulos 2006, Lange and Topel 2006, Lachner 2011, and Oreopoulos and Salvanes 2011). Using the PIAAC dataset provides the opportunity to compare the key skills of individuals among adult working-age independent of their formal education attainment. Therefore, it serves as a good proxy for people's skills level.

Starting from Hanushek et al (2015), while human capital is virtually always identified as the key factor determining systematic differences in individual wages, existing empirical evidence has rested on crude and (almost certainly) biased estimates of its importance. The Mincer (1970, 1974) earnings function, which is widely used, assumes that differences in skills can be captured by measures of educational attainment while disregarding other factors that may have a systematic impact on skills.

Researchers have attempted to address endogeneity issues and have found that education has a strong causal impact on earnings and employment. While the literature on returns to education mostly relies on years of schooling as a measure of human capital, recent works suggest that educational outcomes (the cognitive skills people have actually learned) are more reliable proxies of human capital, than just attainment (how long people stayed in school) (Hanushek and Woessmann 2008, Hanushek and Zhang 2009, Chetty et al. 2011, Hanushek and Rivkin 2012, Cha and Weeden 2014, Hampf and Woessmann 2016, and Hampf et al. 2017). This evidence calls for a focus on educational outcomes, not just attainment, as it is what people know and can do that matters for labor market success, not just how long it took them to reach that achievement. Hanushek and Woessmann (2008) suggests that cognitive abilities of individuals, beyond just their level of educational attainment, are strongly linked to their earnings, income distribution, and overall economic growth. In addition, Hanushek and Woessmann (2012, 2015) find that measuring a country's human capital by the average test scores on international student achievement tests in math and science shows a stronger positive association with long-run growth than measuring it by the average years of schooling of the population.

Analysis of the returns to cognitive skills and their attribution on gender disparities has had to rely on a small number of specialized data sets. In the United States evidence on direct measure of cognitive skills is mostly limited to early-age workers (Haider and Solon, 2006). Fortunately, a studies by Hanushek et al. (2015, 2017) and Hampf et al. (2017) using data from the PIAAC survey of adult skills in OECD and partner countries reveal that higher cognitive skills are systematically related to higher earnings and better employment chances in all surveyed countries. Furthermore, based on their empirical findings, the returns to skills are larger in faster-growing economies, implying that skills are particularly important for adapting to economic changes. This relationship documents the extent to which knowledge-based modern economies place more value on skills. They employed several approaches to address potential threats to the causal identification of wage and employment returns to cognitive skills.

When it comes to the effect of skills on gender wage gap, Aspal (2015) shows that stronger mathematical skills of males substantially affect the gender wage gap. In addition, Tverdostup and Paas (2019) suggests that cognitive numeracy skill is a strong predictor of gender wage gap in most European countries. This aligns with evidence that females have lower numerical abilities, and that numeracy skills have higher wage returns compared to literacy skills. Moreover, Rica and Rebollo-Sanz (2019) based on a pooled restricted sample of PIAAC for 23 OECD countries observe that the gender gap in numeracy skills are crucial for understanding a significant part of the gender gap in the labor market both in terms of wages and labor market participation. A recent study by Kawaguchi and Toriyabe (2022) reveals that differences in skill utilization explain the persistent gender wage gap in the countries where the wage penalty of females is substantial. We are shy away that we could not find any piece of literature that explores the effect of skills on explaining the gender employment gap across countries.

Finally, to the best of our knowledge, there is no previous literature on the relationship between returns to skills and the gender wage gap, but Martins and Pereira (2004), Mussida and Picchio (2014), and Furno (2014, 2020) documented the relationship between returns to education and the gender wage gap. Furno (2020) using Italian data finds that returns to education increase along the wage distribution, while gender wage gap displays a decreasing pattern across quantiles. Mussida and Picchio (2014) reveals that for highly educated women returns to education and gender wage gap increase across quantiles. For low educated women returns to education and gender wage gap decrease across quantiles. Martins and Pereira (2004) find different patterns for different countries among 16 European countries.

This study contributes to existing literature in five ways. First, this study *uniquely contrasts two forms of gender inequality*, revealing that factors influencing wage disparities do not necessarily impact employability in the same way. *This dual-focus approach* offers a more holistic view of gender inequality in the labor market. Second, the cross-country analysis provides insights that are *specific to the socio-economic context of each nation*, a perspective that is often underexplored in broader, global studies. Third, the study identifies how gender disparities evolve over the lifecycle. This age-specific analysis reveals that gender gaps in wages and employability are not static and can widen or narrow depending on the life stage and skill level, an area that has received limited attention in previous studies. Fourth, in terms of methodology, we use Gelbach (2016) decomposition which the estimates are not affected by sequencing and are robust. Fifth, our dual-focus approach suggests that *a one-size-fits-all policy approach may not be effective*. Policies should target the specific causes of gender inequality in each country, considering the unique economic and social conditions that influence gender gaps in wages and employability.

These contributions distinguish this study from existing literature by providing a multi-faceted, comparative analysis of gender inequality in wages and employability, with a focus on *age-specific, skill-specific, and country-specific factors.*

3. Key model and empirical strategy

3.1. Baseline model

Following Hanushek et al. (2015) and Falck et al. (2021) we estimate returns to cognitive skills in a general Mincer framework that relates a person`s human capital to wages and employability in the labor market. This empirical model is analog to a Mincer equation except that it is built on measured cognitive skills, instead of years of schooling, which is one of the several inputs into cognitive skills. Specifically, our cross-country analysis is based on the following regression:

$$y_{in} = \beta_0 + \beta_1 C_{in} + \beta_2 F_{in} + \beta_3 E_{in} + \beta_4 E_{in}^2 + \varepsilon_{in} \qquad (1)$$

Where y_{in} stands for gross hourly wage or employment status (working equals 1 and zero otherwise) of individual i living in country n {Japan, Korea and Singapore}, C_{in} represents individuals' cognitive skills in the PIAAC survey, i.e., numeracy, literacy and problem solving, respectively. F_{in} is gender dummy equal to 1 if a person is female, zero otherwise. E_{in} is actual work experience, and ε is stochastic error. The coefficients of interest are β_1 and β_2, which β_1 indicates the wage and employability changes in percentage when skills increase by one-standard-deviation and β_2 represents the gender gap in wages and employability. For the baseline result we will use ordinary least squares (OLS) estimation. However, in the case of wage model, to provide a more complete picture of the returns to cognitive skills and gender wage gap across the entire distribution of the dependent variable (here: wage) we employ quantile regression. Our primary interest is to shed light on the potential connection between β_1 and β_2 across countries and quantiles. Additionally, we stratify our results into age groups and skill levels to account for heterogeneity across life cycle and skill groups.

3.2. Alternative identification models

As noted by Hampf et al. (2017), using OLS caution must be exercised when interpreting β_1 as the causal effect of cognitive skills on the labor-market outcomes. Several factors can bias the estimates of the returns to skills, including measurement error, reverse causality, and omitted variables (for more discussion see Hanushek et al., 2015).

Measurement error in cognitive skills assessment may bias the coefficient on skills towards zero. It arises due to the test-based nature of PIAAC as it is difficult to measure an individual's proficiency comprehensively in limited response time and with a limited number of test items in a test-based environment. Furthermore, on a single test, the respondent may under- or over-perform concerning his or her actual ability. Reverse causality, where higher earnings may lead to improvements in skills, may upwardly bias the returns-to-skills estimate. Omitted-variable bias may arise if unobserved variables like non-cognitive skills, personality traits, family background, or health status are related to cognitive skills and influence earnings.

Following Hanushek et al. (2015, 2017) and Hampf et al. (2017) we employ a variety of different approaches to address potential threats to causal identification of returns to skills. For instance, to address measurement error, we use literacy skills as an instrument (IV)[3] for numeracy skills. We use years of schooling as instruments for numeracy skills to account for reverse causation. Years of schooling can act as an instrument for skills because it affects skills development but is determined before entering the labor market.Lastly, we additionally control for parents` education and individual health status, albeit limited, to account for some omitted variable bias.

[3] An instrument is a variable that is correlated with the endogenous variable but has no direct effect on the outcome variable and is not related to the outcome through a channel other than the endogenous variable. In other words, the instrument eliminates any bias due to endogeneity and isolate explanatory variable variation which is not correlated with the error term (for a discussion, see Schlotter et al., 2011).

The IV model is commonly estimated using a two-stage least squares (2SLS) estimator. This estimator involves two steps, namely the first and second stages. During the first stage, for example the endogenous regressor, C_{in}, from Eq. (1), is regressed on the instrument Z_{in} and all exogenous regressors contained in the $\mathbf{X_{in}}$ vector.

$$C_{in} = \pi_0 + \pi_1 Z_{in} + \mathbf{X_{in}} \boldsymbol{\pi}_2 + v_{in} \qquad (2)$$

Remember that:

$Cov\ (C_{in}, \varepsilon_{in}) \neq 0$ β_1 is bias; we need to find a valid IV (Z_{in}) satisfies two conditions:

1. Instrument relevance: Corr $(Z_{in}, C_{in}) \neq 0$

2. Instrument exogeneity: Corr $(Z_{in}, \varepsilon_{in}) = 0$

Instrument exogeneity cannot be directly tested and requires judgement based on personal knowledge and common sense due to missing unbiased estimates for ε_{in}. The first stage isolates the uncorrelated variation in C_{in}, overcoming problems like reverse causality and omitted variables, achieving consistent estimation. The second stage of the 2SLS model obtains the causal effect of C on y by regressing y_{in} on predicted values ($\hat{C}_{in}$) and control variables.

$$y_{in} = \beta_0 + \beta_1 \hat{C}_{in} + \beta_2 F_{in} + \beta_3 E_{in} + \beta_4 E_{in}^2 + \omega_{in} \qquad (3)$$

3.3. Gender gap decomposition

The next step is to estimate, how much of the gender gap in wages and employability in Japan, Korea, and Singapore can be attributed to multidimensional human capital components, including accumulated human capital and human capital use[4]. To address this question, we apply a decomposition methodology developed by Gelbach (2016) which the estimates are not affected by sequencing and are robust. To implement Gelbach decomposition and as a basis for comparison, we first estimate the baseline unadjusted (raw) gender wage gap:

$$y_{in} = \beta_0^{base} + \beta_1^{base} F_i + \varepsilon_{in}^{base} \qquad (3)$$

Where β_0 represents the constant term and F_i is female dummy variable. The full preferred model (adjusted gender wage gap) then estimates the following version of equation (1).

$$y_{in} = \beta_0^{full} + \beta_1^{full} F_i + \mathbf{X_{in}} \boldsymbol{\beta}_2^{\mathbf{full}} + \varepsilon_{in}^{full} \qquad (4)$$

Where $\mathbf{X_{in}}$ represents the vector of all other covariates including demographic factors, accumulated human capital, and human capital use components.

