The Economic Significance of Work Experience for Elderly Employment in Thailand

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Abstract

A rapid demographic change to the aging and aged population in Thailand has led to a reduction in the labor force, and an increasing concern about the economic potential of the country. Therefore, a study of older adults who are capable of working, and an analysis of the significance of their work experience is vital for public policy. An analysis of the data from the 2018 Labor Force Survey in Thailand demonstrates that older adults in the age groups of 60-64 and 65-69 who are capable of working constitute 24.2% and 21.2% of the population, respectively. Among these older adults are retirees, who have the highest potential because they are well educated and highly experienced. Multinomial logistic regression was applied to correct the selectivity bias in the analysis of the return on work experience. The results indicate that the marginal return on work experience is 2.75% for high-skilled occupations. There are similar results for semi-skilled and low-skilled occupations (1.99% and 1.73%), however, diminishes more rapidly in the latter than in the former. These findings indicate that the value of experience increases with occupations that require skills, and diminishes significantly in jobs that mainly require physical strength (i.e., low-skilled occupations). This study suggests that older adults with the potential to do so should be encouraged to remain active in the labor market, and that labor demand is enhanced by emphasizing the value of their experience.

Keywords

Aging population; elderly; elderly employment; labor force; work experience

Introduction

One possible way of addressing the economic impact of labor force reduction in an aging and aged society, due to a rapid decline in fertility and mortality rates, is promoting the employment of older adults (60 years old and above who are willing and able to work). Since the current generation of older adults tend to enjoy better health due to advances in medical and nutrition technologies – as indeed will future generations of older adults - as well as higher educational attainment and work experience, these mature individuals can retain their human capital longer than previous generations. The fact is that the work capacity and human capital of older adults do not disappear or decline the moment they reach retirement age. Therefore, in contrast to their potential, capable older adults who retire or decide to remain outside the labor force tend to underutilize resources; hence they could participate in driving the economy and relieve the fiscal limitations experienced by older adults in society (Phijaisanit, 2015).

Most countries with a significant population of older adults have introduced policies to promote employment of older adults, such as the Aged Employment Promotion Act in Korea (Hong & Lee, 2012), and the active aging policies in European countries (Walker & Maltby, 2012). Such measures are aimed not only at mitigating the economic impact of the declining labor force, but also at enhancing the ability of insufficient savings of older adults to support post-retirement consumption.

Thailand has been classified as an aging society (proportion of population aged 65 years and over exceeds 7%) since 2000, and it is projected that it will only take another 25 years before the country becomes a fully-fledged aged society (proportion of the population aged 65 years and over exceeds 14%). This shift is one of the most rapid demographic transitions in Southeast Asia. Seeing as the Thai labor force is projected to decline by at least 10% between 2010 and 2040 (The World Bank, 2016), it is clear that Thailand needs an immediate policy to cope with the possibility of a rapid reduction in its workforce.

However, the labor market for older adults in Thailand displayed an average growth rate of 4.29% between 2007 and 2018, causing the number of elderly workers to increase from 2.77 million in 2007 to 4.36 million in 2018 (Table 1). It should be noted that these elderly workers are overwhelmingly active in the informal sector, and therefore lack legal protection. Consequently, they are incredibly vulnerable to employment and income risks.

Table 1: Thai elderly labor market

Year	Thailand's Elderly Population (age 60+) (million)	Elderly Workers (million)	Growth Rate of Elderly Workers (%)	Proportion of Elderly Workers (%)
2007	7.07	2.77	-	39.18
2008	7.42	2.80	1.08	37.74
2009	7.71	3.08	10.00	39.95
2010	8.03	3.05	-0.97	37.98
2011	8.31	3.24	6.23	38.99
2012	8.63	3.40	4.94	39.40
2013	9.00	3.45	1.47	38.33
2014	10.05	3.84	11.30	38.21
2015	10.42	3.78	-1.56	36.28
2016	10.91	4.02	6.35	36.85
2017	11.35	4.06	1.00	35.77
2018	11.80	4.36	7.39	36.95

Source: National Statistical Office

This paper uses data from the Labor Force Survey (LFS) in Thailand conducted by the National Statistical Office (NSO) of Thailand to quantify the potential contribution of Thailand's elderly population, with an emphasis on their work experience and to correct any possible bias that may occur in estimation. It should be noted that this study does not imply that a potential elderly labor force must or should be active in the labor market. On the contrary, the potential labor force represents an approximation of an underutilized productive resource that could be encouraged to participate in the labor market by means of a policy introduced by policymakers.

The study is structured as follows: Section 2 presents a brief review of the literature on the potential elderly workforce and the contribution of work experience to earnings; the methodology is described in Section 3; Section 4 presents the empirical results; and Section 5, the conclusion.

