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Labor Skills, Economic Returns, and Automatability in Thailand

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Abstract

This study analyzes skill content from the occupational structure of the Thai economy. The measurements of skill inputs show that provincial GDP per capita increased with *non-routine* cognitive analytical skills, *non-routine* interpersonal skills, and *routine* cognitive skills in a monotonic way, while economic value has an inverse relationship with *routine* manual physical skills. Trends in skill content and intensities in aggregate production demonstrate that progress has slowed over the last decade. Regression analysis reveals that occupational skill content could be a useful predictor of hourly earnings, especially for *non-routine* cognitive analytical skills. Lastly, risks of automation are more likely to be harmful to low-income, low-skill workers who are at risk of job replacement by artificial intelligence and robots.

Keywords: labor skills; return to skills; automatability; computerization

JEL Classifications: J20, J21, J23, J24

1. Introduction

Thailand needs to upgrade its capacity to innovate to generate new sources of growth and create higher value-added jobs (Sondergaard et al., 2016). This envisioned future requires more advanced skills in the labor force, which requires a new paradigm in the country for human capital development. As technology races ahead, low-skill, low-wage workers will be reallocated to tasks that are not susceptible to "computerization," such as tasks requiring creative and social intelligence (Frey & Osborne, 2017). Automation does indeed substitute for labor skills. However, it also complements labor by enhancing output in a direction that leads to higher demand for workers with advanced skills (Autor, 2015; Arntz, Gregory, & Zierahn, 2016; Frey & Osborne, 2017; and World Bank, 2019).

Having the necessary skills and competencies is important for individuals to obtain productive employment which can help them secure a promising future and, for those who are poor, help them break out of the cycle of poverty (Sondergaard et al., 2016). Greater emphasis on developing a skilled workforce will also promote the deepening of macroeconomic development (Aedo, Hentschel, Luque, & Moreno, 2013; Aedo et al., 2013). As the intensity of *non-routine* cognitive and interpersonal skills increases, national production will increase along with per capita income in a monotonic way, as is observed in some cross-country comparisons.

The impact of automatability on the labor market is well-established in the literature. Employment in routine occupations declines as occupations consisting of tasks following a set of well-defined procedures can be performed by sophisticated algorithms (Frey & Osborne, 2013, 2017). For instance, Charles, Hurst, and Notowidigdo (2013) and Jaimovich and Siu (2012) argue that the continuing decline in manufacturing employment and the disappearance of other routine jobs in the United States is causing the current low rates of employment. In another example, Lekfuangfu and Nakavachara (2019) argue that if there is no restructuring in the Thai labor market, workers will face serious risk of joblessness in the coming future.

The implications of developments in artificial intelligence (AI) and machine learning on jobs and skills have dominated recent debates on the future of work. In their seminal study on occupational skills, Frey and Osborne

(2013, 2017) suggest that 47% of jobs in the United States are at a high risk of being automated. Based on the groundwork by Frey and Osborne (2013), Nedelkoska and Quintini (2018) find that close to one in two jobs in the 32 OECD countries are likely to be significantly affected by automation, e.g., have a risk that a significant share of tasks could be automated. Specifically, about 14% of jobs in OECD countries, which is equivalent to over 66 million workers, are highly automatable. The World Bank (2016) estimated, based on Frey and Osborne (2013), that two-thirds of all jobs are susceptible to automation in the developing world, but the effects can be moderated by lower wages and slower technology adoption.

Nevertheless, many manufacturers have increased their automatic machines to substitute workers in plants and warehouses with more industrial robots coming into use. Artificial intelligence is disrupting routine customer service in call centers. Big data and machine learning suggest more accurately what consumers should buy. It is a fact that digital technologies are substituting for workers performing tasks in both private and public sectors around the world (World Bank 2016).

Frey and Osborne (2013, 2017) examined how susceptible jobs are to computerization based on machine learning classification to estimate the probability of computerization for 702 detailed occupations. Fundamentally, they postulated that creative jobs are non-automatable. They predicted that high-skilled jobs are relatively resistant to computerization with a lower probability of automatability in the occupations that require higher *non-routine* cognitive analytical and interpersonal skills, such as those with bachelor's degree credentials or higher.

Lekfuangfu and Nakavachara (2019) researched the impacts of trade and technology on labor market structures in Thailand. Extending the methodology from Frey and Osborne (2017), the most vulnerable occupations for AI replacement are clerical workers and plant or machine operators with low skills. Another major group at risk is the labor force with primary or lower education. By age category, workers who are between 35 and 44 years old are the riskiest group because aging makes it more difficult for them to reskill for a more complex labor market. The analysis in Lekfuangfu and Nakavachara (2019) also points out that tasks performed by sales workers or even farmers and fishermen are at substantial risk of automatability. With technology, consumers can access market information and trade through online platforms, creating less demand for sales workers in physical shop locations. Agricultural and fishery workers risk replacement by automatic machines and operational tools, which will progressively become cheaper than labor. Digital disruption already impacts employment in Thailand's financial sector. Many commercial banks are shutting down branches and scaling down the number of bank tellers while simultaneously investing more in technology to adapt to the digital economy. Autonomous driverless vehicles provide another example of how manual tasks in logistics and transportation could easily be automated in the near future.

To the best of the author's knowledge, the literature on Thailand is limited on how skill content alters hourly earnings and, except for a recent study by Lekfuangfu and Nakavachara (2019), how future automatability will impact Thai labor market outcomes. This study fills research gaps by providing empirical evidence on the nexus between occupational skills, labor market returns, and probabilities of automatability. This study follows the skill measurement methodology in Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011), and Aedo et al. (2013). This approach analyzes labor skills by measuring specific tasks associated with different occupations rather than measuring educational credentials of workers performing those tasks. There are five different skill categories: *non-routine* cognitive analytical, *non-routine* cognitive interpersonal, *routine* cognitive, *routine* manual, and *non-routine* manual physical skills. The embedded skill measurement relies on information on skill content for each occupation, which is generated based on the Occupational Information Network (O*NET). The O*NET provides detailed descriptions of task requirements for each occupation.

The study shows that provincial GDP per capita is associated with human skill content embedded in aggregate economic production. This study further investigates labor market returns to different skill categories and documents that the *non-routine* cognitive analytical skills significantly increase hourly earnings. Lastly, the risks of automation are examined using the occupational based approach by Frey and Osborne (2013, 2017). The results on the probability of automatability suggest that workers with lower *non-routine* cognitive analytical skills tend to face a higher risk of automatability.

2. Methodology

2.1 Measurement of Occupational Embedded Skills

This study derives the embedded human skill content of aggregate economic production in Thailand. Five different skills are defined, as proposed initially by Autor et al. (2003), later updated by Acemoglu and Autor (2011), and evaluated for a cross-comparison by Aedo et al. (2013). Autor et al. (2003) and Acemoglu and Autor (2011) constructed five aggregate skill measures by selecting and extracting a subset of sixteen task requirements and classifying them as *non-routine* cognitive analytical skills, *non-routine* cognitive interpersonal skills, *non-routine* manual physical skills, *routine* cognitive skills, and *routine* manual skills. A summary of skills by occupational tasks and expected impacts from computerization is provided in Table 1. It is important here to understand the role of skills in occupationally specific tasks. A task is a unit of work activity to produce output such as goods and services. On the other hand, a skill is a worker's endowment of capabilities to perform various tasks. A worker applies their own skill endowment to tasks in exchange for wages, and skills are applied to tasks to produce output. A worker of a given skill level can perform a variety of tasks, and can change the set of tasks they perform in response to changes in economic conditions and technology.

