Labour Skills, Economic Returns, and Automatability in Thailand

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Abstract

This study analyses the skill content from the occupational structure of the economy. The measurements of skill inputs show that the provincial GDP per capita increased with the *non-routine* cognitive analytical skills and interpersonal skills and the *routine* cognitive skills in a monotonic way, while the economic value has an inverse relationship with the *routine* manual physical skills. The skill content traces the trends of skill intensities of the aggregate production and demonstrates that progress has been slow down in the last decade. The regression analysis reveals that the occupational skill content could be a useful predictor for hourly earnings, especially the *non-routine* cognitive analytical skills. Lastly, risks of automation are more likely to be harmful to the poor and low-skilled workers from job replacement by artificial intelligence and robots.

Keywords: labour skills; return to skills; automatability; computerisation

Subject classification codes: J20, J21, J23, J24

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1. Introduction

Thailand needs to upgrade its innovative and improved engine to generate new sources of growth and create higher value-added jobs (Sondergaard et al., 2016). This envisioned future requires more advanced skills of the labour force and that the country must have a new paradigm for human capital development. As technology races ahead, the low-skilled and low-wage workers will be reallocated to tasks that are non-susceptible to "computerisation" such as tasks requiring creative and social intelligence (Frey & Osborne, 2017). Automation does indeed substitute for labour skills. However, it also complements labour by enhancing output in the direction that leads to higher demand for labours with advanced skills (Autor, 2015; Arntz, Gregory, & Zierahn, 2016; Frey & Osborne, 2017; and World Bank, 2019, among several others).

On the one hand, having the necessary skills and competencies is rigorously 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). On the other hand, greater emphasis on developing a skilled workforce will promote the deepening of the macroeconomic development (Aedo et al., 2013), as the intensity of national production of *non-routine* cognitive and interpersonal skills will increase with per capita income in a monotonic way for some cross-country comparisons.

The impact of automatability on labour market is well-established in the literature on the decline of employment in routine occupations such as occupations intensively consisted of tasks following a set of well-defined procedures that can be performed by sophisticated algorithms (Frey & Osborne, 2013, 2017). For instance, Charles, Hurst, and Notowidigdo (2013) and Jaimovich and Siu (2012) argued 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. Another example is Lekfuangfu and Nakavachara (2019) that if there is no restructuring in the labour markets, Thai workers will face a serious risk of joblessness in the coming future.

The implications of the developments in artificial intelligence and machine learning on jobs and skills have dominated recent debates on the future of work. Frey and Osborne (2013, 2017) conducted a seminal study based on occupational skills suggested that 47% of jobs in the United States are at high risk of being automated. Based on the groundwork by Frey and Osborne (2013), Nedelkoska and Quintini (2018) found 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. World Bank (2016) estimated from a technological standpoint 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 come into use. Artificial intelligence is disrupting the routine customer service of call centres and call centre staffs. Big data and machine learning suggest more accurately what to buy. 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 computerisation based on a machine learning classification to estimate the probability of computerisation for 702 detailed occupations. Fundamentally, they postulated that creative jobs are non-automatable. They predicted that high-skilled jobs are relatively resistant to computerisation with lower probability of automatability in the occupations which require higher *non-routine* cognitive analytical and interpersonal skills such as those with bachelor's degree or higher.

Lekfuangfu and Nakavachara (2019) researched the impacts of trade and technology on labour market structures in Thailand. Extending the methodology from Frey and Osborne (2017), the most vulnerable occupations for the AI replacement are clerical workers and plant or machine operators with low skills. Another major group at risk is the labour force with primary or lower education. By age category, the workers who are between 35-44 are the riskiest group because aging makes them more difficult to reskill for the more complex labour markets. The analysis in Lekfuangfu and Nakavachara (2019) also pointed out that the sales workers or even farmers or fishermen have substantial risks of automatability. With technologies, now people can access to market information and trade through online platforms, so there is less demand for sales workers in the physical shopping locations. For agricultural and fishing workers, the replacement with automatic machines or operational tools will become cheaper than labour costs.

Digital disruption already impacts employment in Thailand’s financial sector as many commercial banks have shut down their branches and scale down the number of bank tellers but invest more in technology to adapt to the digital economy. The autonomous driverless vehicles provide another example of how manual tasks in logistics and transportation could be easily automated in the upcoming future.

To the best of the author’s knowledge, there literature is limited for Thailand on how the skill content alters hourly earnings and, except for a recent study (Lekfuangfu & Nakavachara, 2019), how the future automatability have impacts on Thai labour market outcomes. This study fills such gaps by providing some empirical evidence on the nexus of occupational skills, labour market returns, and probabilities of automatability.

This study follows a skill measurement methodology in Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011), and Aedo et al. (2013). This approach analyses the labour skills by measuring the specific tasks associated with different occupations rather than measuring the 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. The embedded-skill measurement relies on the information of skill content per occupation which is generated based on the Occupational Information Network (O*NET). The O*NET details the description of task requirements.