Literature review

Health and potential elderly workforce

For the purposes of this literature review, in the Thai context, the potential elderly workforce is defined as individuals aged 60 and above who are capable of working. The main factor that determines the work capacity of such individuals is the state of their health (Santiphop & Pattaravanich, 2016). Illnesses and disabilities are the main obstacles that hinder them from being active in the labor market (Phijaisanit, 2015). These findings are consistent with the study of Adhikari, Soonthorndhada, and Haseen (2011), which concluded that elderly members of the

Thai population with health problems (functional status, chronic diseases, psychosocial symptoms, and low self-assessed health status) were less likely to participate in the labor force.

Although the work capacity of the current elderly generation tends to increase as their health improves, their participation in the labor market does not. Wise (2017) used the mortality rate as a proxy of general health and found that the health of the current elderly generation is better than that of their predecessors, while the current employment rate among older adults is lower than that of their predecessors. Cutler, Meara, and Richards-Shubik (2011) found that the health status of individuals aged between 62 and 64 is not significantly different from that of younger individuals. If the older adults do not have access to early social security retirement benefits, their rate of participation in the labor force will increase by more than 15 percentage points.

Significance of work experience in relation to earnings

Work experience has long been recognized as human capital (Becker, 1962; Mincer, 1958, 1974). It is the outcome of the investment in human capital, by giving up some income and other opportunity costs that relate to working in exchange for skills and knowledge, which lead to higher productivity and future earnings. An individual can invest in gaining work experience by learning from formal or informal on-the-job training (OJT) (Mincer, 1962; Rosen, 1972) as well as learning by doing (Arrow, 1971). Work experience tends to increase with the amount of time worked, which implies that work experience is likely to increase with age. If other factors are held constant, older adults tend to possess more human capital than younger workers.

Empirical studies on the return on work experience usually adopt the human capital theory, and earnings function as the fundamental approach (Mincer, 1974). Empirical findings of the effect of work experience are generally consistent with human capital theory. An additional year of experience would increase the wage by 3.3% - 3.5% in Thailand (Tangtipongkul, 2015), 2.86% in Greece (Agiomirgianakis, Lianos, & Tsounis, 2019), 3.15% for the native-born Latinos in the United States (Mattos, 2018), and 3.8% and 6.9% for civil servants and private sectors employees, respectively, in Denmark (Stritch & Villadsen, 2018). In terms of a gender perspective, an additional year of work experience in Turkey would increase the wage by 4.63% for males and 5.72% for females (Alcan & Özsoy, 2019), 6.13% for females in Pakistan (Qadir & Afzal, 2019), and 5.35% and 1.21% for males and females, respectively, in Brazil (Schwaab et al., 2019).

Recent literature has identified a smaller return on work experience in certain countries. In Japan, the effect of additional tenure on earnings declined from 3.4% in 2005-2008 to 2.9% in 2013-2017 (Kimura, Kurachi, & Sugo, 2019). In China, the return on additional work experience with respect to the hourly wage decreased from 2.25% in 2004 to 1.61% in 2011 (Xia & Xu, 2019). In the United States, the effect of an additional year of experience for older workers (aged 50 – 69) on the hourly wage fell from 1.1% in 1999 to 0.6% in 2015, due to technological change, lower labor union participation, increased numbers of older adults, and increases in nontraditional employment (Johnson, 2019).

Although, as far as the method of estimation is concerned, estimating the human capital earning function by the ordinary least squares (OLS) method is popular for the determination of individual earnings, the coefficient of work experience, education, and other covariates which may suffer from sample selection bias. This bias occurs if the unobserved variables of the sample are related to both (1) the probability of self-selection to the sample, and (2) wage level (Griliches, 1977; Heckman, 1979). Regarding return on experience, Grogger (2009) found that the return on the experience of low-skilled workers is a downward bias. Sample selection bias has been identified as a concern in studies on return on other kinds of human capital such as on-the-job training (OJT) (Almeida & de Faria, 2014), tenure (Altonji & Williams, 2005), age (Börsch-Supan & Weiss, 2008), language (Chiswick & Miller, 2003), gender (Isaza Castro, 2014), and education (Meer, 2007; Warunsiri & McNown, 2010)

It is possible that using the instrumental variable (IV) as a proxy for the unobserved variable can correct the sample selection bias, but the appropriate IV is difficult to obtain. Moreover, using the IV related only slightly to the endogenous variable yields a poorer result than the standard OLS estimation (Bound, Jaeger, & Baker, 1995). The estimation with fixed effects in panel data is also used to correct the sample selection bias. However, panel data relating to the workers are scarce and limited. Therefore, the study of the return on experience and other human capital with cross-sectional data by correcting the selection bias is more available (e.g., Almeida & de Faria, 2014; Chiswick & Miller, 2003; Isaza Castro, 2014)