Table 1. Five categories of occupational skills

	Routine Tasks	Non-routine Tasks
	Cognitive Tasks	
Examples	• Calculation • Repetitive customer service • Repeating the same tasks • Being exact or accurate • Doing structured rather than unstructured work	*Analytical* • Analyzing data/information • Thinking creatively • Interpreting information for others *Interpersonal* • Establishing and maintaining relationships • Guiding, directing, and motivating subordinates • Coaching/developing others
Computer impact	Substantial substitution	Strong complementarities
	Manual Tasks	
Examples	• Performing tasks involving repetitive physical motions • Working at pace determined by speed of equipment • Controlling machines and processes	• Operating vehicles, mechanized devices, or equipment • Using hands to handle, control, or feel objects, tools, or controls • Doing work requiring manual dexterity or spatial orientation
Computer impact	Substantial substitution	Limited opportunities for substitution or complementarity

Source: Based on descriptions in Autor et al. (2003) and Aedo et al. (2013). Computer impacts are based on discussion by Frey and Osborne (2013) on how susceptible jobs are to computerization.

The average skill intensity in the aggregate economy is primarily determined by occupational share changes. Each occupation has a skill intensity value for each of the five skills. Therefore, each occupation is defined by a skills vector of five skill aggregates:

$$\boldsymbol{X_i} = \begin{bmatrix} X_i^{Non-routine\ cognitive\ analytical} \\ X_i^{Non-routine\ cognitive\ interpersonal} \\ X_i^{Non-routine\ manual\ physical} \\ X_i^{Routine\ cognitive} \\ X_i^{Routine\ manual} \end{bmatrix} \qquad (1)$$

The skills aggregates are defined following Aedo et al. (2013).

2.1.1 Non-Routine Cognitive Analytical Skills

This set of skills consists of thought processes required for absorption, processing, and decision-making of abstract information. Such tasks include advanced calculation, analyzing information, forming and testing hypotheses, medical diagnosis, legal writing, or any other tasks requiring critical thinking skills. Professional occupations that intensively require such abilities are computer programmers, engineers, statisticians, economists, medical doctors, and lawyers, among many other occupations requiring skills of thinking creatively and analytically. The O*NET skills included in this category are the ability to analyze data and information (ANALYSE), to think creatively (THINK), and to interpret information for others (INTERPRET).

$$X_i^{Non-routine\ cognitive\ analytical} = f(x_i^{ANALYZE}, x_i^{THINK}, x_i^{INTERPRET}) \qquad (2)$$

2.1.2 Non-Routine Cognitive Interpersonal Skills

This set of skills characterizes personality traits that underlie human interactive behaviors such as collaborating, presenting, supervising, reliability, discipline, and teamwork. These skills are important for all team-based work environments, as well as customer services. The O*NET skills included in this category are the capability to establish and maintain personal relationships (RELATIONSHIPS), to guide, direct, and motivate subordinates (GUIDE), and to coach/develop others (COACH).

$$X_i^{Non-routine\ cognitive\ interpersonal} = f(x_i^{RELATIONSHIPS}, x_i^{GUIDE}, x_i^{COACH}) \qquad (3)$$

2.1.3 Non-Routine Manual Physical Skills

This set of skills is characterized by the ability to vary and react to continuously changing circumstances, such as operators of machines or heavy equipment in manufacturing or construction, as well as machinery mechanics and repairers, janitorial services, or truck driving. The O*NET skills included in this category are the ability to operate vehicles, mechanized devices, or equipment (OPERATE), to spend time using hands to handle, control, or feel objects, tools, or controls (HANDLE), manual dexterity (MANUAL), and spatial orientation (SPATIAL).

$$X_i^{Non-routine\ manual\ physical} = f(x_i^{OPERATE}, x_i^{HANDLE}, x_i^{MANUAL}, x_i^{SPATIAL}) \quad (4)$$

2.1.4 Routine Cognitive Skills

This set of skills is characterized by the ability to conduct repetitive, non-physical tasks such as filling forms, reading and calculating bills, or call center services. Monotonous occupations that require such skills are record-keeping, cashier, clerk, and repetitive customer services (such as bank teller or telephone operators). The O*NET skills included in this category are the ability to repeat the same task (REPEAT), to be exact or accurate (ACCURATE), and to handle structured work (STRUCTURED).

$$X_i^{Routine\ cognitive} = f(x_i^{REPEAT}, x_i^{ACCURATE}, x_i^{STRUCTURED}) \quad (5)$$

2.1.5 Routine Manual Skills

This set of skills consists of repetitive physical movements such as labor-intensive agricultural or construction work, some types of machine operation, or assembly lines, such as picking or sorting, or repetitive assembly. The O*NET skills included in this category are the ability to spend time making repetitive physical motions (REPETITIVE), to adapt to a pace determined by the speed of equipment (SPEED), and to control machines and processes (CONTROL).

$$X_i^{Routine\ manual} = f(x_i^{REPETITIVE}, x_i^{SPEED}, x_i^{CONTROL}) \quad (6)$$

A vector is skill information based on the O*NET database for all occupations that can be linked to occupational structures for computing weighted skills measures:

$$X = \begin{bmatrix} X_1' \\ \vdots \\ X_{i=I}' \end{bmatrix}. \tag{7}$$

For each skill category (s) of X^S, country-level skill intensity is calculated as a weighted-average of occupational level skill intensities. The share of active workers in an occupation (i) is defined as

$$\theta_i = \frac{Active\ workers\ on\ occupation\ i}{Total\ active\ workers} \text{ such that } \sum_i \theta_i = 1. \tag{8}$$

The vector of all occupation shares is defined:

$$\boldsymbol{\theta} = [\theta_1 \quad \dots \quad \theta_I]. \tag{9}$$

Therefore, the skill structure of the labor force contains information on skill inputs by occupation as defined by combining all occupations and labor force structure as a vector of average skill intensities:

$$\boldsymbol{\theta X_i} = \begin{bmatrix} \sum_i \theta_i X_i^{Non-routine\ cognitive\ analytical} \\ \sum_i \theta_i X_i^{Non-routine\ cognitive\ interpersonal} \\ \sum_i \theta_i X_i^{Non-routine\ manual\ physical} \\ \sum_i \theta_i X_i^{Routine\ cognitive} \\ \sum_i \theta_i X_i^{Routine\ manual} \end{bmatrix}. \tag{10}$$

Since this study uses only one version of the O*NET database, the skill scores are time-invariant.

2.2 Unconditional Quantile Regression

This study follows previous literature such as Heckman, Stixrud, and Urzu (2006), Lindqvist and Vestman (2011), Hanushek et al. (2015), Deming (2017), and Lee and Wie (2017), among several others, to evaluate the labor market returns to skills. To capture systematic differences of skill content on hourly earnings, this study uses the recentered influence function (RIF) estimator (Firpo, Fortin, & Lemieux, 2009, 2011). The model specification is similar to a Mincerian equation, but focuses on skills as the major explanatory variables.