[4] Accumulated human capital refers to years of schooling, experience, cognitive (numeracy and literacy) skills. Human capital use stands for use of numeracy, literacy, computer, non-cognitive skills and problem-solving skills at work.

Let $\delta = (\beta_1^{base} - \beta_1^{full}) = \sum_{j=1}^{k} \beta_j * \gamma_j$ be the term for explanation of the gender wage gap by the covariates. Using omitted variable bias formula, proposed by Gelbach (2016), we can decompose δ into various explanatory variables. In particular if there are *k* components in the full regression, $\delta_k = \beta_k * \gamma_k$, where γ_k is the coefficient from auxiliary regressions of that k^{th} component. For instance, the portion of the gender wage gap (δ_{num}) explained by numeracy skills (num_{in}) is given by $\beta_{2,num}^{full}\ \gamma_{num}$, where γ_{num} is estimated from the following auxiliary regression.

$$num_{in} = \gamma_0 + \gamma_{num} F_{in} + u_{in} \qquad + \qquad (5)$$

Gelbach decomposition makes clear that for a factor such as numeracy skills to account for a substantial share of the gap, the factor must, (1) be strongly correlated to dependent variable like wage or employability even when conditioning on all other variables ($\beta_{2,\, num}$ is large), and/or (2) there is large gender gap in numeracy skills or γ_{num} is large.

4. PIAAC data and descriptive statistics

PIAAC is an OECD survey measuring individual skills through test results, covering cognitive skills such as numeracy, literacy, and problem-solving in technology-rich environments. It also provides information on employment, earnings, education, skills use, and background for around 5000 individuals per country. Data was collected in three rounds, covering multiple countries worldwide. This analysis focuses on Japan, Korea and Singapore among PIAAC surveyed countries (OECD, 2016)[5] to explore how different are advanced Asian economies. Our primary choice is to use numeracy as our skills measure as it's more comparable across countries than literacy, which can be influenced by language complexity differences. Literacy and problem solving will be used for robustness checks.

Table 1 displays descriptive statistics separately for full, men and women samples for the entire working-age sample aged 16 to 65 years. The gender wage gap exists in all three countries, with Japan having the largest wage gap. In contrast, gender gap in employment is larger in Korea than Japan and Singapore. Japan demonstrates higher scores in cognitive skills across all three skill domains, both in the full sample and when analyzed separately by gender. Women tend to exhibit relatively lower levels of numeracy skills compared to men in all three countries, with the largest disparity observed in Singapore. The gender difference in literacy is negligible in Japan, but significant in Korea and Singapore. Although the gender difference in problem-solving is significant, it is smaller than the gap in numeracy skills in all three countries.

Notably, there is a significant distinction in years of experience between men and women, with Korea displaying the largest difference compared to Japan and Singapore. On average, women in all three countries have lower average years of schooling compared to men. Furthermore, the female

[5] Although as a supplementary result we estimate for other countries as well that can be available upon request.

representation in the sample is substantial, with Singapore having the largest share. Lastly, Cohen's d[6] values across the three countries for the set of variables range from very small to large effect sizes, with the largest differences in wages, employment, and experience in Japan and Korea, but all the effect sizes are small in Singapore.

Table 1. Descriptive Statistics

	Japan				Korea				Singapore			
	Full	Male	Female	Dif.	Full	Male	Female	Dif.	Full	Male	Female	Dif.
Log wage	7.24	7.44	7.03	0.41***	9.28	9.42	9.12	0.30***	2.74	2.81	2.66	0.15***
	(0.54)	(0.54)	(0.45)	<0.82>	(0.67)	(0.65)	(0.66)	<0.46>	(0.69)	(0.71)	(0.67)	<0.22>
Emp	0.77	0.89	0.66	0.23***	0.71	0.87	0.58	0.29***	0.78	0.86	0.71	0.15***
	(0.42)	(0.31)	(0.47)	<0.57>	(0.45)	(0.34)	(0.49)	<0.67>	(0.41)	(0.35)	(0.46)	<0.37>
Numeracy	289.63	295.71	284.09	11.62***	261.70	267.11	257.00	10.11***	256.44	263.86	249.15	14.71***
	(43.38)	(44.91)	(41.17)	<0.27>	(45.85)	(45.30)	(45.81)	<0.22>	(69.47)	(69.39)	(68.78)	<0.21>
Literacy	297.25	298.36	296.24	2.11	271.80	275.06	268.95	6.11***	255.53	259.49	251.64	7.85***
	(39.29)	(40.06)	(38.56)	<0.054>	(41.82)	(41.36)	(42.00)	<0.15>	(61.17)	(60.71)	(61.38)	<0.13>
Problem solving	295.51	299.52	291.18	8.34***	282.96	285.39	280.78	4.61***	287.58	290.16	284.90	5.25***
	(43.28)	(43.70)	(42.41)	<0.19>	(37.64)	(38.11)	(37.08)	<0.12>	(45.18)	(45.69)	(44.50)	<0.12>
Age	41.81	41.59	42.01	-0.43	40.57	40.52	40.60	-0.072	39.39	39.10	39.67	-0.57
	(14.15)	(14.49)	(13.83)	<-0.03>	(13.72)	(13.61)	(13.82)	<-0.005>	(14.05)	(14.14)	(13.95)	<-0.041>
Experience	18.83	22.12	15.79	6.33***	13.35	16.66	10.21	6.45	15.25	16.43	14.06	2.37***
	(12.57)	(13.49)	(10.79)	<0.52>	(10.89)	(11.90)	(8.74)	<0.62>	(12.25)	(12.78)	(11.59)	<0.19>
Years schooling	13.10	13.26	12.90	0.36***	12.62	12.94	12.33	0.61***	11.73	11.93	11.53	0.40***
	(2.43)	(2.66)	(2.17)	<0.15>	(3.30)	(3.22)	(3.33)	<018>	(3.03)	(2.99)	(3.05)	<0.13>
Share		52.21%	47.79%			54.50%	45.50%			52.13%	47.87%	

Note: Standard deviation in (parentheses) and Cohen's d test in <angle brackets>. The measure of experience refers to actual work experience and was collected as the number of years where at least 6 months were spent on paid work. Sample: full-time employees aged 16-65. a Japan and Korea wages divided by 1000. Data source: PIAAC, 2016

Our main analysis utilizes the entire working-age sample, encompassing individuals aged 16 to 65 years. This approach aims to ascertain the overall returns to cognitive skills and the average gender gap in wages and employability across countries and wage quantiles for wages. Thereafter, for considering heterogeneity, we examine returns to cognitive skills and its connection with gender gap across different age groups, specifically early age (16-24), entry-age (25-34), prime-age (35-54), and exit age (55-65) and different skill levels: low, medium and high levels. To ensure comparability, we standardize skills to have a mean of zero and a standard deviation of one in our econometric analysis, and always use the sample weights provided in PIAAC.

[6] Cohen`s d is a standardized effect size for measuring the difference between two group means (Cohen, 2013; Ellis, 2010). Based on Funder and Ozer (2019) the interpretation of Cohen's d is as follows: d < 0.2 is "trivial effect"; 0.2 < d < 0.5 is "small effect"; 0.5 < d < 0.8 is "medium effect"; and d > 0.8 means "large effect".

5. Empirical results

Other things being equal, how do wage and employability returns to cognitive skills differ, and how do the factors contributing to the gender wage gap compare to those influencing the gender employability gap in Japan, Korea and Singapore, based on PIAAC data? To investigate this question, we begin with a set of baseline estimates for the entire sample, by age groups and skill levels, to account for heterogeneity. Then, we adjust our models to explore gender differences in returns to skills and address causality. In the last stage, using Gelbach (2016) decomposition, we compare the contribution of different factors, especially cognitive skills, in explaining the gender wage and employability gap.

5.1. Baseline results

The wage and employability returns to numeracy skills for the entire sample across Japan, Korea, and Singapore are presented in Table 2. Panel (a) of Table 2 reports results on the returns to numeracy skills in terms of hourly wages and gender wage gap. It reveals that numeracy skills significantly increase wage earnings in all three countries, though the magnitude of these returns varies across countries. Singapore has the highest wage returns to numeracy skills, followed by Korea and Japan. A one-standard-deviation increase in numeracy skills is associated with a 39.2-log point increase in wages in Singapore, while in Korea and Japan, the increases are 16.7 and 15.4 log points, respectively. However, conditioning on numeracy skills and experience, there remains a significant gender wage gap in all three countries, where being female is associated with a wage penalty of 33.1 percent in Japan, 22.5 percent in Korea and 7.4 percent in Singapore.