Methodology

Traditional model of human capital earnings function

This study investigates the work experience contribution of an individual of working age (aged 15-59) on the labor market outcome by applying the human capital earnings function of Mincer (1974). The regression model of the human capital earnings function is as follows:

$$\begin{aligned} ln(wage_i) &= \beta_1 + \beta_2 exp_i + \beta_3 exp_i^2 + \beta_4 edu + \beta_5 female_i + \beta_6 mar_i \\ &+ \beta_7 area_i + \beta_8 C_i + \beta_9 N_i + \beta_{10} NE_i + \beta_{11} S_i + u_i \end{aligned} \tag{1}$$

where

$ln(wage_i)$ = natural log of monthly earnings of individual i
exp_i = years of work experience of individual i
exp_i^2 = the squared of work experience of individual i
edu_i = years of schooling of individual i
$female_i$ = dummy variable, 1 = female, 0 otherwise
mar_i = dummy variable, 1 = married, 0 otherwise
$area_i$ = dummy variable, 1 = in municipal area, 0 otherwise
C_i, N_i, NE_i, S_i = dummy variable, 1= Central region, North region, Northeast region, South region, 0 otherwise (Bangkok)
u_i = the error term

Since data on the experience are relatively limited, this study uses potential work experience as a proxy. Potential work experience represents the maximum amount of time (in years) that the individuals spend working after completing school. Potential work experiences are closely correlated with actual work experiences since it is positively related to the opportunity for learning or training (formal and informal on-the-job training, and learning by doing). It is, therefore, possible to use potential work experience as a proxy for actual work experience.

To calculate potential work experience, it is necessary to assume that a full-time job begins at age 15. Therefore, the calculation of potential work experience is divided into two cases, based on the education level:

$$exp_i = \begin{cases} age_i - 15;\ if\ edu_i < 9\ year \\ age_i - edu_i - 6;\ if\ edu_i \geq 9\ year \end{cases} \tag{2}$$

where exp_i is years of potential work experience of individual i, age_i is the age of individual i, and edu_i is years of schooling of individual i. Years of schooling per education level attained are presented in Table 2 below.

Table 2: Years of schooling across education levels

Education Attainment	Total Years of Schooling
No education	0
Primary	6
Lower-secondary	9
Upper-secondary	12
Post-secondary	14
Bachelor	16
Master	18
Ph.D.	23

Source: Author's calculation

Potential experience is based on the following three assumptions: (1) schooling begins at the age of six, (2) all workers start their job immediately after completing school, and (3) the quality of education is not different. The first assumption is conceivable because young Thais start school at age six. However, the second assumption could lead to an overestimation of actual work experience if individuals do not begin working immediately upon completing school. Another possible problem when interpreting potential work experience arises out of the third assumption, as the quality of education in a country (as well as across countries) varies due to differences in the quantity and quality of teaching resources. The quality difference leads to a relative underestimation of actual work experience in the case of high-quality education and a relative overestimation in the case of low-quality education. This study treats potential work experience as the upper bound of actual work experience, and the interpretation of potential work experience is undertaken with care.

From a conceptual perspective, estimated OLS coefficients of equation (1) might be subject to selectivity bias since OLS estimation includes data relating to paid employees only, not individuals who are outside the labor force. If there is an unobserved variable related to both the probability of being wage employed and the wage level, the coefficient estimated from OLS will suffer from the selectivity bias. To illustrate the source of selectivity bias, consider the following model:

$$y = \boldsymbol{X}\beta + u \tag{3}$$

$$w = \begin{cases} 1, \text{if } \boldsymbol{Z}\gamma + \delta > 0 \\ 0, \text{if } \boldsymbol{Z}\gamma + \delta \leq 0 \end{cases} \tag{4}$$

Equation (3) is the reduced form of the human capital earnings function in equation (1), with $\boldsymbol{X}$ being the vector of independent variables, β the vector of coefficients, and u is the error term. Suppose the sample appears in equation (3) only if they are paid employees or w in equation (4) equal to one ($Z\gamma + \delta > 0$, where $\boldsymbol{Z}$ is a vector of variables related to the probability of being wage employed, and δ is the error term), the conditional mean of y of equation (3) given $\boldsymbol{Z}$ and $w = 1$ is:

$$\begin{aligned} E(y|\boldsymbol{Z}, w = 1) &= \boldsymbol{X}\beta + E(u|\boldsymbol{Z}, w = 1) \\ &= \boldsymbol{X}\beta + E(u|\ \boldsymbol{Z}\gamma + \delta > 0) \\ &= \boldsymbol{X}\beta + \rho E(\delta|\delta > -\boldsymbol{Z}\gamma) \\ &= \boldsymbol{X}\beta + \rho\left[\frac{\phi(-\boldsymbol{Z}\gamma)}{1 - \Phi(-\boldsymbol{Z}\gamma)}\right] \\ &= \boldsymbol{X}\beta + \rho\left[\frac{\phi(\boldsymbol{Z}\gamma)}{\Phi(\boldsymbol{Z}\gamma)}\right] \\ &= \boldsymbol{X}\beta + \rho\lambda(\boldsymbol{Z}\gamma) \end{aligned} \tag{5}$$