Consider $IF(y;v)$, the influence function corresponding to an observed wage in a logarithmic form for the distributional statistics of interest, $v(F\_Y)$. The IF captures the effect on $v(F)$ of an infinitesimal contamination of F at point mass y. The RIF is defined as

$$RIF(y;\nu) = \nu(F_Y) + IF(y;\nu), \tag{11}$$

so that it aggregates back to the statistics of interest, e.g. $\int RIF(y;\nu)\, dF(y) = \nu(F_Y)$.

In the case of quantiles, the $IF(y;Q_\tau)$ is given by $(\tau - I\{Y \leq Q_\tau\})/f_Y(Q_\tau)$, where $I\{\cdot\}$ is an indicator function, $f_Y(\cdot)$ is the density of the marginal distribution of Y, and Q_τ is the population τ- quantile of the unconditional distribution of Y. Therefore, $RIF(y;Q_\tau)$ is equal to $Q_\tau + IF(y;Q_\tau)$, and can be rewritten as

$$RIF(y;Q_\tau) = Q_\tau + (\tau - I\{Y \leq Q_\tau\})/f_Y(Q_\tau). \tag{12}$$

The illuminating idea of Firpo et al. (2009) is to regress the RIF on the vector of covariates. In the case of quantiles, the RIF is estimated by computing the sample quantile $\hat{Q}_\tau$, and estimating the density at that particular point using kernel methods. An estimate of the RIF of each observation, $\widehat{RIF}(Y_i;Q_\tau)$, is then obtained by replacing the estimates $\hat{Q}_\tau$ and $\hat{f}(\hat{Q}_\tau)$ into the last equation of the previous paragraph. A change in the marginal quantile Q_τ is explained by a change in the distribution of covariates by means of a simple linear regression,

$$E[RIF(y;Q_\tau|X)] = X\beta, \tag{13}$$

such that an estimate of the unconditional quantile regressions, $\hat{\beta}_\tau$, obtained by a simple ordinary least square regression (OLS) regression is as follows:

$$\hat{\beta}_\tau = (X'X)^{-1}X'\widehat{RIF}(Y_i;Q_\tau). \tag{14}$$

The vector of covariates is composed of the skill content along with other control variables. This study uses a robust and bootstrapped standard error estimation. The kernel function used is Epanechnikov. The vector of the skills required for a specific occupation is thus hypothetically associated with labor market outcomes, which in this study is defined as hourly earnings. The hypothesis for the unconditional regression in this study is that the different skills affect labor market returns differently. The null hypothesis is that labor skills do not affect hourly earnings. The alternative hypothesis is that different labor skills do alter hourly earnings differentially across the earnings distribution.

2.3 Probability of Automatability

Based on the O*NET database, Frey and Osborne (2017) considered a job's automatability to be a function of the skills required to complete the occupational tasks. They used a survey dataset of 702 occupations which cover employment status, income, and skills related to automatability, such as finger dexterity, originality, and persuasion. They organized a workshop for AI researchers to hand-label 70 occupations as being automatable or not. Frey and Osborne (2017) then implemented a Gaussian process classification to estimate the probability of automatability for all occupations by relating the O*NET variables to a binary classification of whether they are automatable or not.

To estimate an occupation's probability of automation in Thailand, this study applies their classification results to 4-digit occupation codes of the ISCO-08 for employed workers aged 16 to 65. As it is expected that the skill content of jobs in the United States is more intensive in *non-routine* and cognitive skills than in Thailand, the results of automatability probabilities in this study are likely to be lower-bound estimates. Nevertheless, this application of the automatability probabilities estimated in Frey and Osborne (2017) has been carried out for other developing countries by the Asian Development Bank (2015), Chang and Huynh (2016), Chang, Rynhart, and Huynh (2016), World Bank (2016), Ng (2017), and Hallward-Driemeier and Nayyar (2018).

From a technological perspective, the reported results from this study represent a partial equilibrium where all other factors are held fixed. For instance, this research implicitly assumes there is no adaptation among workers in the labor force to upgrade themselves with more advanced *non-routine* cognitive analytical skills. It is also assumed that there is no reallocation of tasks between different occupations to facilitate collaboration between machine and human.

3. Data

This study uses quarterly data from multiple waves of the Labor Force Survey (LFS) undertaken by the National Statistics Office of Thailand. The LFS is the primary source of data on the country's labor market and is among the most timely and important economic data series produced. It contains detailed data on individuals over a nearly three-decade time horizon. Individual-level data include information on occupation, employment, education, demographics, and other characteristics. The surveys are representative of five geographic regions until the year 2000, and thereafter subsequently representative of municipal and non-municipal areas within 76 provinces across the five geographic regions. This study focuses on employed workers aged 15–64. All estimates are weighted by the individual sample weights, which are the individual weight multiplied by the number of hours worked.

The LFS classifies occupations according to different versions of the International Standard Classification of Occupations (ISCO) developed by the International Labour Office (ILO). The occupations in LFS 1985-2000 are classified with ISCO-68, while occupations in LFS 2001-2010 and LFS 2011-2018 are classified with ISCO-88 and ISCO-08, respectively. This study establishes occupational equivalents across different ISCO versions based on the crosswalk tables from the ILO. There are kinks in the time trends for some 2-digit and 4-digit occupations. Thus, this study uses the ISCO-88 for the 1-digit occupational categories due to its smoother occupational trends for the LFS 1985Q1-2018Q1. The regression analysis using the LFS 2011Q1-2018Q1 is based on the 4-digit occupation codes from ISCO-08.

In the LFS data, there are different types of reported earnings such as monthly, weekly, daily, and hourly. The number of actual worked hours are used to convert different compensation types into hourly wages. The hourly earnings are in real 2011 terms which are temporally and spatially adjusted. The LFS 2011 Q1-2018 Q1 are used to study the effects of skill attributes across the conditional wage distribution using the quantile regression model. Since the LFS started to use the ISCO-08 codes since 2011, skill content data from the O*NET can be merged using on the 4-digit ISCO-08 codes from that year.

The analysis investigates the measured tasks performed by each occupation and their changes over time. To implement such methodology, this study matches the 4-digit individual occupations with their respective skill content from the O∗NET database, an online service developed for the U.S. Department of Labor. Sixteen specific tasks are combined to create composite scores. There are 12 occupations from a total of 434 occupations that cannot be matched with the O*NET data. All unmatched occupations are not major occupations. For example, the unmatched occupation with the highest sample size is legislators.

As this study is not a cross-country comparison, it does not require adjustments to reflect different meanings and job content of labor markets in developing countries compared to the United States as in Aedo et al. (2013). However, it is still important to emphasize that, as described in Aedo et al. (2013), the occupations which use more *non-routine* type of skills are likely to be less skill-intensive than in more advanced economies. This can cause a potential upward bias in the computations of the measured skill intensity of *non-routine* cognitive analytical and interpersonal skills. Nevertheless, this is a within-country study for Thailand, so it is possible to explore progress and inequality patterns in occupational skills by using a fixed benchmark, similar to what is used in the analysis of poverty that applies specific standard poverty lines to track progress in temporal and spatial comparisons.

The data from the probability of automatability estimated by Frey and Osborne (2013, 2017) is therefore matched with the 4-digit ISCO-08 occupations using a crosswalk approach. The probability data is available in the appendix of Frey and Osborne (2013), which lists occupations ranked by the probability of computerization.