Table 2. Baseline results: returns to numeracy skills and gender gap

Variables	**a. Wage Model**			**b. Employability Model**		
	Japan	**Korea**	**Singapore**	**Japan**	**Korea**	**Singapore**
Numeracy	0.154***	0.167***	0.392***	0.021***	0.036***	0.053***
	[0.009]	[0.012]	[0.009]	[0.007]	[0.006]	[0.006]
Female	-0.331***	-0.225***	-0.074***	-0.244***	-0.209***	-0.117***
	[0.017]	[0.025]	[0.019]	[0.013]	[0.012]	[0.011]
Experience	0.036***	0.035***	0.063***	0.019***	0.015***	0.009***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
Experience^2	-0.056***	-0.064***	-0.118***	-0.041***	-0.029***	-0.014***
	[0.006]	[0.011]	[0.007]	[0.004]	[0.005]	[0.004]
R^2	0.313	0.148	0.395	0.109	0.105	0.058
Observations	3,311	3,160	3,383	4564	5466	4524

Note: Robust standard errors in [brackets]. Dependent variables are log hourly wages (Log wage) and employability (Emp.) in each country. Numeracy skill is standardized to have mean zero and SD of one. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Similarly, panel (b) of Table 2 shows the association between numeracy skills and the probability of being employed, as well as the gender gap in employability. It shows that numeracy skills also positively influence employability in Japan, Korea, and Singapore, but the effects are generally lower than those observed for wages. The lower employability returns can be attributed to the fact that they only capture the quantitative outcome of skills in the labor market - whether a person is employed or not - without considering job quality. In contrast, wage returns reflect the quality of employment, which obviously should be higher.

In Singapore, numeracy has the strongest association with employability 5.3 percent**,** followed by Korea 3.6 percent and Japan 2.1 percent. However, the gender employability gap remains significant across all three countries. Japan has the largest gender employability gap, with women being less likely to be employed by a margin of 24.4 percent compared to men. Korea follows closely with a gap of 20.9 percent, and Singapore has a smaller but still significant gap of 11.7 percent. This indicates that while numeracy skills enhance employability, women face greater challenges in accessing employment opportunities relative to men. Overall, Singapore is doing better regarding returns to skills and the associated gender gap in the labor market.

In the wage model, we also use quantile regression to analyze how wage returns, and the gender wage gap vary across different wage distributions. As shown in Fig. A1 in the appendix, higher wage returns to numeracy skills correlate with a greater gender wage gap across all quantiles in the three countries[7]. Specifically, as wage returns to numeracy skills increase, so does the gender wage gap; both peak together and decline in tandem thereafter[8]. A particular feature of Korea is that the peak of wage returns, and wage gaps is around the median, while this point is almost close to the top-end of wage distribution in Japan and Singapore.

It is worth nothing that we reveal diminishing wage returns to numeracy skills and gender wage gap across quantiles in all three countries. As supported by Paccagnella (2015), the reason for diminishing wage returns across quantiles could be that PIAAC measures primarily capture general skills. While at the top-end of the wage distributions, the labor market rewards specialized knowledge that is necessarily acquired through tertiary education. Likewise, at the bottom-end of the wage distributions, there is less need for PIAAC-measured general skills. One possible interpretation that wage returns to skills and the gender wage gap are linked across quantiles is that wherever skills are more valuable, an individual's gain more if they have them and lose more if they lack them. Another potential reason is that the gender gap in characteristics could be larger in between but smaller at the top and bottom ends.

[7] The results are quite robust when we use literacy skills and problem-solving skills instead of numeracy skills, as evidenced by Fig. A2 and Fig. A3 in the appendix.

[8] We estimate the results for other countries surveyed by PIAAC in the first and second round and are available upon request. We find that countries such as Canada, Denmark, Finland, France, Germany, Ireland, Netherlands, Spain, Sweden, UK, USA, Chile, Greece, Lithuania, Slovenia, and Turkey follow similar patterns as Korea, Japan, and Singapore across quantiles. However, countries such as Belgium, Czech Republic, Estonia, Italy, Norway, Poland, Slovak Republic, Israel, and New Zealand do not show any connection between returns to cognitive skills and the gender wage gap across quantiles, and it's hard to explain why. We do not estimate for Indonesia and Russia because their data are not representative for the entire country, and Australia, which is not publicly available.

It should be noted that these estimates cannot be interpreted as causal effects of cognitive skills on labor market outcomes, including wages and employability. In addition, there may be heterogeneity over the life cycle and skills levels, as well as gender differences in returns to skills, the results of which we present in the following subsections.

5.2. Heterogeneity over the life cycle

Although, the PIAAC dataset is purely cross-sectional and does not allow tracing the trajectories of individuals' labor market outcomes over the life cycle. Hence, to track differences in returns and the gender gap over the life cycle, we estimate our results for different age groups separately. By doing so, we observe heterogeneity at different stages of the life cycle. Table 4 presents the results of wage and employability returns to numeracy skills and the gender gap by age group across Japan, Korea, and Singapore.

The analysis of Table 3 reveals distinct patterns in how numeracy skills affect wage returns and employability across different age groups in Japan, Korea, and Singapore[9]. In Japan, numeracy's impact on wages generally increases with age, peaking during the prime-age years (35-54), where it also coincides with a larger gender wage gap. However, as we move towards the exit age, the gender wage gap continues to widen but the wage return declines. This suggests that while numeracy skills are highly rewarded as individuals age, women face increasing wage penalties compared to men. On the other hand, the impact of numeracy on employability in Japan is less pronounced and peaks in the entry-age group (25-34). The gender employability gap also peaks in the entry age group, after which, although significant, it decreases with age, indicating that while women may face barriers to their labor force participation, especially at the entry age stage, but it decreases to some extent with increasing age.

In Korea, a somewhat similar trend is observed, where numeracy has a more substantial impact on wages during the prime-age years, with the gender wage gap also widening significantly during this period. However, the employability returns to numeracy in Korea are generally weaker across all age groups, and while passing by early-age the gender employability gap is significant and like that of Japan it peaks at entry-age level. Although this gap narrows with age, it is still large enough to worry about.

Singapore presents a different picture where numeracy skills yield the highest wage returns, particularly during the prime-age years, with women experiencing relatively smaller wage gaps across age groups. Interestingly, in the early-age group (under 24), women in Singapore even appear to earn more than men, which is an unusual finding compared to Japan and Korea. However, the employability returns to numeracy in Singapore are generally lower than wage, and the gender employability gap tends to increase with age, particularly in the exit-age group (55-65). This suggests that while numeracy skills are highly valued in the Singapore labor market, particularly in terms of wage earnings, women

[9] We also estimate our results by 10-year and 5-year age cohorts, which follow the same patterns as the 4 age groups. Based on 5-year age cohorts, the gender employability gap is larger for the 30-34 cohort in Japan and Korea.

face greater challenges in securing employment as they age, despite relatively smaller wage disparities.

A common feature of the labor market in Japan and Korea is that the gender employability gap is at its highest level during the entry-age group due to discontinuity in labor market participation as an outcome of marriage and child-rearing, especially for women aged 30-34. However, at this age stage, the gender wage gap is smaller in both societies and even negligible in Korea. One possible reason is that women with higher opportunity costs of having children remain in the labor market because they earn higher wages, so the gender wage gap is narrow at this age group. While entering the prime age, the employability gap narrows as women begin to re-enter the labor market, but the wage gap continues to peak. Nonetheless, Singapore is quite different because it does not experience a discontinuity in women labor market participation.

Table 3. Returns to numeracy skills and gender gap by age group

Variables	Age group				
	Full sample Age 16-65	Early-age Age 16 - 24	Entry-age Age 25 - 34	Prime-age Age 35 – 54	Exit age Age 55 - 65
Panel a. Wage model					
			Japan		
Numeracy	0.154*** [0.009]	0.094*** [0.015]	0.127**** [0.017]	0.176*** [0.013]	0.125*** [0.022]
Female	-0.331*** [0.017]	-0.026 [0.036]	-0.169*** [0.030]	-0.409*** [0.026]	-0.533*** [0.060]
R-squared	0.313	0.111	0.157	0.343	0.265
No. of obs.	3,311	352	673	1,621	665
			Korea		
Numeracy	0.167*** [0.012]	0.036 [0.046]	0.123*** [0.025]	0.189*** [0.016]	0.155*** [0.041]
Female	-0.225*** [0.025]	0.039 [0.084]	-0.014 [0.044]	-0.378*** [0.034]	-0.181* [0.106]
R-squared	0.148	0.006	0.040	0.218	0.097
No. of obs.	3,160	303	832	1,651	374
			Singapore		
Numeracy	0.392*** [0.009]	0.174*** [0.034]	0.307*** [0.021]	0.448*** [0.013]	0.384*** [0.028]
Female	-0.074*** [0.019]	0.169*** [0.054]	-0.016 [0.033]	-0.141*** [0.028]	-0.046 [0.056]
R-squared	0.395	0.103	0.239	0.458	0.353
No. of obs.	3,383	442	856	1,607	478
Panel b. Employability model					
			Japan		
Numeracy	0.021*** [0.007]	0.027 [0.026]	0.040*** [0.014]	0.010 [0.008]	-0.002 [0.014]
Female	-0.244*** [0.013]	-0.088* [0.050]	-0.273*** [0.028]	-0.188*** [0.018]	-0.082** [0.037]
R-squared	0.109	0.043	0.185	0.225	0.078
No. of obs.	4,564	293	860	2,191	1,194
			Korea		
Numeracy	0.036*** [0.006]	-0.011 [0.034]	0.015 [0.016]	0.016** [0.008]	0.012 [0.014]

Female	-0.209***	-0.027	-0.269***	-0.158***	-0.193***
	[0.012]	[0.052]	[0.026]	[0.015]	[0.036]
R-squared	0.105	0.017	0.109	0.150	0.159
No. of obs.	5,466	308	1,156	2,908	1,094
			Singapore		
Numeracy	0.053***	0.030	0.038***	0.009	0.022
	[0.006]	[0.027]	[0.015]	[0.008]	[0.015]
Female	-0.117***	0.092***	-0.105***	-0.118***	-0.139***
	[0.011]	[0.037]	[0.021]	[0.015]	[0.031]
R-squared	0.058	0.046	0.046	0.082	0.153
No. of obs.	4,524	450	1,031	2,180	863

Note: Robust standard errors in [brackets]. In the wage model, the dependent variable is the log hourly wage, and in the employment model, the dependent variable is binary, where 1 indicates working and 0 not working. Robust standard error in brackets. All regressions control for a quadratic polynomial in actual work experience. ****p<0.01, ** p<0.05, * p<0.1*

The next step involves estimating the gender differences in returns to cognitive skills for both the full sample and each age group separately. This analysis allows us to examine whether gender differences in returns to cognitive skills exist. As presented in Table A1 in the appendix, Japan and Korea exhibit similar patterns where numeracy skills generally yield lower returns for women, both in terms of wages and employability, particularly during their prime-age stage. In contrast, Singapore shows more variability, with young women (early-age group) receiving higher wage returns to numeracy than men, though this advantage does not extend into later age groups. Moreover, women in Singapore seem to experience slightly better employability returns to numeracy compared to men, as indicated by the positive interaction term Fem*Num for the full sample, yet there are no significant differences across age groups.