where ϕ is the probability density function, Φ is the cumulative density function, $\rho = \frac{\sigma_{u\delta}}{\sigma_\delta^2}$, $\lambda \equiv \frac{\phi(\boldsymbol{Z}\gamma)}{\Phi(\boldsymbol{Z}\gamma)}$, and λ is the inverse Mills ratio. Equation (5) implies that if the OLS model ignores the inverse Mills ratio (λ) and ρ is statistically different from zero, the coefficient β in equation (3) is biased.

Heckman's two-step correction

The two-step procedure suggested by Heckman (1979) can correct the selectivity bias. Step one is to estimate the inverse Mills ratio ($\hat{\lambda}$) from the probit model like equation (3). Step two is to include the estimation of the inverse Mills ratio ($\hat{\lambda}$) as another independent variable of the OLS model. The coefficients estimated in terms of the Heckman procedure will converge to the true coefficient asymptotically.

Work experience in different jobs

This research also investigates the economic significance of work experience in various types of jobs to identify the group of older adults who could potentially enter the labor force. Still, these older adults require support in promoting employment because their work experience may not have much of an effect on their wage. This paper applies the International Standard Classification of Occupations (ISCO-08) (International Labour Office, 2012) to classify samples into three groups: (1) high-skilled occupations (skill levels 3 and 4 in ISCO-08) involving complex technical and practical tasks, complicated problem-solving, and creativity, which require a high level of literacy and numeracy and excellent interpersonal communication (e.g., managers, professionals, and technicians and associate professionals); (2) semi-skilled occupations (skill level 2 in ISCO-08) requiring a moderate level of literacy, numeracy, and interpersonal communication skill (e.g., clerical support workers, services and sale workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, and plant and machine operators and assemblers); and (3) low-skilled occupations (skill level 1 in ISCO-08) - elementary occupations requiring primarily physical strength or endurance (e.g., office cleaners, agricultural laborers, transport and storage laborers). The next step is to estimate equation (1) for each occupational group using the OLS method.

The coefficient from OLS estimation is unbiased if the sample is randomly selected for each group. If it is not, OLS regressions may be biased. As discussed earlier, the bias occurs as a result of the unobserved characteristics related to both the selection into occupational groups and the wage level. In this case, the two-step Heckman correction cannot overcome the selectivity bias in each occupational group. The limitation is that this procedure can only be applied in the case of binary variables (e.g., equal to 1 if wage employed and 0 otherwise). However, in the case of multiple choices (four choices from three occupational groups and one group sample who remain outside the labor market), this study applies the generalization of Heckman's procedure proposed by Lee (1983) to correct the selectivity bias. Like the Heckman procedure, it has two steps. Step one is to use a multinomial logit model to estimate the selection term. Step two is to include selection terms as additional independent variables of the OLS regression model. The multinomial logit model in step one is as follows:

$$\pi_{ij} = \frac{e^{\alpha_j+\beta_j X_i}}{\sum_{j=1}^{4} e^{\alpha_j+\beta_j X_i}} \tag{6}$$

where π_{ij} is the probabilities that individual i select in alternative j (j = 1,2,3, and 4 if high-skilled occupation, semi-skilled occupation, low-skilled occupation, respectively); X being the vector of independent variables including the same variables as in equation (1), except use age and age squared instead of work experience (exp) and work experience squared (exp^2) and include dummy variable "$Head$" where 1 = head of household and 0 otherwise.

Results

This study uses a cross-sectional data set from the 2018 LFS in Thailand made available by the Thai NSO. The survey uses stratified two-stage sampling. The various provinces of Thailand constitute 77 strata, and each stratum is divided into municipal and non-municipal areas. The survey collects data on individual socioeconomic status, education, employment status, occupation, as well as earnings. The original sample size of 860,441 individuals was reduced to 697,138 after cleaning data and excluding those individuals under the age of 15. The sample is divided into those within and outside the labor force. The former group consists of the employed, unemployed, and seasonally inactive labor force (Tables 3). Although individuals can legally work full-time when they reach the age of 15, the labor force participation rate of teenagers is only 17.41%, as a disproportionate number of them attend school. The labor participation rate increases with age and peaks (88.73%) between the age of 40 and 44. After the official retirement age, the labor participation rate drops to 57.90% for the 60–64 and 43.74% for the 65–69 age groups, respectively.