4. Results

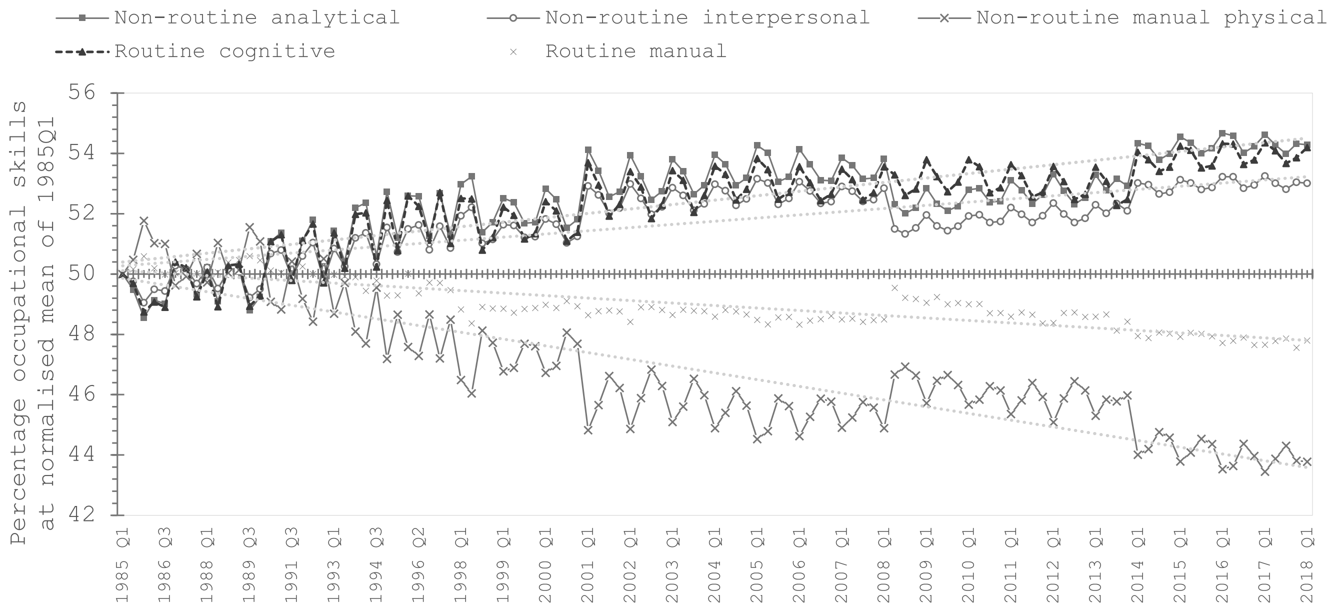
4.1 Aggregate Trends

Figure 1 illustrates the extent of embedded skill change in the occupational labor supply over the period 1985 to 2018. By construction, each task variable has been normalized to have a mean of 50 centiles in the first quarter of 1985 as its initial point. Subsequent points depict the employment-weighted mean from each quarter. Cyclical trajectories along the megatrends reflect the seasonal agriculture production patterns by quarter, so it is not a surprise to observe narrower oscillations in recent years than twenty years ago. The trends persist for occupational skill inputs in the economy.

The shares of the labor force employed in occupations that made intensive use of the *non-routine* analytical skills, *non-routine* interpersonal skills, and *routine* cognitive skills have substantially increased during the last three decades. This is the right direction for future productivity development. However, the content of the *non-routine* occupational skills and *routine* cognitive skills increased faster in the 1990s during the pre-computer era than in the last decades. We should note the slower progress and years of stagnation after 2008. An increase in *routine* cognitive skills comes with the potential risk of computerization in low-skilled occupations. Workers in these occupations are largely from disadvantaged backgrounds and work in low-wage jobs such as machine operators or production assemblers, labor-intensive farmers, or construction workers.

The trend has a remarkable shift around the early 2000s when the economy started to take off after the 1997 Asian Financial Crisis, and again around the period of the 2008 economic downturn. Beyond the period of these two points, the trends are quite steady after eliminating the quarterly seasonal fluctuations. The dispersion between (i) *non-routine* analytical skills, *non-routine* interpersonal skills and *routine* cognitive skills and (ii) *non-routine* and *routine* manual physical skills became slower in the years after 2008. This observation is consistent with the stalling of structural transformation and a slowdown in non-agricultural employment growth as the country struggled to move labor from low- to high-productivity jobs.

Figure 1. Trends in routine and non-routine skill inputs, 1985Q1 to 2018Q1



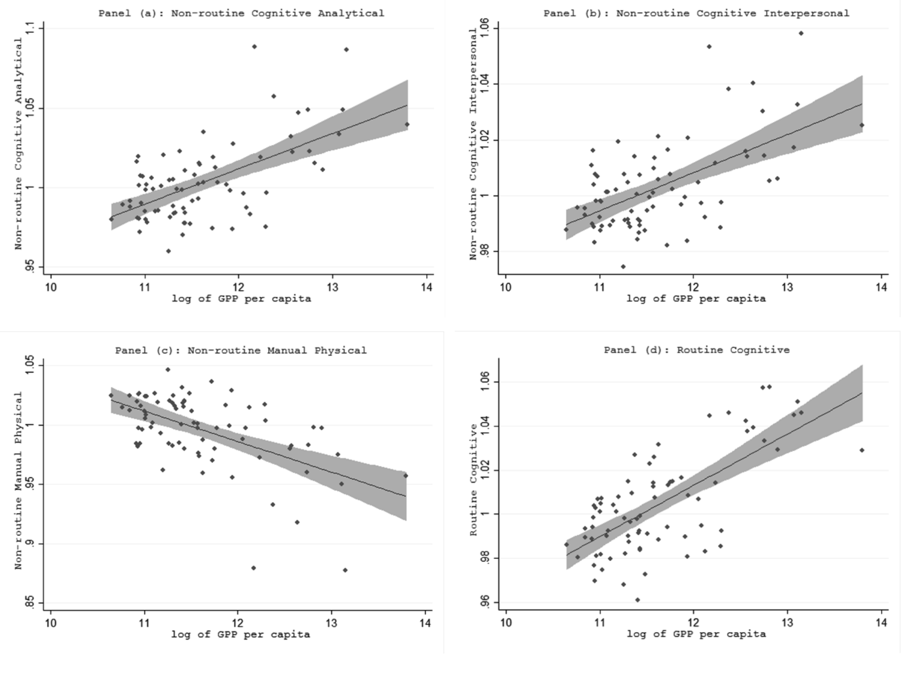
Source: Occupational employment from LFS and skill content data from O*NET.

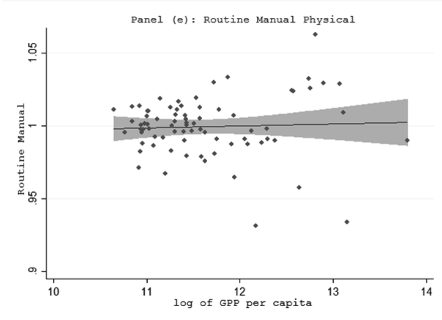
4.2 Labor Market Returns to Skills

4.2.1 Cross-Province Analysis

Aedo et al. (2013) provide an international perspective of skill content and national gross production and demonstrated that the intensity of skills is highly associated with the level of economic development. This study applies the same approach to evaluate the occupation-based skill-measurement for each province in Thailand. Figure 2 illustrates the skill intensity scores and provincial GDP per capita in 2018. The plotted lines estimate the linear relationship between the skill scores and provincial GDP per capita, with the grey areas visualizing the 95% confidence interval.