To sum up, numeracy skills are valuable in both wage and employability outcomes across Japan, Korea, and Singapore, but the benefits differ by gender and age group. Japan and Korea tend to show greater gender disparities in returns to numeracy, particularly during prime working years. In contrast, Singapore demonstrates some instances where young women benefit more from numeracy than men, though this trend does not hold as strongly in later years. Overall, the data indicate persistent gender gaps in the labor market, even when women possess equivalent numeracy skills to men.

5.3. Heterogeneity over skill levels

Heterogeneity exists not only across age groups but also across skill levels. PIAAC divides individuals into 6 proficiency levels based on their scores in literacy and numeracy skills[10]. Considering number of observations and using small area estimation technique, we categorize those proficiency levels into three skill groups: low-skilled (below level one and level one), medium-skilled (level two and level three), and high-skilled (level four and level five).

[10] PIAAC results are reported as averages on a 500-point scale or proficiency levels. Profeciancy levels are divided into six levels and a specific score range defines each level. Proficiency level and score range: Below level 1 (0-175), level 1 (176-225), level 2 (226-275), level 3 (276-325), level 4 (326-375), and level 5 (376-500). Source: NCES (https://nces.ed.gov/surveys/piaac/measure.asp?section=2&sub_section=3)

Table 4 presents our estimation results across three skill groups[11]. Medium-skilled workers consistently benefit the most from numeracy skills in terms of wage returns in all three countries, while high-skilled workers have negligible returns in Korea and Singapore, as do low-skilled workers in Japan and Korea. Singapore stands out for having the highest wage returns, especially for medium-skilled workers, and the smallest gender wage gap, while Japan and Korea show a larger gender wage gap across all skill levels. Although the gender wage gap in Japan is roughly similar for medium- and high-skilled workers, overall, the gender wage gap for high-skilled workers is profoundly large in all three countries. It may be due to the lower share of women in management positions and/or being in lower-paying management roles.

Table 4. Heterogeneity in returns to numeracy skills and gender gap across skill groups

Variables	Skill groups			
	Full sample (1)	Low-skilled (2)	Medium-skilled (3)	High-skilled (4)
Panel a. Wage model				
		Japan		
Numeracy	0.154***	0.017	0.165***	0.141***
	[0.009]	[0.068]	[0.016]	[0.040]
Female	-0.331***	-0.292***	-0.326***	-0.325***
	[0.017]	[0.063]	[0.020]	[0.041]
R-squared	0.313	0.175	0.258	0.288
No. of obs.	3,311 (100%)	207 (6.3%)	2,338 (70.6%)	766 (23.1%)
		Korea		
Numeracy	0.167***	0.071	0.173***	0.034
	[0.012]	[0.051]	[0.024]	[0.131]
Female	-0.225***	-0.207***	-0.226***	-0.271***
	[0.025]	[0.065]	[0.028]	[0.082]
R-squared	0.148	0.048	0.124	0.250
No. of obs.	3,160 (100%)	507 (16.0%)	2,403 (76.0%)	250 (8.0%)
		Singapore		
Numeracy	0.392***	0.222***	0.536***	0.029
	[0.009]	[0.028]	[0.033]	[0.076]
Female	-0.074***	-0.107***	-0.054**	-0.138***
	[0.019]	[0.036]	[0.026]	[0.047]
R-squared	0.395	0.134	0.258	0.429
No. of obs.	3,383 (100%)	891 (26.3%)	1983 (58.6%)	509 (15.1%)
Panel b. Employability model				
		Japan		
Numeracy	0.021***	0.012	0.012	0.006
	[0.007]	[0.052]	[0.013]	[0.025]
Female	-0.244***	-0.185***	-0.238***	-0.288***
	[0.013]	[0.056]	[0.015]	[0.029]
R-squared	0.109	0.058	0.099	0.157
No. of obs.	4,564 (100%)	328 (7.2%)	3,267 (71.6%)	969 (21.2%)

[11] Note that due to the small number of observations, we must be cautious in interpreting the results for high- and low-skilled groups.

		Korea		
Numeracy	0.036*** [0.006]	0.072*** [0.025]	0.043*** [0.011]	-0.002 [0.064]
Female	-0.209*** [0.012]	-0.181*** [0.031]	-0.216*** [0.013]	-0.220*** [0.053]
R-squared	0.105	0.084	0.107	0.141
No. of obs.	5,466 (100%)	1,103 (20.2%)	4,018 (73.5%)	345 (6.3%)
		Singapore		
Numeracy	0.053*** [0.006]	0.042** [0.019]	0.075*** [0.018]	0.007 [0.036]
Female	-0.117*** [0.011]	-0.163*** [0.024]	-0.093*** [0.014]	-0.111*** [0.031]
R-squared	0.058	0.070	0.034	0.034
No. of obs.	4,524 (100%)	1335 (29.5%)	2580 (57.0%)	609 (13.5%)

Note: Robust standard errors in [brackets] and proportion of observations in each skills group in (parentheses). In the wage model, the dependent variable is the log hourly wage, and in the employment model, the dependent variable is binary, where 1 indicates working and 0 not working. Robust standard error in brackets. All regressions control for a quadratic polynomial in actual work experience. ****p<0.01, ** p<0.05, * p<0.1*

In terms of employability, numeracy returns are significant for low- and medium-skilled workers in Korea and Singapore, where they show cross-level similarity, but negligible across all skill groups in Japan. The gender employability gap in Japan and Korea widens with increasing skill levels (especially in Japan), but in Singapore, the gap is most concentrated among low-skilled workers and remains large for high-skilled workers. One reason for the wider gender employability gap among high-skilled workers is that in the workplace, women tend to be considered less productive because they may need time off for maternity leave and can only spend a certain amount of time in the office if they have childcare responsibilities. Therefore, employers may be hesitant to hire women, especially for higher-paying jobs that generally require higher skills and involve more leadership and responsibility roles. However, women are expected to be the primary caregivers even if they work full-time, so it's a lose-lose situation for them (LKY, 2019)[12].

There could be two main reasons for the wider gender employability gap for low-skilled workers compared medium- and high-skilled in Singapore. First, low-skilled women often leave their jobs as soon as they get married or have their first child because the pay, they receive does not adequately compensate for the extra effort required to continue working and make it difficult for them to balance work and family life effectively (Sun, 2009; Mathew and Ng, 2016). The second reason is that industries with a higher concentration of low-skilled jobs may traditionally employ more men, further widening the gap. Overall, in Singapore, medium-skilled workers show higher returns and smaller gaps than the other two skill groups.

[12] Source: Lee Kuan Yew School of Public Policy (2019). Retrieved from: https://lkyspp.nus.edu.sg/gia/article/the-gender-wage-gap-problem-is-more-complex-than-you-think

5.4. Alternative Identifications Results

The primary focus of our analysis is to examine the relationship between changes in cognitive skills of workers and the corresponding effects on wages and employability over life cycle and skill levels. Specifically, we aim to quantify the extent to which an increase in cognitive skills leads to changes in wages and the gender wage gap. It should be noted that we do not claim causality; rather, we want to confirm that the pattern of results using different identification schemes is consistent with our baseline estimates.

In Table 5, we address measurement error and reverse causality, respectively, using literacy skills and years of schooling as instruments for numeracy skills. Model 1 and Model 2 show that the trends in returns and the gender gap are consistent with the baseline model across the age cycle, although the magnitudes are different. Model 1 of Table 5 shows that when correcting for measurement error estimated wage returns decrease while the wage gap increases slightly in Japan and Singapore. In contrast, in Korea, wage returns increase, and the wage gap decreases slightly. Nevertheless, estimated employability returns decline in Korea and Japan, and remain almost unchanged for Singapore, though the employability gap remains roughly like baseline estimates in all three countries.

The reason for the weak relationship between numeracy and employability in the literacy IV in Korea and Japan is that better literacy are themselves not associated with higher employability, as unemployed or inactive adults often have similar or higher literacy levels than employed ones (OECD, 2016).

Considering reverse causality in model 2 of Table 5, in both cases, estimated returns to numeracy skills increases substantially and the gender gap decreases. As we already mentioned, we do not interpret them as causal effects (for more discussion see Hampf et al., 2017). To address omitted variable bias, we additionally control for parents' education and individual health status, yielding results consistent with the baseline model. For brevity, we do not report these results in the Table.