The study shows that provincial GDP per capita is associated with the embedded human skill content of the aggregate economic production. This study further investigates the labour market returns to different skill categories and documents that the *non-routine* cognitive analytical skills significantly increase the 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 automatibility suggest that the 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.

The summary of skills by occupational tasks and expected impacts from computerisation 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 outputs 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 own skill endowment to tasks in exchange for wages. Skills are applied to tasks to produce outputs. A given skill level can perform a variety of tasks and change the set of tasks they performed 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** • Analysing 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, mechanised 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 computerisation.

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

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

Following Aedo et al. (2013), the skills aggregates are defined.

(1) *Non-routine cognitive analytical skills*: This set of skills consisting of thought processes required for absorption, processing, and decision-making of abstract information. Tasks such as advanced calculation, analysing information, forming and testing hypotheses, medical diagnosis, legal writing, or any tasks requiring critical thinking skills. Professional occupations require such abilities intensively 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 analyse 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) *Non-routine cognitive interpersonal skills*: This set of skills characterises personality traits that underlie human interactive behaviours 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).

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

(3) *Non-routine manual physical skills*: This set of skills characterise the ability to vary and react to the continuously changing circumstances– operators of a machine or heavy equipment in manufacturing or construction as well as machinery mechanics and repairers, janitor services or truck driving. The O*NET skills included in this category are the ability to operate vehicles, mechanised 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).

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

(4) *Routine cognitive skills*: This set of skills characterises the ability to conduct repetitive, non-physical tasks such as filling forms, reading and calculating bills, or call centre services. The monotonous occupations 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).

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

(5) *Routine manual skills*: This set of skills consisting of repetitive physical movements such as labour-intensive agricultural or construction workers, 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), to control machines and processes (CONTROL).

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

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

$$X = \begin{bmatrix} X_1' \\ \vdots \\ X_{i=I}' \end{bmatrix} \quad (7)$$

For each skill category (s) of X^s, the 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

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

The vector of all occupation shares is defined:

$$\boldsymbol{\theta} = [\theta_1 \quad \dots \quad \theta_I] \quad (9)$$

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

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

Since this study uses only one version of O*NET database, the skill scores are time-invariant, an essential feature of any standard poverty measure that can be used to analyse poverty in an economy.

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 labour 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), which the model set is a specification similar to a Mincerian equation, by focusing on the skills as the major explanatory variables.

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

$$RIF(y;\nu) = \nu(F_Y) + IF(y;\nu), \qquad (11)$$

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

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

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 previous paragraph.

So that a change in the marginal quantile Q_τ is going to be explained by a change in the distribution of the covariates by means of a simple linear regression:

$$E[RIF(y;Q_\tau|X)] = X\beta \qquad (13)$$

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:

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

The vector of covariates composes 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 set required for a specific occupation is thus hypothetically associated with the labour market outcomes, which in this case this study considers the hourly earnings. The hypothesis for the unconditional regression in this study is that the different skills affect the labour market returns differently. The null hypothesis is that the labour skills do not affect the hourly earnings. The alternative hypothesis is that different labour 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 the survey dataset of

702 occupations which cover employment status, income, and skills related to automatability such as finger dexterity, originality, and persuasion. They organised a workshop for AI researchers to hand-label 70 occupations as being automatable or not. Then, Frey and Osborne (2017) implemented a Gaussian process classification to estimate the probability of automatability for all occupations that relates the O*NET variables to a binary classification of whether they are automatable or not.

To estimate the occupational probability of automation in Thailand, this study applies their classification results to the 4-digit occupation codes of the ISCO-08 for the employed workers aged 16-65. 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 the 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 Asian Development Bank (2015), Chang and Huynh (2016), Chang, Rynhart, and Huynh, P. (2016), World Bank (2016), Ng (2017), and Hallward-Driemeier and Nayyar (2018).

From the technological perspective, the reported results from this study provide the partial equilibrium points of view that all other factors being held fixed. For instance, this research implicitly assumes there is no adaptation in labour force to upgrade themselves with the advanced *non-routine* cognitive analytical skills or there are no reallocations of the tasks between different occupations that facilitate the collaborations between machine and human.

3. Data

This study uses quarterly data from multiple waves of the Labour Force Survey (LFS) undertaken by the National Statistics Office of Thailand. The LFS is the primary source of data on the country's labour 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 5 geographic regions until the year 2000, and thereafter subsequently representative of 76 provinces within the 5 geographic regions separated by municipality and non-municipality into 9 areas. This study focuses on employed workers aged 15 to 64. All estimates are weighted by the individual sample weights which are the individual weight multiplied with 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. 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 established equivalences of the occupations across different ISCO versions based on the crosswalk tables from ILO. There are kinks on the time trends of 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 of the LFS 1985Q1-2018Q1. The regression analysis using the LFS 2011Q1-2018Q1 is based on the 4-digit occupation codes from the 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 the hourly wage. The hourly earnings are in real 2011 terms which are temporally and spatially adjusted. The LFS 2011 Q1-2018 Q1 is used to study the effects of skill attributes across the conditional wage distribution with the quantile regression model, as the LFS starts to use the ISCO-08 since 2011, so this study can merge the ISCO-08, 4 digits with the skill content data from O*NET.