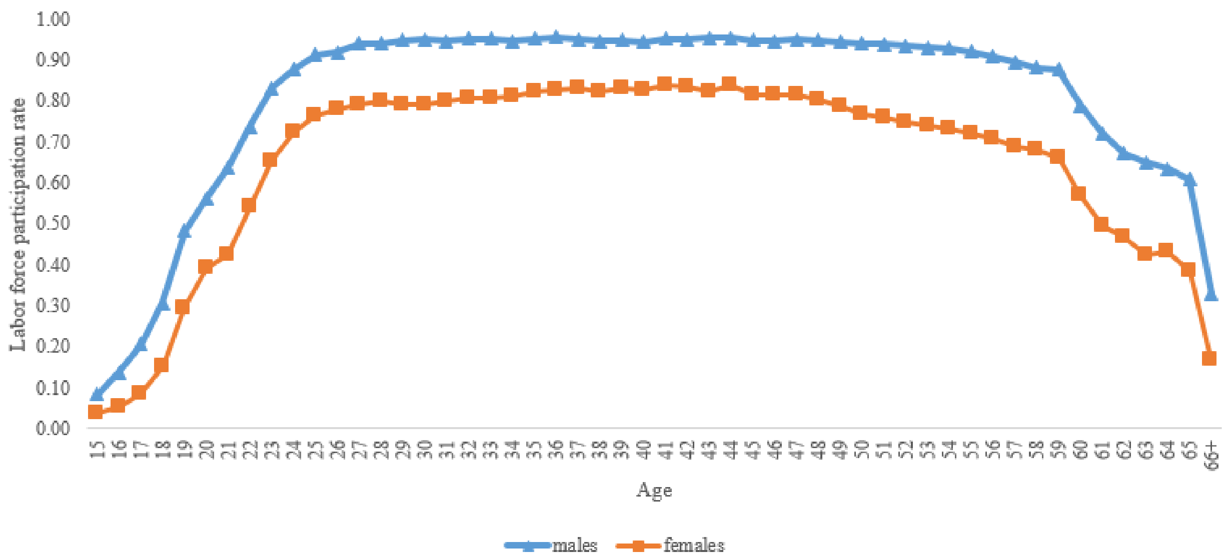
Table 3: Labor market status, 2018 (Unit: persons, percentage in parenthesis)

Age	Labor Force			Labor Force Participation (4) = [(1)+(2)+(3)]	Non-Participation (5)	Total Sample (6) = (4)+(5)
	Employed (1)	Unemployed (2)	Seasonally Inactive (3)			
15-19	7,797	473	84	8,354	39,636	47,990
	(16.25)	(0.98)	(0.18)	(17.41)	(82.59)	(100.00)
20-24	23,806	1,288	88	25,182	13,981	39,163
	(60.79)	(3.29)	(0.22)	(64.30)	(35.70)	(100.00)
25-29	37,529	762	84	38,375	6,340	44,715
	(83.93)	(1.70)	(0.19)	(85.82)	(14.18)	(100.00)
30-34	42,602	362	106	43,070	6,124	49,194
	(86.60)	(0.74)	(0.22)	(87.55)	(12.45)	(100.00)
35–39	49,770	249	107	50,126	6,414	56,540
	(88.03)	(0.44)	(0.19)	(88.66)	(11.34)	(100.00)
40–44	55,940	190	166	56,296	7,149	63,445
	(88.17)	(0.30)	(0.26)	(88.73)	(11.27)	(100.00)
45-49	61,174	157	231	61,562	9,060	70,622
	(86.62)	(0.22)	(0.33)	(87.17)	(12.83)	(100.00)
50-54	61,616	121	284	62,021	12,279	74,300
	(82.93)	(0.16)	(0.38)	(83.47)	(16.53)	(100.00)
55-59	52,922	94	332	53,348	14,604	67,952
	(77.88)	(0.14)	(4.88)	(78.51)	(21.49)	(100.00)
60-64	35,078	43	303	35,424	25,752	61,176
	(57.34)	(0.07)	(0.49)	(57.90)	(42.10)	(100.00)
65-69	19,445	10	189	19,644	25,269	44,913
	(43.29)	(0.02)	(0.42)	(43.74)	(56.26)	(100.00)
70+	11,973	7	88	12,068	65,060	77,128
	(15.52)	(0.01)	(0.11)	(15.65)	(84.35)	(100.00)
Total	459,652	3,756	2,062	465,470	231,668	697,138
	(65.93)	(0.54)	(0.29)	(66.77)	(33.23)	(100.00)

Source: National Statistical Office

Similarly, the labor force participation rates of males and females also increase with age, but decrease after reaching their peak between the age of 40 and 44 (Figure 1). Although the overall female labor force participation rate is less than that of males - due to household responsibilities - Thai women are considerably active in the labor market.