Table 5. Alternative identification model

Variables	Age group				
	Full sample Age 16-65	Early-age Age 16 - 24	Entry-age Age 25 - 34	Prime-age Age 35 – 54	Exit age Age 55 - 65
Panel a. Wage model					
	Japan				
Model 1: Measurement error					
Numeracy – Literacy (IV)	0.138***	0.104***	0.105***	0.151***	0.113***
	[0.010]	[0.018]	[0.020]	[0.015]	[0.024]
Female	-0.336***	-0.024	-0.172***	-0.420***	-0.540***
	[0.017]	[0.036]	[0.030]	[0.026]	[0.060]
Model 2: Reverse Causality					
Numeracy – Yrs Schooling (IV)	0.405***	0.182***	0.355***	0.487***	0.357***
	[0.023]	[0.055]	[0.049]	[0.037]	[0.054]
Female	-0.234***	-0.016	-0.138***	-0.280***	-0.397***
	[0.021]	[0.038]	[0.035]	[0.034]	[0.068]

No. of obs.	3,311	352	673	1,621	665
		Korea			
Model 1: Measurement error					
Numeracy – Literacy (IV)	0.186***	0.104*	0.136***	0.201***	0.169***
	[0.014]	[0.055]	[0.028]	[0.019]	[0.048]
Female	-0.220***	0.029	-0.014	-0.375***	-0.177*
	[0.025]	[0.084]	[0.043]	[0.034]	[0.105]
Model 2: Reverse Causality					
Numeracy – Yrs Schooling (IV)	0.510***	0.732	0.438***	0.542***	0.505***
	[0.030]	[0.450]	[0.082]	[0.039]	[0.085
Female	-0.137***	-0.064	-0.028	-0.275***	-0.080
	[0.029]	[0.116]	[0.047]	[0.042]	[0.124]
No. of obs.	3,160	303	832	1,651	374
		Singapore			
Model 1: Measurement error					
Numeracy – Literacy (IV)	0.384***	0.202***	0.318***	0.437***	0.354***
	[0.009]	[0.043]	[0.025]	[0.015]	[0.028]
Female	-0.076***	0.168***	-0.014	-0.143***	-0.045
	[0.020]	[0.053]	[0.033]	[0.028]	[0.055]
Model 2: Reverse Causality					
Numeracy – Yrs Schooling (IV)	0.660***	0.665***	0.649***	0.711***	0.616***
	[0.018]	[0.100]	[0.045]	[0.025]	[0.048]
Female	-0.025	0.134***	0.046	-0.094***	-0.050
	[0.021]	[0.062]	[0.038]	[0.031]	[0.058]
No. of obs.	3,383	442	856	1,607	478
Panel b. Employability model					
		Japan			
Model 1: Measurement error					
Numeracy – Literacy (IV)	0.017**	0.012	0.014	-0.009	-0.0003
	[0.008]	[0.030]	[0.018]	[0.010]	[0.0164]
Female	-0.246***	-0.088***	-0.277**	-0.195***	-0.082**
	[0.013]	[0.050]	[0.028]	[0.018]	[0.037]
Model 2: Reverse Causality					
Numeracy – Yrs Schooling (IV)	0.051***	0.138**	0.170***	0.044**	0.035
	[0.014]	[0.059]	[0.039]	[0.018]	[0.031]
Female	-0.234***	-0.086*	-0.250***	-0.176***	-0.067*
	[0.021]	[0.052]	[0.030]	[0.018]	[0.039]
No. of obs.	4,564	293	860	2,191	1,194
		Korea			
Model 1: Measurement error					
Numeracy – Literacy (IV)	0.027***	-0.066*	-0.009	0.007	-0.003
	[0.007]	[0.037]	[0.019]	[0.009]	[0.015]
Female	-0.212***	-0.021	-0.270***	-0.161**	-0.200***
	[0.012]	[0.052]	[0.026]	[0.015]	[0.036]
Model 2: Reverse Causality					
Numeracy – Yrs Schooling (IV)	0.090***	-0.0014	0.133***	0.033*	0.037
	[0.012]	[0.140]	[0.045]	[0.017]	[0.025]
Female	-0.190***	-0.029	-0.262***	-0.154***	-0.181***
	[0.013]	[0.056]	[0.026]	[0.015]	[0.037]
No. of obs.	5,466	308	1,156	2,908	1,094
		Singapore			
Model 1: Measurement error					
Numeracy – Literacy (IV)	0.053***	0.020	0.032**	0.008	0.014
	[0.006]	[0.032]	[0.016]	[0.009]	[0.016]
Female	-0.117***	0.092**	-0.106***	-0.119***	-0.140***
	[0.011]	[0.037]	[0.021]	[0.015]	[0.031]

Model 2: Reverse Causality					
Numeracy – Yrs Schooling (IV)	0.090*** [0.009]	0.0251 [0.058]	0.051* [0.027]	0.043*** [0.013]	0.051** [0.021]
Female	-0.108*** [0.011]	0.092** [0.037]	-0.102*** [0.021]	-0.112*** [0.015]	-0.138 [0.031]
No. of obs.	4,524	450	1,031	2,180	863

Note: : Robust standard errors in [brackets]. In the wage model, the dependent variable is the log hourly wage, and in the employment model, the dependent variable is binary, where 1 indicates working and 0 not working. Robust standard error in brackets. All regressions control for a quadratic polynomial in actual work experience. ****p<0.01, ** p<0.05, * p<0.1*

5.5. Gender gap decomposition

In this section, we report our results for the Gelbach (2016) decomposition to decompose the gender gap in wages and employability from a multidimensional human capital perspective. Panel (a) of Table 6 shows that more than 50 percent [13] of the wage gap can be explained by the differences in multidimensional human capital components, both accumulated human capital and human capital use and the contribution is much larger in Singapore. In Japan and Korea, the main problem is not the gap in human capital, rather it is the gap in human capital use. Mostly women face to underutilization of human capital. It is true for the full sample and across age groups. In these countries, if women have the same opportunity to use their accumulated human capital at work as men do, the wage gap would be much smaller than what it is. However, the situation is different in Singapore, where the gap in human capital, particularly numeracy skills, is the main driver of the wage gap, suggesting that women's human capital is well utilized in the labor market.

Decomposing the employability gap has its own complexity because 1) human capital use in the workplace cannot be observed for individuals who are not working, and 2) various other factors that cannot be measured based on data influence people's decisions to work. Therefore, we only analyze based on accumulated human capital.

Panel (b) of Table 6 shows that human capital still plays a significant role in reducing the employability gap for the full sample, though its role varies across age groups. Gender gap in experience is the main driver of employability gap for the full sample across all three countries. Interestingly, numeracy and literacy skills play opposite roles, numeracy skills reduce the gap, but literacy skills increase it. This is because adults who are not working have similar or even larger literacy skills than those who are working (OECD, 2016). Coincidentally, women make up a larger proportion of observations among those who are not working. The accumulated human capital components play the greatest role in reducing the employability gap for the exit-age group and the least and even negative for the entry-age group. For entry-age groups, demographic factors like age, children and marital status are the main source of explained part of the gender gap in Japan and Korea, but for Singapore demographic factors generally play no role.

[13] Japan (50.24 percent), Korea (51.50 percent), and Singapore (68.71 percent) for the full sample.

Comparing factors contributing to the wage gap with those of the employability gap, since we can only compare accumulated human capital components, the gender gap in experience is the main contributing factor in explaining the gap in Japan and Korea for both cases followed by years of schooling. In Singapore, numeracy is the main contributing factor in explaining the wage gap, but experience does so for the employability gap. Years of schooling rank the second to explaining the gender gap in wages and employability in Singapore.

Our primary focus is on the dual role of cognitive skills. In Japan, numeracy skills contribute significantly to both explaining the gender gap in wages and employability. Nevertheless, the contribution of literacy skills is negligible, as gender difference in literacy is insignificant. In Korea, numeracy skills contribute significantly to the gender employability gap, but insignificantly to the wage gap. Literacy skills play a contrasting role, widening the employability gap but narrowing the wage gap, yet insignificantly. Finally, in Singapore, numeracy explains a significant portion of the wage gap but contributes minimally to the employability gap. The contribution of literacy skills in both cases is almost insignificant. Overall, numeracy and literacy skills play a dual role in explaining the wage and employability gap.

Table 6. Gender gap decomposition from a multi-dimensional human capital perspective

Variables	Age groups				
	Full sample Age 16-65	Early-age Age<=24	Entry-age Age 25-34	Prime-age Age 35-54	Exit-age Age>=55
a. Wage gap					
			Japan		
Unadjusted gap	-0.412***	-0.037	-0.183***	-0.535***	-0.546***
Adjusted gap	-0.205***	0.010	-0.128***	-0.271***	-0.262***
Demographic	0.005*	-0.006	0.009	0.001	0.008
Years schooling	-0.014***	0.000	0.003	-0.022***	-0.025***
Experience	-0.070***	-0.012	-0.003	-0.076***	-0.076***
Numeracy	-0.0031***	-0.003	-0.010	-0.049***	-0.013
Literacy	0.004	0.000	0.000	0.009**	0.003
Literacy use	-0.042***	-0.007	-0.015	-0.066***	-0.091***
Numeracy use	-0.016***	-0.026**	-0.006	-0.009	-0.030
Computer use	-0.009***	-0.000	0.001	-0.017***	-0.010
Non-cog. use	-0.025***	-0.003	-0.024***	-0.023**	-0.007
PS skill use	-0.010**	0.009	-0.009*	-0.012*	-0.043***
Total Contri	-0.207***	-0.048**	-0.055***	-0.264***	-0.284***
No. Obs.	3,219	349	671	1,610	661
			Korea		
Unadjusted gap	-0.303***	0.022	0.014	-0.478***	-0.334***
Adjusted gap	-0.147***	-0.012	0.041	-0.262***	-0.196***
Demographic	-0.008**	-0.005	-0.011	0.004	-0.004
Years schooling	-0.019***	0.002	0.018**	-0.046***	-0.014
Experience	-0.043***	0.004	0.003	-0.052***	0.001
Numeracy	-0.005	-0.001	0.001	-0.015*	0.045
Literacy	-0.001	0.017	-0.002	0.002	-0.056