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 US 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 a major occupation. For example, the unmatched occupation with the highest sample size is the legislators.

As this study is not a cross-country comparison, it does not require adjustments to reflect the different meanings and job contents of labour markets in developing countries compared to the United States as in Aedo et al. (2013). But it is still important to emphasise that, as described in Aedo et al. (2013), the occupations which use a 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 the progress and inequality patterns in occupational skills by similarly using a fixed measurement as a poverty measurement analysis that applied a specific standard of 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 from a crosswalk approach. The probability data is available in the appendix of Frey and Osborne (2013) which is a list of occupations ranked by the probability of computerisation.

4. Results

3.1 Aggregate trends

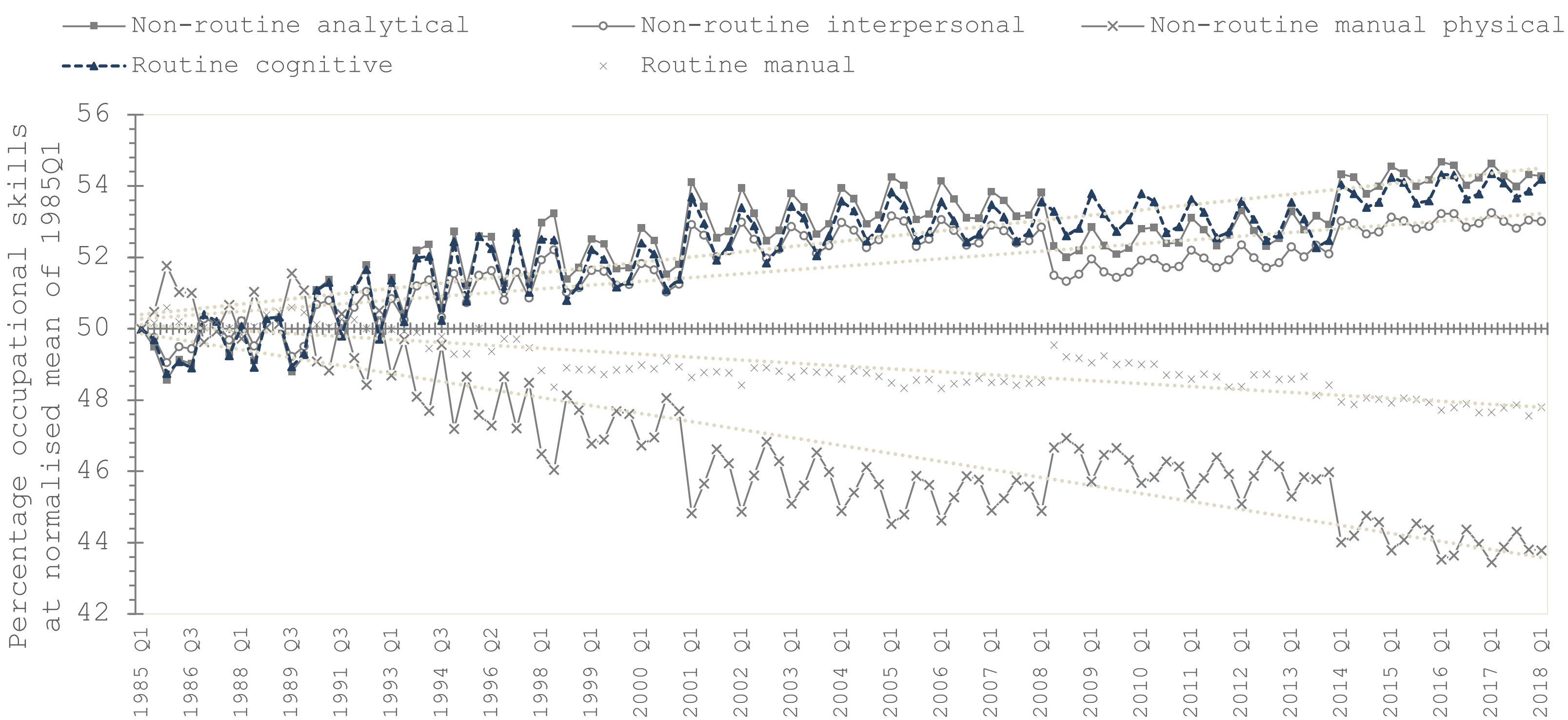
Figure 1 illustrates the extent of embedded skills changed in the occupational labour supply over the period 1985 to 2018. By construction, each task variable has been normalised to have a mean of 50 centiles in the first quarter of 1985 as its initial point. Subsequent points depict the employment-weighted 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 than twenty years ago. The trends persisted for occupational skill inputs in the economy.