Figure 1: Labor force participation rate by gender, 2018



Source: National Statistical Office

Potential elderly labor force in Thailand

This paper investigates older adults aged between 60 and 69 who could potentially be employed in Thailand, are in good health and capable of working, but are currently not part of the labor force. Again, this study does not imply that these potential employees should be active in the labor market; rather, this group represents an approximation of an underutilized resource that could be encouraged to participate in the labor market through the introduction of an appropriate policy by policymakers.

Older adults will remain outside the labor market if they are (1) engaged in household work, (2) too old to work, (3) ill or disabled, (4) voluntarily idle, and (5) retired (Table 4). The share of those who are outside the labor market increases dramatically after the retirement age of 60 is reached (i.e., from 21.46% for the age group 55-59 to 42.08% for the age group 60-64). The main reason they exit the labor market after retirement is that they are too old to work.

Table 4: People outside the labor force, 2018 (Unit: percentage)

Age	Outside Labor Market	Incapable of Working			Capable of Working			
		Too Old to Work	Illnesses and Disabilities	Other Reasons	Engaged in Household Work	Voluntarily Idle	Retired	Total
50-54	16.51	0.00	3.02	0.26	12.23	1.00	0.00	13.23
55–59	21.46	0.00	3.92	0.28	14.65	1.58	1.03	17.26
60–64	42.08	13.34	4.35	0.19	14.94	1.04	8.22	24.20
65-69	56.27	30.31	4.61	0.16	13.07	0.77	7.36	21.20
70+	84.35	68.92	5.04	0.08	5.66	0.25	4.40	10.31

Source: National Statistical Office

It has been argued that health is the main factor that determines work capacity (Cutler et al., 2011; Wise, 2017). This study uses health status to determine whether those older adults who remain outside the labor force are capable of working. Unfortunately, the dataset does not reflect the health status of the sample, and therefore the reason for remaining outside the labor force is used as the proxy for health status. Those who are too old to work and are in poor health (due to either illnesses or disability) are treated as those who have health problems and are unable to work. The remaining sample is assumed to be the potential labor force as they are healthy and have the capacity to perform a job. Table 4 illustrates that 24.20% and 21.20% of the 60–64 and 65–69 age groups, respectively, could potentially be active in the labor force.

The composition of the potential labor force differs between males and females. In most cases, men are retired, while women are engaged in household work as well as retired (Tables 5)

Table 5: People outside the labor force by gender, 2018 (Unit: percentage)

Age	Outside Labor Market	Incapable of Working			Capable of Working			
		Too Old to Work	Illnesses and Disabilities	Other Reasons	Engaged in Household Work	Voluntarily Idle	Retired	Total
Male								
60–64	30.17	11.42	4.99	0.08	1.57	1.51	10.61	13.69
65-69	44.15	26.14	5.70	0.08	1.22	1.11	9.91	12.24
Female								
60–64	51.71	14.88	3.84	0.27	25.76	0.67	6.29	32.72
65-69	66.25	33.74	3.71	0.22	22.83	0.49	5.26	28.58

Source: National Statistical Office

Work capacity depends not only on health but also on education. As is clear from Table 6 and 7, most of the potential labor force who are engaged in household work are uneducated. By contrast, retired workers are predominantly college graduates. To sum up, the Thai economy has a considerable potential labor force at its disposal - with 22.7% of the population age between 60 and 69. Moreover, a special mention should be made of retirees, who are generally educated and experienced, and who constitute approximately 7.8% of the population aged between 60 and 69.

Table 6: Education attainment of potential male labor force, 2018 (Unit: percentage)

Year of Schooling	60–64 years			65–69 years		
	Engaged in Household Work	Voluntarily Idle	Retired	Engaged in Household Work	Voluntarily Idle	Retired
No schooling	7.26	6.45	2.60	7.27	6.06	4.20
Primary	1.31	1.15	1.17	0.93	0.61	2.06
Lower-secondary	1.31	0.88	8.65	0.44	0.57	10.54
Upper-secondary	0.94	1.45	13.90	0.69	0.81	15.06
Vocational	0.16	0.35	4.55	0.20	0.48	5.53
Bachelor's degree	0.46	0.67	36.21	0.32	0.36	35.37
Master's degree	0.00	0.05	9.51	0.04	0.16	7.95
Ph.D.	0.03	0.00	0.40	0.08	0.00	0.28

Source: National Statistical Office

Table 7: Education attainment of potential female labor force, 2018 (Unit: percentage)

Year of Schooling	60–64 years			65–69 years		
	Engaged in Household Work	Voluntarily Idle	Retired	Engaged in Household Work	Voluntarily Idle	Retired
No schooling	61.21	1.41	0.43	66.45	1.39	0.50
Primary	7.09	0.23	0.16	6.73	0.09	0.18
Lower-secondary	3.40	0.09	0.54	2.53	0.03	0.53
Upper-secondary	3.79	0.12	1.52	2.38	0.06	1.48
Vocational	0.97	0.04	1.03	0.58	0.00	1.42
Bachelor's degree	2.09	0.14	13.87	1.12	0.11	12.53
Master's degree	0.18	0.01	1.61	0.09	0.04	1.59
Ph.D.	0.01	0.00	0.05	0.00	0.00	0.16

Source: National Statistical Office

Significance of work experience

This section examines the effect of work experience on wages by estimating equation (1) for each occupational group. It should be noted that after cleaning the data and focusing on individuals aged between 15 and 59, the sample was reduced to 183,626 individuals.