Literacy use	-0.036***	0.050	-0.010	-0.042***	-0.089
Numeracy use	-0.014***	-0.008	-0.014	-0.017	0.020
Computer use	-0.004*	-0.018	-0.006	-0.014**	-0.026
Non-cog. use	-0.024***	0.005	-0.004	-0.031***	-0.029
PS skill use	-0.003	-0.012	-0.001	0.005	0.013
Total Contri.	-0.156***	0.033	-0.027	-0.215***	-0.138**
No. Obs.	3,158	303	832	1,649	374
			Singapore		
Unadjusted gap	-0.147***	0.204***	-0.044	-0.284***	-0.101
Adjusted gap	-0.046***	0.121***	-0.041	-0.102***	-0.028
Demographic	-0.009	0.004	0.004	-0.000	-0.006
Years schooling	-0.022***	0.054***	0.003	-0.056***	-0.005
Experience	-0.016***	0.002	0.025***	-0.016***	-0.017*
Numeracy	-0.024***	-0.000	-0.017*	-0.047***	-0.015
Literacy	0.002	0.005	0.000	0.006	-0.007
Literacy use	-0.005	0.040**	-0.003	-0.015	-0.001
Numeracy use	-0.004	-0.005	-0.007	-0.009	-0.001
Computer use	0.000	-0.005	-0.000	-0.006	0.007
Non-cognitive use	-0.019***	-0.016*	-0.003	-0.033***	-0.009
PS skill use	-0.004	0.004	-0.005	-0.006	-0.017*
Total Contri.	-0.101***	0.083***	-0.003	-0.182***	-0.073
No. Obs.	3,376	442	856	1,601	476
b. Employability gap					
			Japan		
Unadjusted gap	-0.214***	-0.068*	-0.260***	-0.245***	-0.178***
Adjusted gap	-0.115***	-0.055	-0.171***	-0.126***	-0.036
Demographic	0.003	-0.018	-0.048***	-0.001	0.016*
Years schooling	-0.004***	0.009	0.000	-0.006***	-0.010*
Experience	-0.089***	0.001	-0.029***	-0.101***	-0.158***
Numeracy	-0.010***	0.000	-0.011*	-0.015***	0.011
Literacy	0.001	-0.005	0.001	0.003	0.001
Total Contri.	-0.099***	-0.013	-0.086***	-0.119***	-0.141***
No. Obs.	4,560	293	884	2,190	1,193
			Korea		
Unadjusted gap	-0.235***	0.031	-0.245***	-0.239***	-0.314***
Adjusted gap	-0.149***	0.050	-0.240***	-0.151***	-0.157***
Demographic	0.001	-0.034**	-0.031***	0.005*	-0.009*
Years schooling	-0.003**	0.012	0.009**	-0.003	-0.008
Experience	-0.082***	0.022**	0.024***	-0.090***	-0.140***
Numeracy	-0.011***	0.002	-0.003	-0.009**	-0.025**
Literacy	0.008***	-0.022	-0.004	0.008**	0.025**
Total Contri.	-0.086***	-0.020	-0.005	-0.089***	-0.157***
No. Obs.	5,465	308	1,156	2,907	1,094
			Singapore		
Unadjusted gap	-0.125***	0.105***	-0.096***	-0.147***	-0.225***
Adjusted gap	-0.090***	0.104***	-0.102***	-0.113***	-0.126***
Demographic	-0.001	0.002	-0.007	0.002	0.004
Years schooling	-0.004***	-0.006	0.001	-0.010***	-0.006
Experience	-0.030***	0.007	0.016***	-0.030***	-0.093***

Numeracy	-0.004	-0.002	-0.010*	0.002	-0.009
Literacy	0.004*	-0.000	0.005	0.002	0.004
Total Contri.	-0.035***	0.001	0.006	-0.033***	-0.099***
No. Obs.	4,523	450	1,031	2,179	863

Note: In the wage model, the dependent variable is the log hourly wage, and in the employability model, the dependent variable is binary, where 1 indicates working and 0 not working. To save space we do not report standard errors and are available upon request. Accumulated human capital refers to years of schooling, experience, numeracy skills, and literacy skills. Human capital use stands for use of numeracy, literacy, computer, non-cognitive skills and problem-solving skills at work. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

6. Mechanisms: Why?

Singapore`s economic development indeed began later than that of Korea and Japan. While Japan started its industrialization in the late 19th century (Shin, 1996), Korea`s significant economic development initiatives started in the early 1960s following the Korean War, driven by government-led industrialization and export-oriented policies (Amsden, 1992). In contrast, Singapore`s transformation only commenced after its independence in 1965, focusing on attracting foreign investment and developing a skilled workforce (Lee, 2000; Low, 2001). While Japan and Korea have faced structural challenges, Singapore`s model highlighted to be more effective even in terms of gender economic parity including wage and employment (Takenoshita, 2020), which reflects different historical and strategic contexts. However, some argue that Singapore late start allowed it to learn from the experience of its predecessors leading to a more refined approach to economic development (Lee, 2000; Keng Swee, 1972).

The first key question is that how can we claim that Singapore is doing much better in terms of gender equality in the labor market? The best way is to see the labor market trend over time. Starting from labor force participation rate (LFPR), Panel (a) of Figure 1 shows that at the beginning of the period the gender gap in LFPR is much larger in Singapore and over time Singapore could reduce much faster and with higher degree. However, Korea is very slow in reducing the gap in LFPR. Although the gap in Korea was smaller than that of Japan and Singapore at the beginning of the period, it remained much larger at the end. In this trend, Japan moves in the middle line between Korea and Singapore.

Not only is the gender gap in LFPR large in Korea, but the LFPR of both genders is lower than in Japan and Singapore over the entire period, as shown in Panel (b) of Figure 1. Japan has the highest LFPR for men and women, followed by Singapore. However, Singapore is relatively successful in reducing the distance between men and women LFPR. One fact is that men's LFPR is almost constant over the entire period for all three countries. The main competition on the ground among countries is the efforts to increase the participation rate of women.

To further explore the issue of labor market participation, the LFPR over the life cycle by gender is presented in panels (a) and (b) of Figure 2. At first sight, we can see that women follow an M-shape curve over the life cycle in Korea and Japan, which is stronger for Korea. In both societies, women in their 30s leave the labor market for the purpose of marriage and having children, and they re-enter the labor force on their 40s. In contrast we do not see M-Shape pattern in female LFPR in Singapore. It means that Singapore provides a better ground for married women and young mothers to stay in the labor market.

Another fact as you can see in Figure 2 is that the LFPR among young Koreans is lower than in Japan and Singapore for both genders, while the participation rate among older Koreans is relatively higher. This poses a challenge because younger individuals, who are more productive, are participating less, whereas older, less productive individuals are participating more. As a result, overall labor productivity could be lower. This trend may also be attributed to limited social support for older Koreans, forcing them to work in order to meet their basic financial needs. On the other hand, it might be due to Korean people over-investing in education at younger ages and making up for it in old ages.

When it comes to the share of women in management positions, as the trend over time is shown in Figure 3, panel (a), from the beginning of the period to 2016, Korea has the lowest proportion. From 2016 onwards, the proportion of women in management positions in Korea has increased, to the point where it has overtaken Japan since 2018. Though, the proportion in Japan increases at a very slow rate over the entire period. It is worth noting that Japan and Korea are the worst OECD countries in terms of the share of women in management positions (OECD, 2022). But the situation in Singapore is quite different. The share of women is much higher than Japan and Korea for the entire period, where the pace has increased even more since 2017. It ranks above the OECD average of 34 percent in 2022, with 40 percent of women in management positions.

The share of women in vulnerable employment in Korea, although declining over time, is higher than in Japan and Singapore (ILO, 2024); for the trend over time see Figure 3, Panel (b). Singapore has the lowest share of women in vulnerable employment and the trend is somehow consistent over time. Surprisingly, the average time women spend on unpaid domestic and care work in Korea and Japan is lower than in many other advanced countries with only 14 and 15 percent of their day (UNSTAT, 2024)[14].

For the trend of gender wage gap, defined as the unadjusted difference between the median wages of men and women relative to the median wages of men, see Figure 4, Panel (a). In terms of the gender wage gap, Korea is the largest and Japan only one notch below is the second largest among OECD countries. Based on the Singapore Ministry of Manpower (MOM, 2024) while Singapore's gender wage gap is still much better than what it is like in countries like Korea and Japan, it shows there has been hardly any progress between 2006 to 2017. From 2018 onwards, the gender wage gap narrowed as the occupational profile of females improved more than the improvement seen for men. The fertility rate trend is also not favorable for Korea, especially after 2016, as shown in Figure 4, panel (b).

[14] Unfortunately, data is not available for Singapore for Proportion of time spent on unpaid domestic and care work.

A unique fact about Korea is that starting from 2016, two contrasting trends emerge: a bright side and a dark side. On the bright side, the proportion of women in managerial positions rises, and the gender pay gap narrows more quickly than before. On the dark side, the fertility rate drops sharply, and the decline in women's share in vulnerable employment slows down. A combination of policy progress on gender equality and economic barriers to family life produced these contrasting results around the same period.

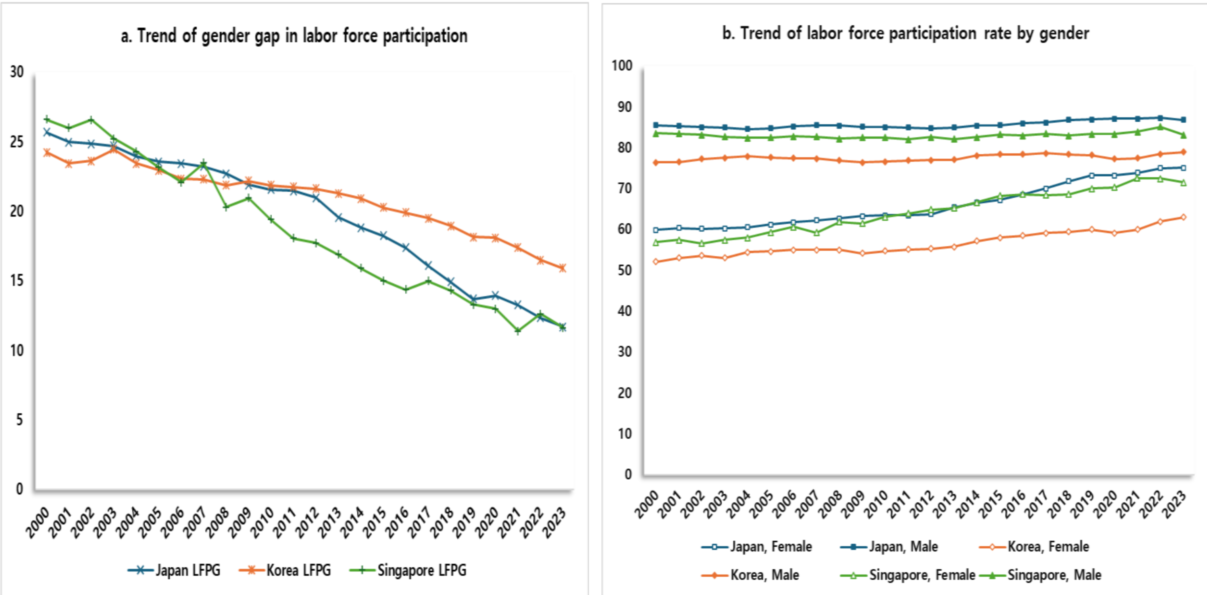

Figure 1. Labor force participation by gender and gender gap. Source: International Labour Organization. "ILO modelled estimates database" ILOSTAT, Feb 6, 2024. Data retrieved from World Bank Gender Data Portal, https://genderdata.worldbank.org/en/economies