Figure 2. Association between skill intensity and provincial gross domestic products





Notes: Construction of normalized skill scores at the provincial level used O*NET matched with occupations of employed persons aged 15-65.

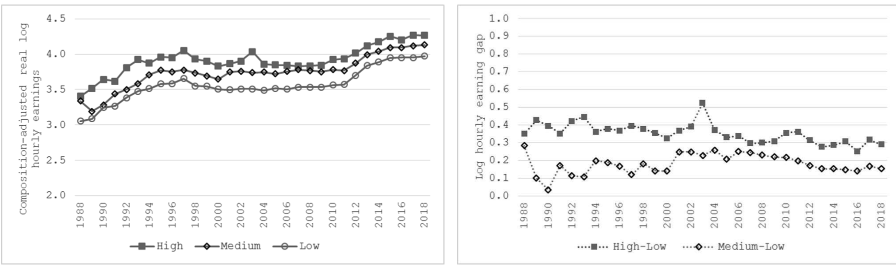
Source: LFS 2018Q1 from the National Statistical Office (NSO) and provincial GDP per capita data from the Office of the National Economic and Social Development Council (NESDC).

Provincial measures of skill content show that the intensity of *non-routine* manual physical skills declines with provincial GDP per capita in a monotonic way, while we find an inverse relationship with the *non-routine* cognitive and interpersonal skills and the *routine* cognitive skills. However, there is no linear relationship with *routine* manual physical skills, which are important for occupations in the manufacturing and construction sectors. The results suggest that fundamentally, economic development favors *non-routine* skills. Provinces with occupational structures that use *non-routine* analytical and interpersonal skills more intensively have higher output per capita, possibly reflecting labor market returns to more advanced skills.

4.2.2 Returns to Skill by Occupation

This study estimates the composition-adjusted log hourly earnings of employed workers aged 15-64. This composition adjustment holds constant relative employment and socioeconomic characteristics. Specifically, this study computes the mean of log real hourly earnings in each year using the weighted average characteristics of the employed population. The key message here is that the average hourly earnings gaps between the high-skilled or medium-skilled occupations over the low-skilled occupations are steady over the last three decades as plotted in Figure 3. This implies that the monetary gaps in real monetary value have been expanding. Thus, the disparities in employment income are worsening, as the same growth rates in logarithmic terms imply a higher gap in hourly earnings.

Figure 3. Composition adjusted log hourly earnings and premium gaps, 1985-2018



Notes: Log hourly earnings for employed workers aged 15-65 for each year are regressed separately by occupational skill level with covariates of a female dummy variable, years of experience, education dummy variables (primary, lower secondary, and college or higher), dummy variables for the industrial sectors, and urban and regional dummy variables. The composition adjusted mean for log hourly earnings is the predicted mean conditional on average characteristics of all employed workers in each year to compare different skills. The sample weight is the population weight multiplied with the total hours worked. Only the third quarter is used for each LFS year, except for the first quarter of 2018.

Source: Labor Force Surveys 1988-2018.

4.2.3 Economic Returns to Embedded Skills

This study uses unconditional quantile regression (Firpo et al., 2009, 2011) to evaluate the impacts of *non-routine* cognitive analytical skills, *non-routine* cognitive interpersonal skills, *routine* cognitive skills, *routine* manual skills, and *non-routine* manual physical skills across the distribution of the log hourly earnings. The regression model includes education level, instead of replacing education with the skills. Arguably, higher education could be correlated with more sophisticated analytical skills, but different fields of study develop skills differently such as STEM fields compared with a degree in business management or social sciences. Thus, this study preserves education level in the regression model as a control variable. The variance inflation factor (VIF) analysis reports that there was no multicollinearity in the reported regression models. The robustness checks confirm strong associations between skills and hourly earnings. Excluding the education variables provide the same pattern of distributional effects of the five skills, but including the education variables lower the size of the impacts. This confirms the robustness of the estimated results.

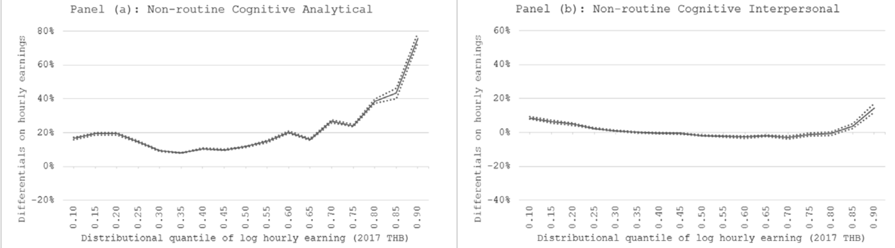
Table 2. OLS and unconditional quantile regression of hourly earnings

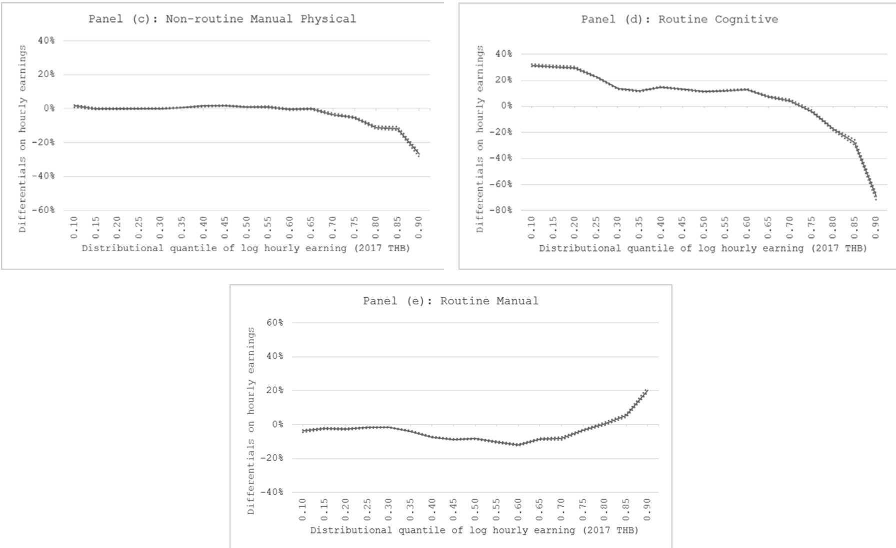
Dependent variable: log of hourly earnings	OLS	Q(.25)	Q(.50)	Q(.75)
Non-routine cognitive analytical skills	0.236***	0.147***	0.117***	0.241***
	(104.36)	(53.18)	(54.69)	(69.31)
Non-routine cognitive interpersonal skills	0.0446***	0.0241***	-0.0177***	-0.0131**
	(18.55)	(9.98)	(-7.43)	(-3.27)
Non-routine manual physical skills	-0.0438***	0.000580	0.0102***	-0.0527***
	(-24.97)	(0.25)	(5.48)	(-20.03)
Routine cognitive skills	0.0426***	0.225***	0.114***	-0.0366***
	(18.39)	(73.80)	(53.19)	(-8.89)
Routine manual skills	-0.0155***	-0.0172***	-0.0821***	-0.0336***
	(-9.07)	(-7.57)	(-45.75)	(-12.29)

Notes: LFS 2011Q1-2018Q1. The t-statistics are in parentheses with * p<0.05, ** p<0.01, *** p<0.001. The full models for the unconditional quantile regression (Firpo, Fortin, and Lemieux, 2009, 2011) are reported in Table A1 in the Appendix.