The shares of the labour 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. Although the content of the *non-routine* occupational skills and *routine* cognitive skills increased faster in the 1990s of the pre-computer eras than in the last decades. We should note the slower progress in years of stagnation after 2008.

An increase in *routine* cognitive skills exhibits potential risks of the probability of computerisation in the low-skilled occupations. They are those from disadvantaged families who worked for low income from jobs such as machine operators or production assemblers, labour-intensive farmers, or construction workers.

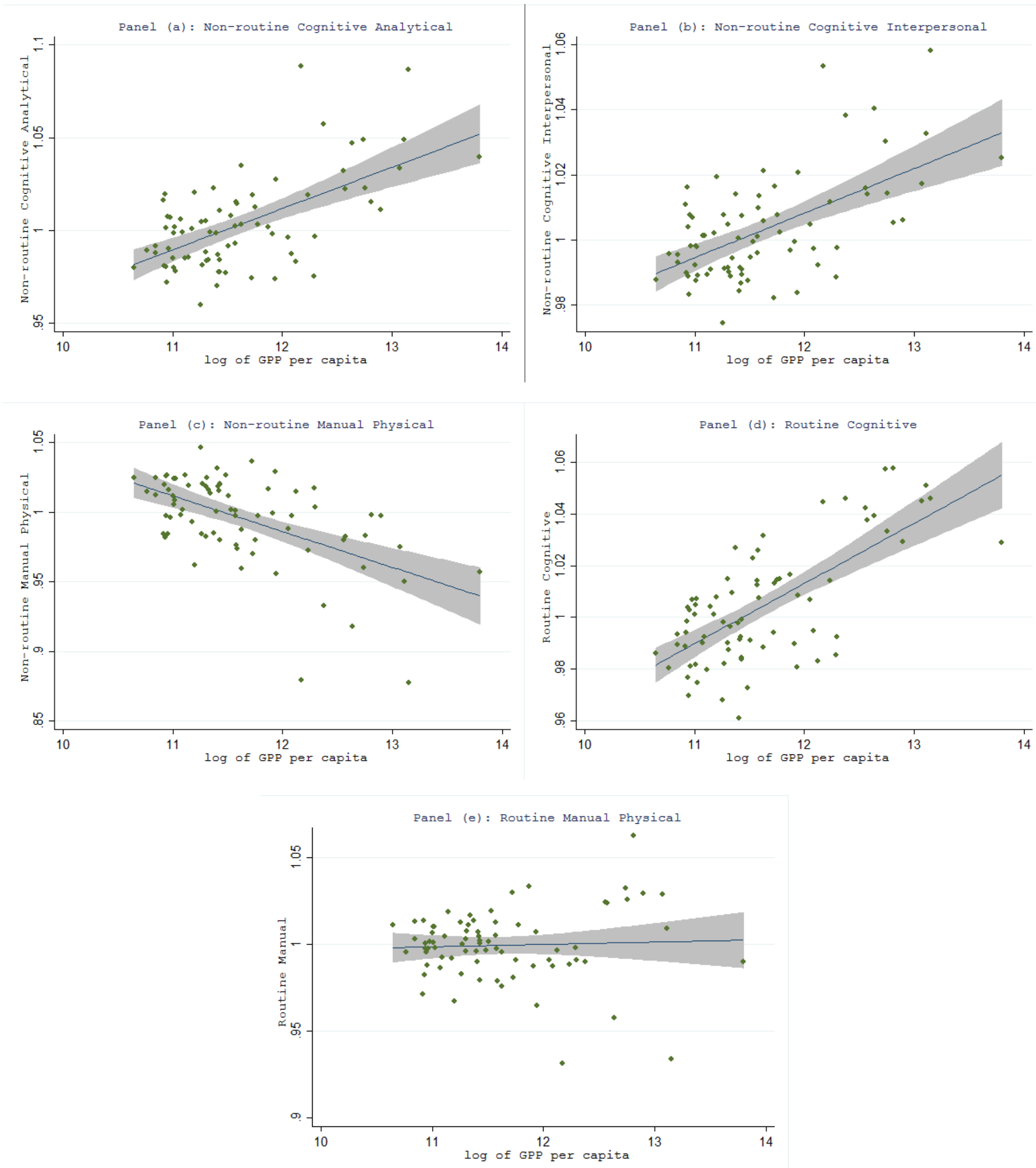
The trend patterns have remarkable shifts around the early 2000s when the economy started to take off again, after the 1997 Financial crisis, and around the period of 2008 with another economic downturn. Beyond the period of these two points, the trends are quite steady after eliminated the quarterly seasonal fluctuations. The dispersions between (i) the *non-routine* analytical skills, *non-routine* interpersonal skills and the *routine* cognitive skills and (ii) the *non-routine* and *routine* manual physical skills became slower in recent years after 2008. This observation is consistent with the stalling of structural transformation and slowdown in non-agricultural employment growth – as a country struggled to move labour from low- to higher-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.