Table 8 presents the results of OLS estimation on the earnings function of high-skilled, semi-skilled, and low-skilled occupations. Work experience is positively related to monthly wage with a small diminishing effect, and it is statistically significant at the 1% level for all occupational groups. The return on work experience varies based on occupational groups. Marginal return on work experience $\left(\frac{\partial \ln(wage)}{\partial(exp)}\right)$ for novice workers in high-skilled occupations is 2.9% and decline by 0.2 percentage points every 10 years. For semi-skilled occupations, marginal return for novice workers is 1.03%, which declines by 0.08 percentage points every 10 years. For low–skilled occupations, marginal return for novice workers is 1.19%, which declines by 0.4 percentage points every 10 years (Table 9).

Table 8: Estimated earnings function without corrected selectivity bias

Variables	High-Skilled Occupation	Semi-Skilled Occupation	Low-Skilled Occupation
exp	0.0290***	0.0103***	0.0119***
exp^2	-0.0001***	-0.00004***	-0.0002***
edu	0.1344***	0.0570***	0.0165***
$female$	-0.0604***	-0.1390***	-0.0530***
mar	0.0414***	0.0444***	0.0558***
$area$	0.1184***	0.1073***	0.0842***
$Central$	-0.1701***	-0.1352***	-0.2757***
$North$	-0.3049***	-0.2994***	-0.5296***
$Northeast$	-0.3502***	-0.3383***	-0.4869***
$South$	-0.2901***	-0.3783***	-0.3169***
$Constant$	7.5359	8.6504	8.9158***
Observation	45,304	100,346	37,976
F – value	3,052.37	3,834.05	781.89
Adjusted R-squared	0.4828	0.3208	0.1570

Source: Author's calculation

*Note: (1) *, **, and *** are statistically significant at 10%, 5% and 1% respectively.*
(2) Standard error of OLS regression model is robust

Table 9: Marginal return on work experience without corrected selectivity bias (Unit: Percentage)

Years of Work Experience	High-Skilled Occupation	Semi-Skilled Occupation	Low-Skilled Occupation
0	2.90	1.03	1.19
10	2.70	0.95	0.79
20	2.50	0.87	0.39
30	2.30	0.79	-0.01

Source: Author's calculation

The OLS estimation results in Table 8 may suffer from selectivity bias if there are any unobservable variables that relate both to the probability of working in a particular occupation and to earnings. We apply the methodology of Lee (1983) and use SELMLOG, the STATA module to correct selectivity bias (Bourguignon, Fournier, & Gurgand, 2007). Similar to Heckman's procedure, this process involves a two-step process. The first step is to set up the multinomial logit model to estimate the probability of observing the sample working in high-skilled, semi-skilled, and low-skilled occupations. The second step is to calculate the selection correction term and include it in the OLS regression model in each occupational group. The results are presented in Table 10 below.

Table 10: Estimated earnings function with corrected selectivity bias

Variables	High-Skilled Occupation	Semi-Skilled Occupation	Low-Skilled Occupation
exp	0.0275***	0.0199***	0.0173***
exp^2	-0.0001***	-0.0003***	-0.0004***
edu	0.1216***	0.0547***	-0.0002
$female$	-0.0557***	-0.3491***	-0.0907***
mar	0.0437***	0.0457***	0.0240***
$area$	0.1194***	0.1221***	0.0649***
$Central$	-0.1648***	-0.1042***	-0.2631***
$North$	-0.3003***	-0.3479***	-0.4835***
$Northeast$	-0.3529***	-0.4167***	-0.4688***
$South$	-0.2851***	-0.3649***	-0.3263***
Correction term	0.0658***	-0.4921***	-0.2237***
Constant	7.8033	8.3134	8.7295
Observation	45,304	100,346	37,976

Source: Author' calculation
*Note: (1) *, **, and *** are statistically significant at 10%, 5% and 1% respectively.*

The correction term of all occupational groups (high-skilled, semi-skilled, low-skilled, and outside labor force) is statistically significant. This implies that the unobserved factor related to wage level is significantly correlated with the unobserved factor that determines the probability of selection into each occupational group. In other words, the coefficients in Table 8 are biased. After correcting the selectivity bias, the coefficient of work experience (exp) is slightly changed and statistically different from zero. The work experience coefficient of high-skilled occupations has decreased somewhat from 0.0290 to 0.0275. By contrast, the work experience coefficient increases from 0.0103 to 0.0199 and from 0.0119 to 0.0173 for semi-skilled and low–skilled occupations, respectively.