Table 2 reports the RIF-regression coefficients for the five skills. It shows the marginal effects of the explanatory variables on hourly earnings from both the OLS and unconditional quantile regressions. Estimation results indicate that skill content has statistically significant impacts on hourly wages, but the impacts differ across the entire hourly wage distributional space, as illustrated in Figure 4.

Figure 4. Impacts from occupational skills on hourly earnings





Notes: Unconditional quantile regression's estimated coefficients (solid lines) and their associated clustered and robust 95% confidence intervals (dotted lines) at every 5 percentiles are plotted. Full results with all covariates for the 0.25th, 0.50th, and 0.75th quantiles are available in Table A1 of the Appendix.

Source: LFS 2011Q1-2018Q1.

4.2.3.1 Non-routine Cognitive Analytical Skills

The results show that economic returns to *non-routine* cognitive analytical skills are positive and statistically significant. *Non-routine* cognitive analytical skills provide increasing returns to skills, especially for workers with high hourly earnings, such as those with hourly earnings higher than the 70th percentile. The main occupations associated with high *non-routine* cognitive analytical skills are managers, professionals, and technicians and associate professionals. The positive impacts from cognitive analytical skills on hourly earnings are highest among all five occupational embedded skills. Ceteris paribus, this implies that *non-routine* cognitive analytical skills are the most important skills in determining wage returns in the labor market. We can posit that these skills are the main boosters of economic productivity by the labor supply.

4.2.3.2 Non-routine Cognitive Interpersonal Skills

Non-routine cognitive interpersonal skills have only positive impacts at the tails of the hourly earnings distribution. Occupations with high scores in the *non-routine* cognitive interpersonal skills are managers, professionals, technicians and associate professionals, and services and sales workers. The labor market returns in these occupations are likely to be positive from interpersonal skills. However, the impacts are significantly smaller than impacts from *non-routine* cognitive analytical skills.

4.2.3.3 Non-routine Physical Skills

Non-routine manual skills have no impact on most parts of the hourly earnings distribution except some negative impacts on the distribution's right tail. The occupations with high scores in *non-routine* manual skills are: low-skill occupations such as skilled agricultural, forestry and fishery workers; craft and related trades workers; plant and machine operators, and assemblers; and elementary occupations.

4.2.3.4 Routine Cognitive Skills

Routine cognitive skills highly enhance the hourly earnings for the left tail of the distribution. The size of impact reaches a 20 percent increase in hourly earnings for those below the 30th percentile. However, *routine* cognitive skills also highly diminish the hourly earnings at the top of the distribution, which implies that the top paid occupations with high intensity in repetitive tasks have declining market returns. The occupations with high scores in *routine* cognitive skills are all medium- and low-skill occupations (especially clerical support workers, plant and machine operators, and assemblers), except skilled agricultural, forestry, and fishery workers.

4.3.2.5 Routine Manual Skills

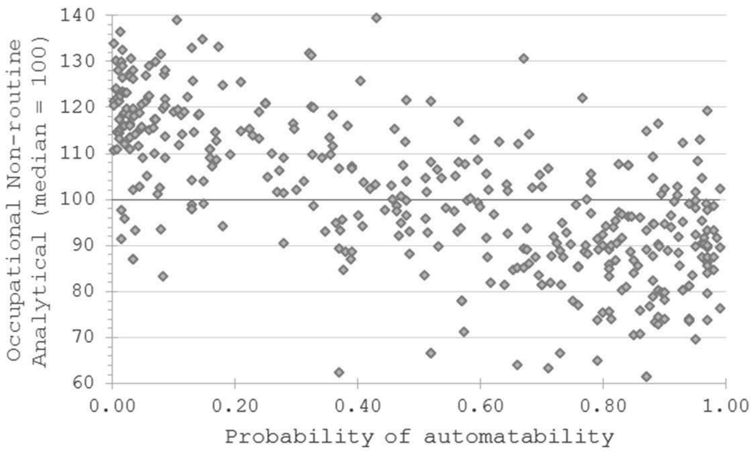
Routine manual skills largely have no impact on hourly earnings, but slightly decreased hourly earnings between the 30th and 80th percentiles. However, there are positive impacts at the top of the distribution. Occupations with high scores on *routine* manual skills are plant and machine operators, and assemblers, along with other low-skill occupations.

Beyond the skills discussion, there are some results from the regression of log hourly earnings as shown in Table A1 in the Appendix. There is a gender gap in which women have lower earnings than men, ceteris paribus. The returns to additional years of work experience are increasing at a decreasing rate. Furthermore, returns from education are not a linear constant, but rather progressive with increasing marginal effects at higher education levels. The results for women and disadvantaged population gaps confirm previous findings in the literature (Nakavachara, 2010; Khorpetch & Kulkolkarn, 2011; Bui & Permpoonwiwat, 2015; Jithitikulchai 2018).

4.3 Occupational Risk of Automatability

Figure 5 exhibits that occupations with higher *non-routine* cognitive analytical skills have a lower probability of automatability. The key prediction is that automation will mainly substitute tasks found in low-skill jobs belonging primarily to economically disadvantaged workers. In contrast, high-skill occupations are less likely to be automated. The data supports this hypothesis: we find (not reported) a reverse association between hourly earnings and probability of automatability, which signifies higher risk for low-income populations.

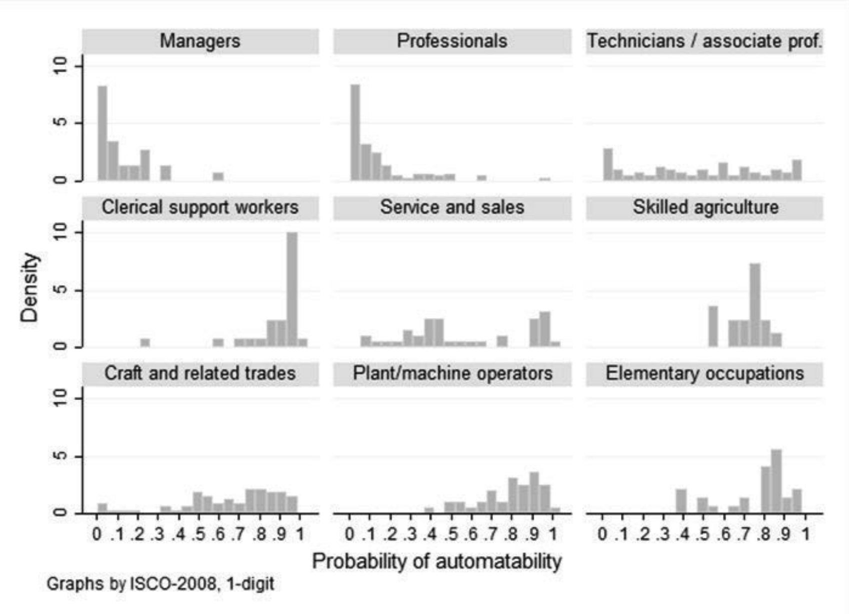
Figure 5. Non-routine cognitive analytical skills and risk of automatability



Notes: Scores for non-routine analytical skills are the mean from each occupation.

Source: Frey and Osborne (2013)'s probability of automatability and LFS 2018Q1.