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



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).
Note: Using O*NET matched with occupations of the employment aged 15-65 to construct the normalised skill scores at the provincial level.

3.2 Labour market returns to skills

<u>Cross-province analysis</u>

Aedo et al. (2013) provided 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 visualising the 95% confidence interval.

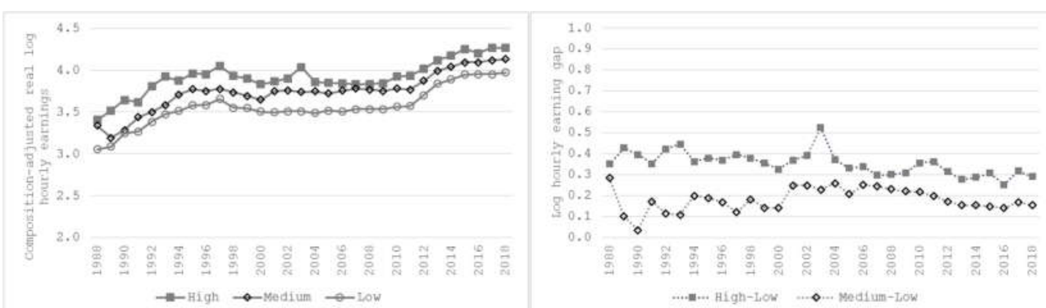
Provincial measures of skill content show that the intensity of *non-routine* manual physical skills declines with provincial GDP per capita in a monotonic way, while we find an inverse relationship with the *non-routine* cognitive and interpersonal skills and the *routine* cognitive skills. However, there is no linear relationship for the *routine* manual physical skills which are intensified for those occupations in the manufacturing and construction sectors.

Fundamentally, economic development favours the *non-routine* skills. They are provinces with occupational structure enriched with high intensity of the *non-routine* analytical and interpersonal skills. Their output per capita could reflect in higher value for the more advanced skills. Using provincial GDP per worker as a measure of economic productivity provides the same conclusions for associating the provincial productivity with the occupational skill inputs.

<u>Returns to skill by occupation</u>

This study estimates the composition-adjusted log hourly earnings of the employed workers aged 15-64. This composition adjustment holds constant the 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 employment-population.

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



Source: Labor Force Surveys 1988-2018.

Note: 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.

The key message here is that the hourly earnings gaps between the high-skilled or medium-skilled occupations over the low-skilled occupations are averagely 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 the higher gap in hourly earnings.

<u>Economic returns to embedded skills</u>

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 covers the 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. So, this study preserves the education level in the regression model as other control variables. The variance inflation factor (VIF) analysis reported that there was no multicollinearity in the reported regression models. The robustness checks confirm the strong associations of skills and hourly earnings. Excluding the educational variables provides the same patterns of distributional effects of five skills but including the educational variables would lower the size of impacts. This still confirms the robustness of implications from the estimated results.