Figure 2. Labor force participation rates of male and female by age in 2021. Data extracted from International Labor Statistics from the following website in October 2024**:** https://statdb.mol.gov.tw/html/nat/natehidx01.htm

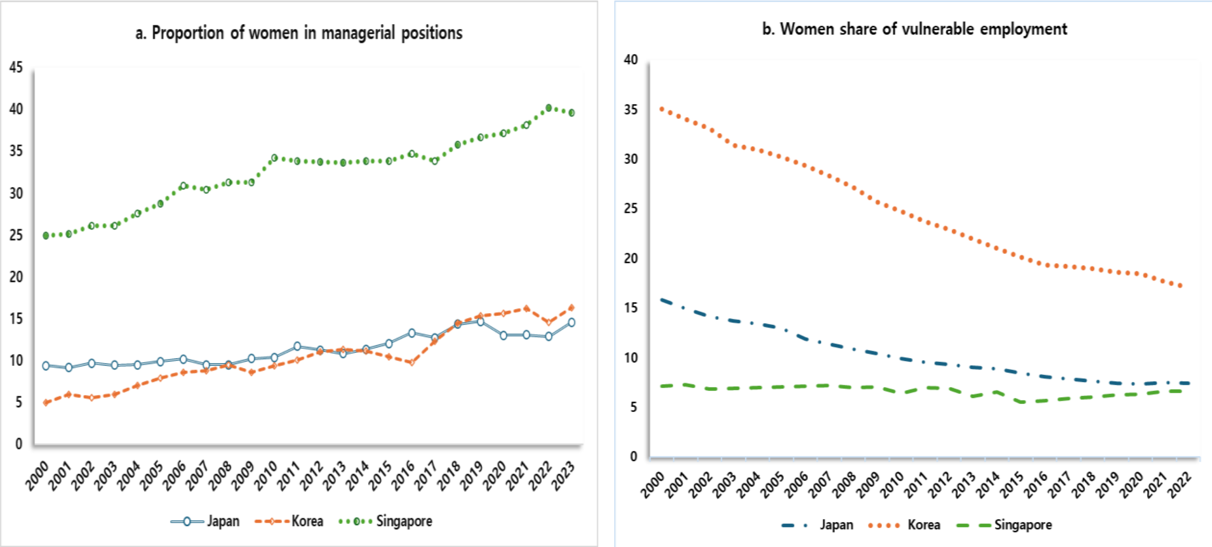

Fig. 3: Women share of managerial positions and vulnerable employment over the years. Source: ILO (2024), "ILOSTAT Database", SDG indicator 5.5.2 - Female share of employment in managerial positions (%) – Website: https://ilostat.ilo.org/data. Data for vulnerable employment: World Bank Gender Data Portal (2024)

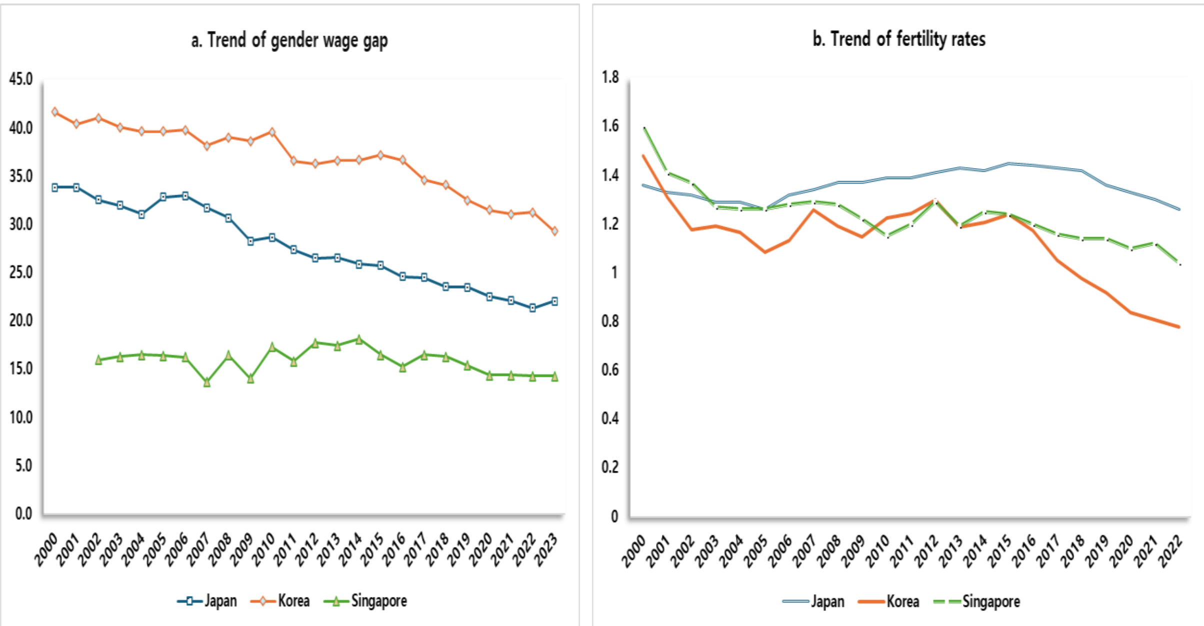

Fig. 4: Trend of gender wage gap and fertility rates over the years. Gender wage gaps defined as the unadjusted difference between median wages of men and women relative to the median wages of men. Source: Gender wage gap data for Korea and Japan are obtained from OECD (2024) and for Singapore from MOM (2024). Fertility: World Bank (2024)

The second key question is, why are experience and human capital use components the main drivers of the gender wage gap in Japan and Korea? This is because women tend to shoulder greater caregiving responsibilities in Korea and Japan, such as raising children or caring for family members (Lee, 2022; Sato, 2021). These responsibilities can lead to career interruptions, shorter work experience, reduced work hours, and skills underutilization, ultimately affecting their earning potential. Among them, the influence of the seniority-based wage system makes the shorter work experience of women the primary factor explaining the gender wage gap in Korea and Japan. Despite the introduction of performance-based wages since the 2000s, the seniority-based system still determines the basic salary in Korea (Lee, 2022). Japan implemented equal pay for equal work regulations in April 2020 to address unreasonable disparities, yet the term "unreasonable disparities" remains unclear to many employers (Chiba, 2021).

Gender-related norms and taking parental leave by married women leads to lower earnings of full-time female workers than full-time male workers in Korea. First, conservative gender-related norms continue to persist despite the country's remarkable economic growth (Hyunsoo, 2021). Despite being a successful economy, Korea has not fully overcome traditional gender norms (Lee, 2022). These cultural attitudes shape the dynamics of the labor market, resulting in unequal wages between genders. Second, Kawaguchi and Toriyabe (2022) suggest that taking parental leave can potentially result in statistical discrimination against certain types of women by employers, as it widens the gender gap in skill use among moderately skilled women, ultimately leading to lower earnings for women.

7. Conclusion

This study uncovers the issue of gender disparities in the labor market of three advanced Asian economies – Japan, Korea and Singapore – from a dual-focus approach. In this approach we focus on both qualitative and quantitative aspects of labor market outcomes, particularly, from a skill-based perspective. We consider employability as a quantitative and wage as a qualitative labor market outcome. Employability only reveals whether a person is employed or not, it does not provide anything about the quality of the job. On the other hand, wage level is a good proxy for having a better quality or decent job, albeit not perfect. It means that a decent wage can be regarded as a payoff for a decent job.

To this end, we first estimate the wage and employability returns to cognitive skills, as well as related gender gaps, focusing on country-specific, age-specific, and skill-specific. Our country-specific results show that numeracy cognitive skills are strongly associated with higher wage returns in all three countries and that employability returns, though positive, are generally lower than wage returns. Singapore stands out with the smallest gender disparities in both wages and employability, while Japan and Korea exhibit remarkable gaps.

On the other hand, age-specific analysis shows that wage returns peak during the prime-age groups in all three countries, while employability returns generally higher for entry-age groups. The gender wage gap increases with age in Japan, while in Korea and Singapore, the highest gender wage gap accumulates in the prime-age stage. In contrast, the employability gap peaks in entry-age groups in Japan and Korea, after which, although significant, it decreases with age. Singapore presents a different picture, where employability gap tends to increase with age. In Japan and Korea, higher employability gap in the earlier age stage (entry-age) leads to higher wage gap in the latter (prime-age) due to M-shape women's labor force participation. The skill-specific approach shows that heterogeneity in returns and gender gaps also exist across skill groups.

The results of Gelbach decomposition based on multidimensional human capital components reveal that human capital use components are the main drivers of the gender wage gap in Japan and Korea rather than accumulated human capital. This suggests that women in these countries face insufficient use of human capital. This is because they work in non-managerial or lower-paid managerial positions, even though they have higher skills. Conversely, in Singapore, the gap in human capital, particularly the difference in numeracy skills, is the key driver of the gender wage gap. In Singapore, the proportion of women in management positions is quite large, and in vulnerable employment, it is very low. Therefore, women's human capital is well utilized in Singapore's labor market. The employability gap in the entry-age stage in Korea and Japan due to marriage and having children leads to shorter work experience in the next stages of life, where this shortage of experience is the main cause of the employability gap and wage gap later and even leads to underutilization of skills.