Figure 6. Probability of automatability by occupation category

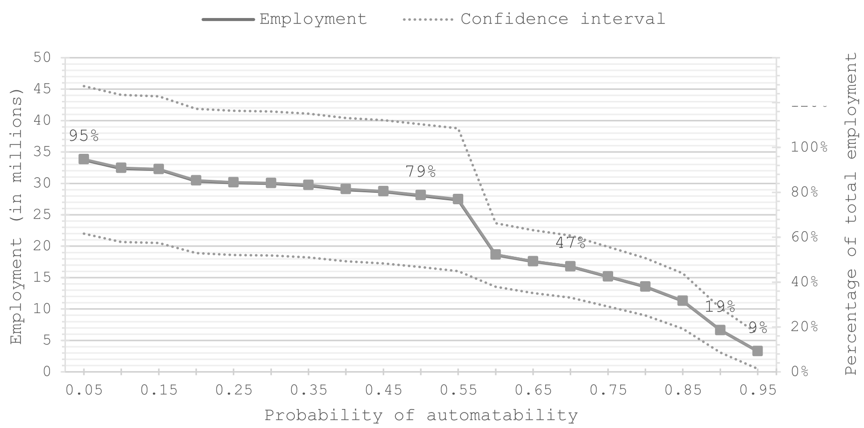


Notes: Each category of the combined bar graphs shows probability density of automatability.
Source: Frey and Osborne (2013)'s probability of automatability and LFS 2018Q1.

Each occupational category has a specific distribution of the risk of automatability, as reported in Figure 6. High-skilled occupations have a lower risk of automatability. Most occupations in the managerial and professional categories have a probabilistic distribution of automatability concentrated in the left tails. On the other hand, most of the low- or medium-skilled occupation categories confront high automatability risk. For instance, jobs within clerical work, some service and sales, agriculture, craft and trades, plant or machine operation, and elementary occupations are clustered on the right tails of the distributions of occupational probability of computerization, which indicates a high risk of automatability.

Figure 7 illustrates the number of jobs by different levels of automation risk. Each point on the curve represents both total employment (left vertical axis) and its share of the labor force (right vertical axis) at a specific probability of automatability. This figure reports the cumulative distribution of employment over the probability of automatability distribution, showing that, for example, 9% and 19% of total employment (or, equivalently, 3.3 and 6.6 million jobs), have 95% and 90% chance of automatability, respectively. Frey and Osborne (2013, 2017) define high-risk occupations as having a probability of automatability of 0.7. Figure 7 shows that about 47% of total employment—equivalent to about 17 million jobs in Thailand—have a high risk of partial or full automation relatively soon, perhaps over the next decade or two.

Figure 7. Employment affected by automatability



Notes: Both vertical axes are synchronized to have employment and percentage on the same line. The information interpretation should start from the bottom right corner. The dotted lines represent the bootstrap 95% confidence interval of the accumulated employment.

Source: Frey and Osborne (2013)'s probability of automatability and LFS 2018Q1.

Table A2 in the Appendix lists all occupations with an employment share of more than one percent. The list includes 20 occupations, accounting for a total of 19.5 million jobs in 2018. According to the predicted probability from Frey and Osborne (2013), there are only two occupations on the list (shopkeepers and primary school teachers) that have less than 50% probability of automatability. Therefore, the remaining 18 occupations account for a total of 18 million jobs with a probability of automation higher than 50%. There are two additional critical points that must be highlighted. First, Thailand has a total of 30 occupations with a probability of automation higher than 95%, which accounts for 3.3 million jobs in 2018. Second, field crop and vegetable growers, which account for 4.4 million jobs, have a probability of automatability of 57%. Therefore, we can expect large impacts from automation on the working-age population and their dependents in the near future.

5. Discussion and Conclusion

The empirical evidence from both the provincial perspective and at the individual level of Thailand's economy provides the same conclusion, namely that economic progress highly favors *non-routine* analytical skills. This study also finds that, commencing in the 1990s, labor input using *non-routine* analytical and interpersonal skills rose, but *routine* cognitive and manual skills declined. Shifts in the input intensity of these skills accelerated over the period accompanied by rapid economic growth, but progress has slowed. Lastly, this study argues that one should prepare for impacts from automatability with workers from disadvantaged socioeconomic backgrounds most likely to be replaced.

Given the threat of "creative disruption," we can view the probability of automatability as not only as job loss risk, but also pressure on the development of skills required to survive in the future. The automatability risk results can be interpreted as the potential impact on occupations that are vulnerable to substitution by big data algorithms and robots over a wide range of *routine* tasks involving rule-based activities, as well as those with *non-routine* cognitive tasks. The diverse impacts depend on the degree of complementarity or substitution between automation and the skill content of tasks embedded in each occupation. Therefore, industries and occupations must adjust their nature of work to survive automatability risk. Recent trends in technological development appear to have directly replaced workers in certain occupations and tasks in Thailand. As discussed in Autor et al. (2003), technological developments have enabled information and communication technologies to either directly permit or perform job tasks that had been performed by middle- and low-skill workers.

The forthcoming risk could be an important cause of a substantial shift in the assignment of skills to occupational tasks. The economic reform options for human capital and skills must take into account the rapid diffusion of new technologies that directly substitute capital for labor in tasks previously performed by low- and moderate-skilled workers. The routine-skilled occupations, especially jobs that require *routine* cognitive skills that have been expanding over three decades, will be at high risk for substantial substitution by automation. This phenomenon reflects the expansion of low-skilled labor in the manufacturing and service sectors. More likely, those with disadvantaged backgrounds and lower education will be affected the most.

As discussed in Sondergaard et al. (2016), even secondary or post-secondary educated workers were pushed back into the agricultural sector as structural transformation slowed. This signifies that workers increasingly find it harder to maintain a quality job. According to a recent firm-level survey, Thailand Productivity and Investment Climate Study (PICS) 2015 conducted by the Ministry of Industry and Thailand Productivity Institute, worker skills often do not match with expectations from firms. Therefore, a critical policy priority is to improve the education and skills of the workforce. See Lekfuangfu and Nakavachara (2019) for policy recommendations for Thailand. See Mason and Shetty (2019) for experience from around the world and their suggestive policy directions.

This study is subject to some limitations. In order to obtain the harmonized occupational codes across three ISCO versions for the three-decade labor force survey data, this study applies the 1-digit classification of ISCO-88 to study the evolution of Thai labor skills. Therefore, the results can be interpreted as an approximation rather than a precise estimation of the exact methods in Autor et al. (2003), Acemoglu and Autor (2011), and Aedo et al. (2013).

Furthermore, the skill content from the O*NET Database and the probability of automatability from Frey and Osborne (2017) are based on the United States economy, which has more sophisticated technology and higher professional standards, implying different skill profiles for specific occupations. Therefore, the estimated results of automatability in this study tend to be an optimistic outlook. For example, teachers in the United States are more likely to have better innovative ICT and teaching tools than in Thailand. Furthermore, STEM-related professions in the US probably have better access to advanced knowledge and cutting-edge equipment which impacts their skill content and how technological capital complements their advanced skills in carrying out non-routine and creative problem-solving and complex communication tasks. Therefore, occupations which use less routine types of skills in more advanced economic settings such as in the United States are likely to be more skill-intensive than in Thailand. On the other hand, the results on the probability of automatability could be compensated by an overestimation, as several occupations labelled as high-risk occupations still contain a substantial share of tasks that are hard to automate, which Frey and Osborne (2013) refers to as a "computerization bottleneck."