Table 2. OLS and unconditional quantile regression of hourly earnings

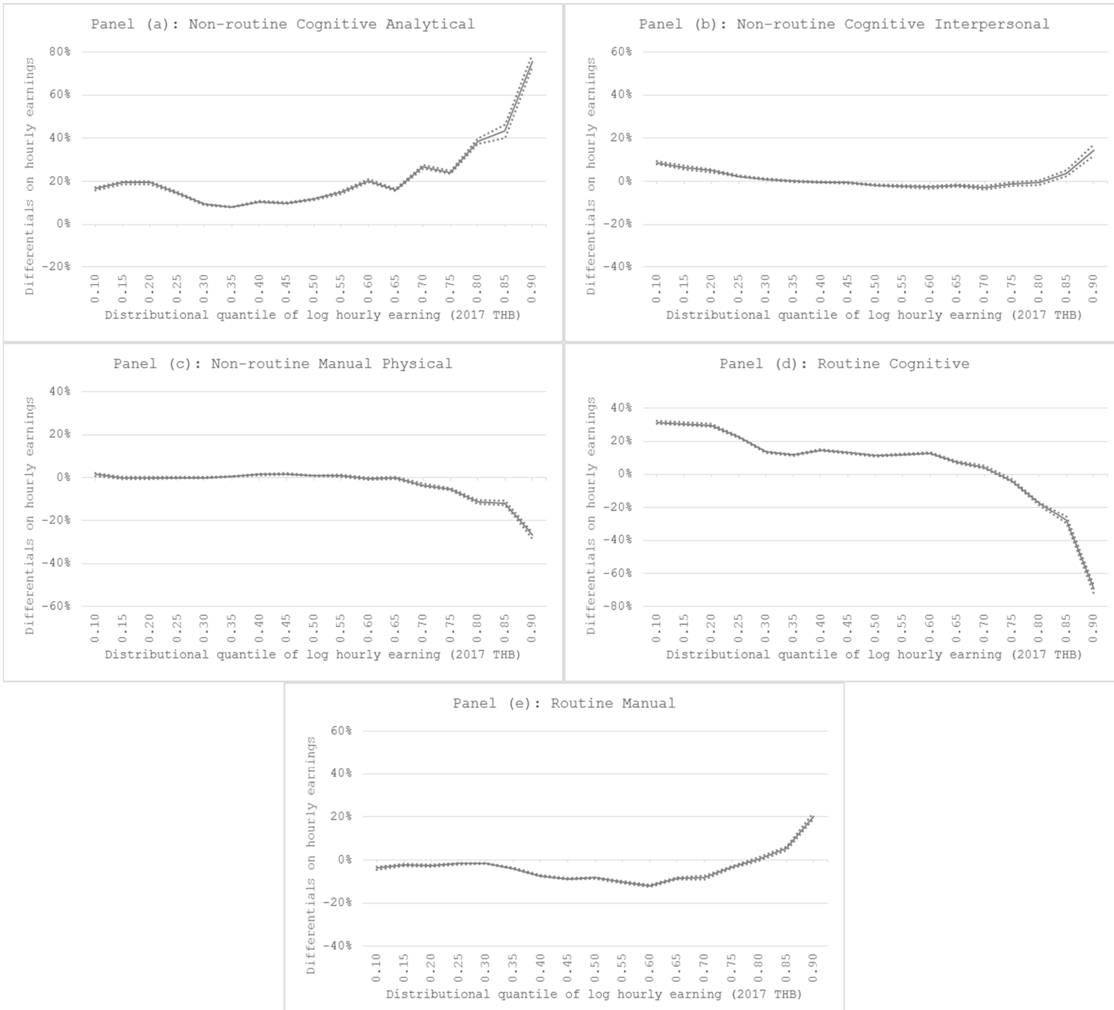
Dependent variable: log of hourly earnings	**OLS**	**Q(.25)**	**Q(.50)**	**Q(.75)**
Non-routine cognitive analytical skills	0.236***	0.147***	0.117***	0.241***
	104.36	53.18	54.69	69.31
Non-routine cognitive interpersonal skills	0.0446***	0.0241***	-0.0177***	-0.0131**
	18.55	9.98	-7.43	-3.27
Non-routine 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

Note: LFS 2011Q1-2018Q1. The *t*-statistics are in second row 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 of five skills. It shows the marginal effects of explanatory variables on the hourly earnings from both the OLS and unconditional quantile regressions.

Estimation results indicate the statistical significance in the skill contents. Thus, there are different impacts of skills on the hourly earnings across its entire distributional space as illustrated in Figure 4.

Figure 4. Impacts from occupational skills on hourly earnings



Source: LFS 2011Q1-2018Q1.

Note: 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.

Figure 4 illustrates the distributional effects of the occupational skills from the unconditional quantile regression as follows.

(a) *Non-routine cognitive analytical skills*: The results show that economic returns to the *non-routine* cognitive analytical skills are positively and significantly correlated. The *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 0.70th percentiles. Specifically, the main occupations with high *non-routine* cognitive analytical skills are managers; professionals; and technicians and associate professionals.

The positive impacts from the 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 to determine the returns for labours in the market economy. We can posit that this skill is the main driver of labour supply to boost economic productivity.

(b) *Non-routine cognitive interpersonal skills*: The *non-routine* cognitive interpersonal skills have only positive impacts on the tails of the hourly earnings distribution. The occupations with high scores in the *non-routine* cognitive interpersonal skill are managers; professionals; technicians and associate professionals; and services and sales workers. Thus, the labour market returns in these occupations are likely to have positive impacts from the interpersonal skills. However, the impacts are significantly smaller than impacts from the *non-routine* cognitive analytical skills.

(c) *Non-routine physical skills*: The *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 the *non-routine* manual skills are the low skilled occupations such as skilled agricultural, forestry and fishery workers; craft and related trades workers; plant and machine operators, and assemblers; and elementary occupations.

(d) *Routine cognitive skills*: The *routine* cognitive skills highly enhance the hourly earnings for the left tail of the distribution. The size of impacts reaches 20 percentage increased on hourly earnings for those below the 0.30th percentile. However, the *routine* cognitive skills also highly diminished the hourly earnings at the top of the distribution, which implies that the top paid occupations with high intensity in repetitive tasks will descending their market returns. The occupations with high scores in *routine* cognitive skills are all occupations in medium and low skills (especially clerical support workers, plant and machine operators, and assemblers), except the skilled agricultural, forestry, and fishery workers.