The study's findings highlight the dual role of cognitive skills in shaping wage and employability outcomes and emphasize that higher skill returns alone do not necessarily close gender gaps, and that skill utilization is a key driver of inequality. These disparities underscore the need for targeted policies that not only focus on improving skills but also address systemic barriers to equal opportunities for women skills utilizations in the workforce.

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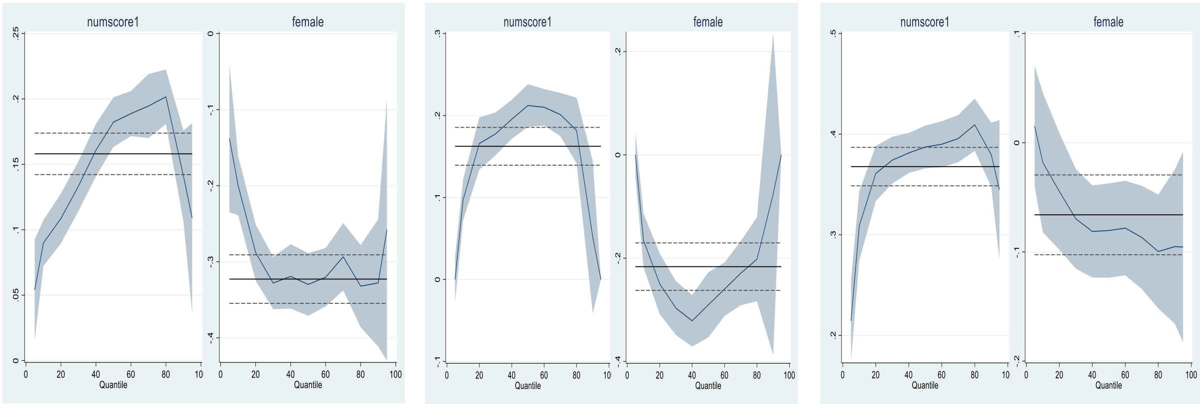
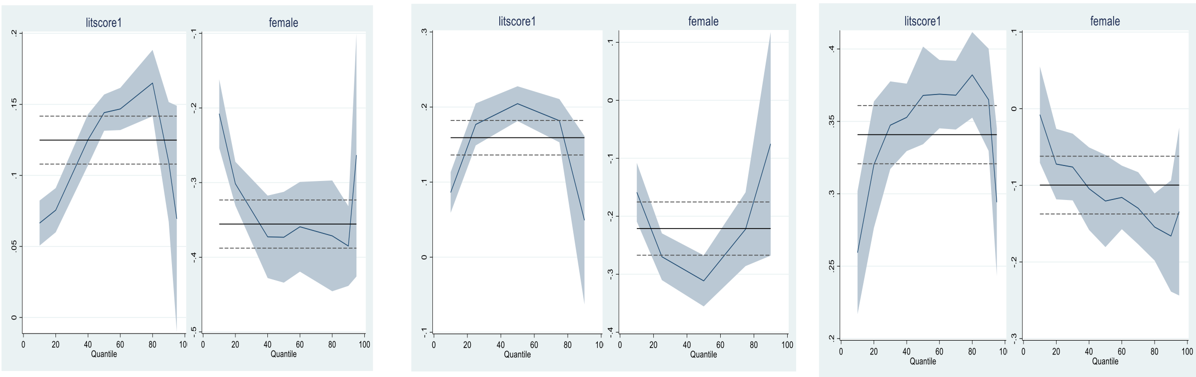
Appendix



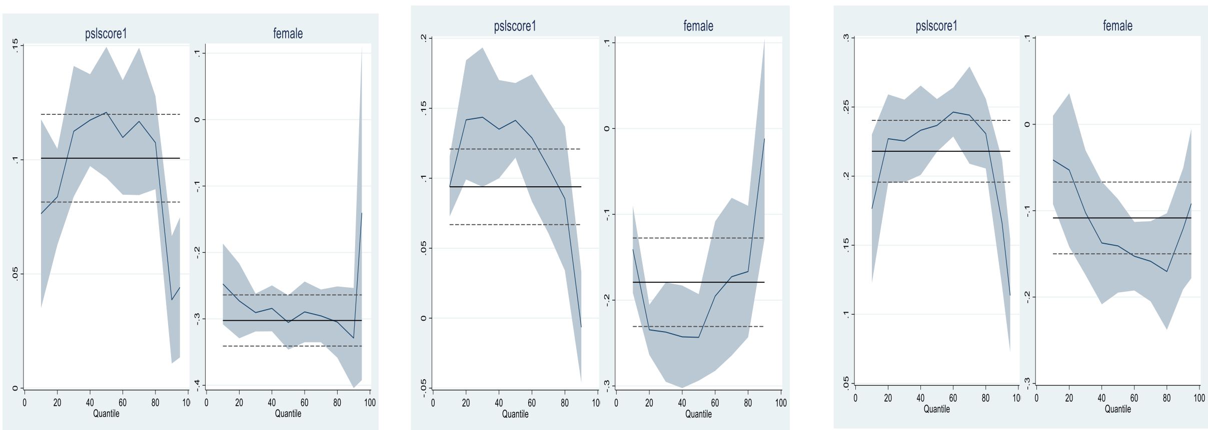
a. Japan b. Korea c. Singapore

Fig. 1. Returns to numeracy skills and gender wage gap. *Note:* Scatter plot of returns to numeracy skills and gender wage gaps across different quantiles of wage distributions.



a. Japan b) Korea c) Singapore

Fig. A1. Returns to literacy skills and gender wage gap. *Note:* Scatter plot of returns to literacy skills and gender wage gaps across different quantiles of wage distributions.



a) Japan b) Korea c) Singapore

Fig. A2. Returns to problem solving skills and gender wage gap. *Note:* Scatter plot of returns to problem solving skills and gender wage gap across different quantiles of wage distribution

Table A1. Gender differences in wage and employability returns to numeracy skills by age group

Variables	Age group				
	Full Sample Age 16-65	Early-age Age<=24	Entry-age Age 25 - 34	Prime-age Age 35 – 54	Exit-age Age 55 - 65
Panel a. Wage model					
Japan					
Numeracy	0.162*** [.0112]	0.082*** [0.022]	0.110*** [0.024]	0.196*** [0.017]	0.155*** [0.031]
FemNumeracy	-0.021 [0.017]	-0.029 [0.029]	0.044 [0.033]	-0.055** [0.025]	-0.078* [0.044]
Female	-0.330*** [0.017]	-0.021 [0.037]	-0.179*** [0.031]	-0.401*** [0.026]	-0.557*** [0.060]
R-squared	0.314	0.113	0.160	0.345	0.269
No. of obs.	3,311	352	673	1,621	665
Korea					
Numeracy	0.181*** 0.016	0.074 [0.067]	0.132*** [0.031]	0.216*** 0.019	0.163*** [0.050]
FemNumeracy	-0.032 0.025	-0.082 [0.089]	-0.023 [0.053]	-0.066** [0.033]	-0.029 [0.085]
Female	-0.221*** [0.025]	0.058 [0.087]	-0.005 [0.052]	-0.375*** [0.034]	-0.197* [0.113]
R-squared	0.149	0.008	0.040	0.220	0.097
No. of obs.	3,160	303	832	1,651	374
Singapore					
Numeracy	0.399*** [0.013]	0.057 [0.044]	0.280*** [0.031]	0.461*** [0.017]	0.401*** [0.037]
FemNumeracy	-0.014 [0.019]	0.215*** [0.064]	0.056 [0.043]	-0.028 [0.026]	-0.041 [0.057]
Female	-0.073*** [0.020]	0.088* [0.050]	-0.041*** [0.038]	-0.141*** [0.028]	-0.069 [0.068]
R-squared	0.395	0.122	0.240	0.458	0.354
No. of obs.	3,383	442	856	1,607	478
Panel b. Employment model					
Japan					
Numeracy	0.028*** [0.008]	0.048 [0.030]	0.026** [0.013]	0.031*** [0.008]	0.010 [0.018]
FemNumeracy	-0.244*** [0.013]	-0.098* [0.050]	-0.279*** [0.029]	-0.181*** [0.018]	-0.092*** [0.038]
Female	-0.016 [0.014]	-0.043 [0.053]	0.031 [0.029]	-0.044** [0.019]	-0.030 [0.029]
R-squared	0.110	0.045	0.186	0.228	0.079
No. of obs.	4564	293	886	2,191	1,194
Korea					
Numeracy	0.038*** [0.008]	-0.067** [0.032]	0.005 [0.020]	0.045*** [0.009]	0.018 [0.018]
FemNumeracy	-0.209*** [0.012]	-0.048 [0.053]	-0.278*** [0.029]	-0.158*** [0.015]	-0.201*** [0.041]
Female	-0.005 [0.012]	0.105 [0.065]	0.024 [0.033]	-0.063*** [0.017]	-0.013 [0.028]
R-squared	0.105	0.031	0.110	0.155	0.159

No. of obs.	5466	308	1,156	2,908	1,094
Singapore					
Numeracy	0.038***	0.040	0.038**	0.015	0.019
	[0.007]	[0.039]	[0.019]	[0.009]	[0.018]
FemNumeracy	-0.117***	-0.100***	-0.105***	-0.118***	-0.135***
	[0.011]	[0.043]	[0.026]	[0.015]	[0.035]
Female	0.031***	-0.019	0.002	-0.012	0.008
	[0.012]	[0.053]	[0.030]	[0.016]	[0.029]
R-squared	0.060	0.046	0.046	0.083	0.154
No. of obs.	4524	450	1,031	2,180	863

Note: In the wage model, the dependent variable is the log hourly wage, and in the employment model, the dependent variable is binary, where 1 indicates working and 0 not working. Robust standard error in brackets. All regressions control for a quadratic polynomial in actual work experience. ****p<0.01, ** p<0.05, * p<0.1*