Given the aforementioned technical restrictions on measurement and interpretation, this is an important research area which the author feels should be brought to the attention of scholars and policymakers. This study illustrates the evolution of skill inputs and discusses automatability in Thailand, which merits further work for better understanding of labor market impacts on economic productivity and provide empirical evidence to identify key issues and prioritize options in human capital and skills development planning and policy, along with adaptations in the private sector and labor force to mitigate and cope with the automatability risk.

An analytical possibility in the future is to apply the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), as used by Aedo et al (2013), or use the World Bank's STEP Skills Measurement Surveys conducted for several countries with the Thai labor occupational profile. Future research can weight measurable skill inputs with some macroeconomic development indicators, such as the Global Competitiveness Index. Another more ideal research idea on skills and automatability is to collect primary data using online tools or conduct a national-scale labor force survey with support from governmental agencies to collect the country's profile. See Moroz et al. (2019) for some lessons from Malaysia's Critical Skills Monitoring Committee (CSC) and the Critical Occupations List.

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Appendix

Table A1. Full results of OLS and unconditional quantile regression for hourly earnings

Dependent variable: log of hourly earnings	OLS	Q(.25)	Q(.50)	Q(.75)
Non-routine cognitive analytical skills	0.236***	0.147***	0.117***	0.241***
	(104.36)	(53.18)	(54.69)	(69.31)
Non-routine cognitive interpersonal skills	0.0446***	0.0241***	-0.0177***	-0.0131**
	(18.55)	(9.98)	(-7.43)	(-3.27)
Non-routine manual physical skills	-0.0438***	0.000580	0.0102***	-0.0527***
	(-24.97)	(0.25)	(5.48)	(-20.03)
Routine cognitive skills	0.0426***	0.225***	0.114***	-0.0366***
	(18.39)	(73.80)	(53.19)	(-8.89)
Routine manual skills	-0.0155***	-0.0172***	-0.0821***	-0.0336***
	(-9.07)	(-7.57)	(-45.75)	(-12.29)
Female (relative to male)	-0.119***	-0.0761***	-0.0890***	-0.119***
	(-95.37)	(-47.04)	(-62.73)	(-56.47)
Year of work experience	0.0284***	0.0170***	0.0175***	0.0301***
	(159.55)	(66.06)	(83.06)	(93.30)
Year of work experience^2	-0.000385***	-0.000320***	-0.000248***	-0.000354***
	(-95.61)	(-56.85)	(-56.73)	(-55.17)
Lower secondary education indicator	0.213***	0.171***	0.157***	0.182***
	(123.70)	(71.39)	(73.84)	(78.55)

Upper secondary education indicator	0.388***	0.322***	0.353***	0.400***
	(223.12)	(114.59)	(119.21)	(105.82)
College or higher indicator	1.000***	0.486***	0.669***	1.402***
	(397.10)	(153.87)	(148.95)	(121.83)
Year 2012 (relative to 2011)	0.0838***	0.137***	0.0566***	0.0419***
	(33.52)	(38.00)	(18.99)	(14.89)
Year 2013 (relative to 2011)	0.188***	0.335***	0.116***	0.0886***
	(76.02)	(80.51)	(42.80)	(26.39)
Year 2014 (relative to 2011)	0.218***	0.412***	0.149***	0.0507***
	(94.14)	(91.40)	(63.65)	(4.38)
Year 2015 (relative to 2011)	0.265***	0.463***	0.181***	0.154***
	(115.77)	(104.58)	(91.16)	(40.27)
Year 2016 (relative to 2011)	0.269***	0.476***	0.190***	0.151***
	(119.27)	(133.98)	(88.19)	(45.07)
Year 2017 (relative to 2011)	0.272***	0.489***	0.205***	0.0866***
	(121.04)	(142.86)	(91.62)	(23.49)
Year 2018 (relative to 2011)	0.290***	0.526***	0.221***	0.0853***
	(83.00)	(92.69)	(61.23)	(13.81)
Annual quarter 2 (relative to quarter 1)	-0.0153***	0.0141***	-0.0158***	-0.0425***
	(-9.51)	(5.81)	(-9.82)	(-21.18)
Annual quarter 3 (relative to quarter 1)	0.0000835	0.0505***	-0.00306	-0.0428***
	(0.05)	(27.44)	(-1.71)	(-17.85)
Annual quarter 4 (relative to quarter 1)	0.00469**	0.0610***	0.00406*	-0.0389***
	(2.85)	(27.85)	(2.31)	(-14.21)
Urban (relative to rural)	0.0308***	0.0345***	0.00976***	0.0138***
	(28.16)	(18.74)	(6.97)	(8.19)
Constant	2.469***	1.801***	2.944***	3.330***
	(240.75)	(113.52)	(271.76)	(207.67)
Number of observations	1,427,737	1,427,737	1,427,737	1,427,737
R-squared	0.579	0.335	0.408	0.487

Notes: LFS 2011Q1-2018Q1. The clustered-robust standard errors are estimated with bootstrapping for the data potentially intercorrelated in time and space with * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table A2. Risk of automatability in occupations with more than one percent share of total employment

	Occupations (ISCO-08, 2 digits)	Occupations (ISCO-08, 4 digits)	Employment (thousands)	Share of employment (%)	Probability of automatability
1	Market-oriented skilled agricultural workers	Field crop and vegetable growers	4,388.3	12.21	0.57
2	Market-oriented skilled agricultural workers	Tree and shrub crop growers	2,857.3	7.95	0.57
3	Sales workers	Shop sales assistants	1,255.3	3.49	0.95
4	Sales workers	Shop keepers	1,158.4	3.22	0.16
5	Subsistence farmers, fishers, hunters and gatherers	Subsistence crop farmers	961.1	2.67	0.87
6	Agricultural, forestry and fishery laborers	Crop farm laborers	910.4	2.53	0.87
7	Drivers and mobile plant operators	Car, taxi and van drivers	868.3	2.42	0.57
8	Sales workers	Stall and market salespersons	854.5	2.38	0.94
9	Sales workers	Food service counter attendants	780.0	2.17	0.93
10	Personal service workers	Cooks	706.8	1.97	0.73
11	Market-oriented skilled agricultural workers	Livestock and dairy producers	699.0	1.95	0.76
12	General and keyboard clerks	General office clerks	575.6	1.60	0.97

13	Laborers in mining, construction, manufacturing and transport	Building construction laborers	565.7	1.57	0.80
14	Business and administration associate professionals	Accounting associate professionals	439.4	1.22	0.98
15	Sales workers	Street food salespersons	412.7	1.15	0.90
16	Metal, machinery and related trades workers	Motor vehicle mechanics and repairers	409.7	1.14	0.65
17	Teaching professionals	Primary school teachers	403.0	1.12	0.09
18	Cleaners and helpers	Cleaners and helpers in offices, hotels and other establishments	396.1	1.10	0.57
19	Street and related sales and service workers	Street vendors (excluding food)	395.9	1.10	0.94
20	Stationary plant and machine operators	Sewing machine operators	372.3	1.04	0.89
		Total	19,409.7	54.0	

Source: Labor Force Survey 2018Q1 and probability of automatability from Frey and Osborne (2013).