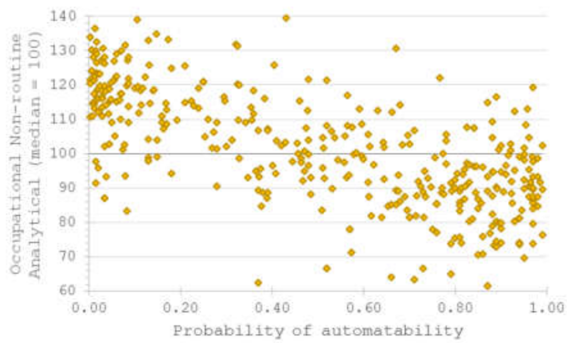
(e) *Routine manual skills*: The *routine* manual skills mostly have no impacts on hourly earnings but slightly decreased the hourly earnings between the 0.30th to 0.80th percentile. However, there are positive impacts at the top of the distribution. The occupations with high scores on the *routine* manual skills are plant and machine operators, and assemblers, along with other low skilled 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 that female has lower earnings than male, ceteris paribus. The returns to additional years of work experience are increased at a decreasing rate. Furthermore, returns from education are not a linear constant but progressed with increasing the marginal effect of higher education levels. These results of women and disadvantaged population gaps confirm previous findings in the literature (Nakavachara, 2010; Khorpetch & Kulkolkarn, 2011; Bui & Permpoonwiwat, 2015; and Jithitikulchai 2018).

3.3 Occupational risk of automatability

Figure 5 exhibits that occupations with higher *non-routine* cognitive analytical skills have a lower probability of automatability. The key message predicts that automation will mainly substitute tasks of low-skill jobs of those economically disadvantaged workers. In contrast, high-skilled occupations are less likely to be automated. We have the same findings for another figure of the reverse associations between hourly earnings and probability of automatability which signify higher risks for poorer populations.

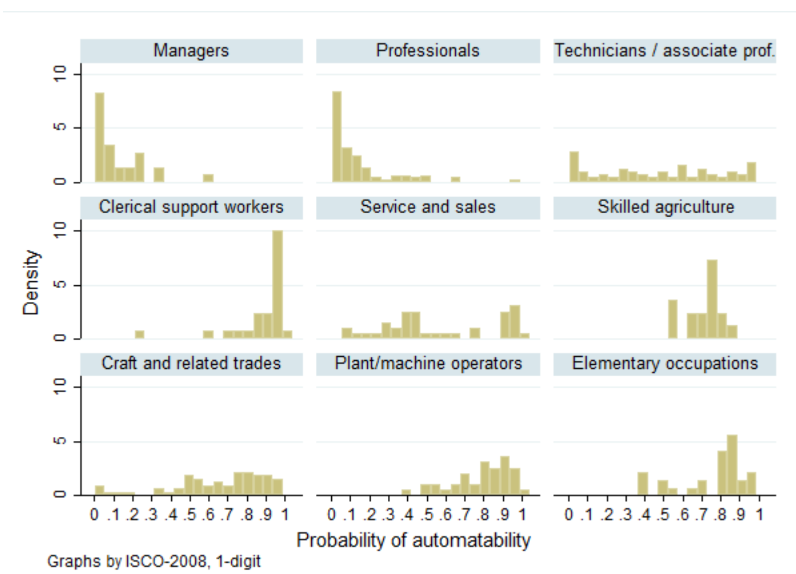
Figure 5. Non-routine cognitive analytical skills and risk of automatability



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

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

Figure 6. Probability of automatability by occupation category



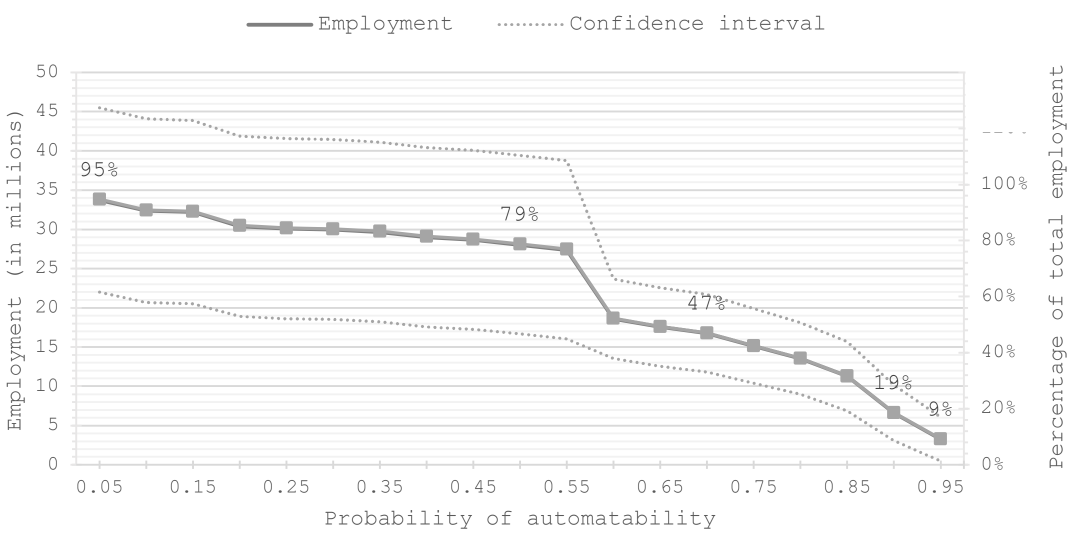
Source: Frey and Osborne (2013)'s probability of automatability and LFS 2018Q1.