The marginal return on work experience is highest in high-skilled occupations (Table 11). On average, an additional year of work experience raises earnings by 2.75%, and decreases by 0.2 percentage points every ten years in high-skilled occupations. For semi-skilled occupations, the marginal return in the first year of work experience is 1.99%, and decreases by 0.60 percentage points every ten years. For low-skilled occupations, the marginal return in the first year of work experience is 1.73%, and decreases by 0.80 percentage points every ten years.

Table 11: Marginal return on work experience with corrected selectivity bias (Unit: percentage)

Years of Work Experience	High-Skilled Occupation	Semi-Skilled Occupation	Low-Skilled Occupation
0	2.75	1.99	1.73
10	2.55	1.39	0.93
20	2.35	0.79	0.13
30	2.15	0.19	-0.67

Source: Author's calculation

Over and above the marginal return on work experience presented above, Table 10 illustrates the interesting result of earning determination. The return on education is 12.16% for high–skilled occupations, 5.47% for semi-skilled occupations, and -0.02% (statistically insignificant) for low–skilled occupations. Females receive lower wages than males in all occupational groups, especially in semi-skilled occupations, where females receive 34.91% less than their male counterparts. Married individuals receive wages that are approximately 2%-5% higher than other groups. Individuals who are municipal residents earn higher wages than rural residents: 12% higher for high-skilled and semi-skilled occupations, but only 6% higher for low–skilled occupations.

Conclusion and discussion

Promoting employment of older adults is one of the possible solutions to offset shortages in the labor force in an aging economy. This paper aims to quantify the potential contribution of older adults in Thailand, emphasizing their work experience as their outstanding human capital. Individuals aged between 60 and 69 who are in good health and are capable of working, but remain outside the labor market, are an underutilized resource and defined as potential elderly workers. This study has identified that Thailand has a considerable number of potential elderly workers. In 2018, potential elderly workers constituted 24.20% and 21.20% of the total sample age groups of 60–64 and 65–69, respectively. The retirees in the sample were predominately male, while a disproportionate number of females were engaged in household work. Retirees have high potential because, in an overwhelming number of cases, they are educated and highly experienced. A policy that encourages potential elderly workers is necessary since it could mitigate the economic impact of the declining labor force. As Phijaisanit (2015) found, if at least 50% of potential elderly workers were to participate in the labor market, the Thai GDP would exceed the baseline case (no elderly employment) by 7.30%-10.63% between 2025 and 2040.

Work experience constitutes the outstanding human capital of potential elderly workers. It plays an important role in Thailand's labor market, especially in high-skilled occupations, as is clear from the fact that work experience yields the highest marginal return. Empirically, an additional year of work experience for novice workers raises earnings by 2.75%, and decreases by 0.2

percentage point every ten years. The marginal returns on experience for workers in semi-skilled and low-skilled occupations are 1.99% and 1.73%, respectively, but decrease more in the latter than the former. This indicates that the value of experience increases with skills and diminishes significantly in jobs that require more physical strength (i.e., low-skilled occupations). Therefore, the policymakers need to formulate policies to encourage potential elderly workers to remain active in the labor market and enhance labor demand by emphasizing the value of work experience for highly educated individuals previously employed in high-skilled occupations. The policy should also prioritize supporting potential elderly workers with a low level of education who were previously employed in semi-skilled and low-skilled occupations, since their work experience has a relatively small effect on wages, and they may therefore find it difficult to successfully find employment in their old age.

A comparison of the return on work experience in this study (1.73%-2.75% in 2018) with previous studies in Thailand revealed that economic return on work experience in the Thai labor market tends to decrease. In 1985, the return on work experience was 5.4%-7.8% (Hawley, 2004). Between 1989-1995, the return on work experience declined slightly to 6.2%–7.0% (Moenjak & Worswick, 2003), and to 4.0%–4.2% in 2002 (Wannakrairoj, 2013). In 2007-2010 the return on work experience continued to drop to 3.3%-3.5% (Tangtipongkul, 2015). This decreasing return on work experience could lead to financial risk for older adults in Thailand. Furthermore, the decreasing trend of return on work experience is also found in other countries, such as the United States (Johnson, 2019), Japan (Kimura et al., 2019), and China (Xia & Xu, 2019). Johnson (2019) argues that 1) technological change, 2) lower labor union participation, and 3) growth in the number of older adults are the main reasons for this decline. Policymakers need to take into account the smaller return on experience when formulating a policy to encourage potential elderly workers to be active in the labor market. In addition, the causes of the decreasing trend in return on work experience need to be investigated in future research.

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