Note: Each category of the combined bar graphs shows probability density of automatability.

Different occupation categories have specific distributions of risk of automatability as reported in Figure 6. The higher-skilled occupations have lower risks of automatability. Most occupations in the managerial and professional categories have the probabilistic distribution of automatability concentrated on the left tails. On the other hand, most of the low- or medium-skilled occupation categories confront high automatability risks. For instance, they are clerical workers, some service and sales, agriculture, craft and trades, plant or machine operators, and elementary occupations. Many occupations in the mentioned categories are clustered on the right tails of the distribution of the occupational probability of computerisation which indicates a high risk of automatability.

Figure 7 illustrates many jobs that are potentially automatable by different levels of risk. Each point on the curve represents both the total employment and its percentage on the same lines for both left and right vertical axes at a specific probability level which represents the risk of automatability. This figure reports accumulated distribution of occupational employment over the probability of automatability such as 9% and 19% of total employment (or, equivalently, 3.3 and 6.6 million jobs) have 95% and 90% chance of automatability, respectively.

Figure 7. Employment affected by automatability



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

Frey and Osborne (2013, 2017) distinguished the high-risk occupations with a probability of 0.7 of automatability. Figure 7 shows that about 47% of total employment or equivalent to about 17 million jobs have a high risk that could be partially or fully automated relatively soon, perhaps over the next decade or two.

Table A2 in the Appendix illustrates all occupations with their employment share of more than one percent. It accounts for 20 occupations with a total of 19.5 million jobs in 2018. According to the predicted probability from Frey and Osborne (2013), there are only two occupations (shop keepers 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 an automatable probability higher than 50%.

Besides, there are other two additional critical points. First, Thailand has a total of 30 occupations with a probability 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 at 57%. Therefore, we can expect the large impacts to the working-age population and its dependents.

4. Discussion and Conclusion

The empirical evidence from both the provincial perspective and individual level of the economy of Thailand provides the same conclusion that the economic progress highly favours the *non-routine* analytical skills. This study also examined that commencing in the 1990s labour input of the *non-routine* analytical and interpersonal skills rose, but the *routine* cognitive and manual skills declined. Shifts in labour input intensity of the skills were accelerated in the periods with rapid economic growth, and the progress has been slow down. Lastly, this study argues that one should prepare for the impacts from automatability, and workers from disadvantaged socioeconomic backgrounds are most likely to be replaced.

Given the threat of "creative disruption", we can view the probability of automatability as not only the job loss risk but also the pressure on development of skills required to survive in the future. The results on automatability risk can be interpreted as the impacts on occupations that are vulnerable to be substituted by algorithms on big data and robots in a wide range from *routine* tasks involving rule-based activities to those with *non-routine* cognitive tasks. The diverse impacts are found to depend on the degrees of skill content in the complementary or substitutional nature of the tasks embedded in each occupation. Therefore, the industries and occupations must adjust their nature of work to survive the automatability risk.

Recent trends in technological developments appear to have directly replaced workers in certain occupations and tasks in Thailand. As discussed in Autor et al. (2003), the technological developments have enabled information and communication technologies to either directly permit or perform the 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 labour in tasks previously performed by low- and moderate-skilled workers. The routine-skilled occupations especially the *routine* cognitive skills that have been on the expansion trajectory over the three decades will be at high risk of substantial substitution by automation. This phenomenon reflects the expansion of low-skilled labours in manufacturing and service sectors. More likely, those with disadvantaged backgrounds and lower education are 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 the slowdown in structural transformation. This signifies that workers increasingly experience the tougher situation that it is harder to have 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, the country has an issue that the worker skills do not match with the expectation from the 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 subjected to some limitations. In order to obtain the harmonised occupational codes across three ISCO versions for the three-decade labour force survey data, this study applies the 1-digit classification of ISCO-88 to study the evolution of Thai labour skills. Therefore, the results can be interpreted as an approximation rather than the 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 US economy which has more sophisticated technology and higher professional standards which imply 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 US are more likely to have better innovative ICT and teaching tools than in Thailand. Furthermore, the 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, the occupations which use less routine type of skills in more advanced economic settings such as in the US 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 as Frey and Osborne (2013) called "computerisation bottleneck".

Given the aforementioned technical restrictions on measurement and interpretation, this is an important research area, which the author feels that it should bring attention to scholars and policymakers. This study illustrates the evolution of skill inputs and a discussion on automatability in Thailand, which merits further work on better understanding the labour market impacts on economic productivity and provide empirical evidence to identify key issues and prioritise options in human capital and skills development planning and policy, along with adaptations in private sector and labour 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 Aedo et al (2013) or use the World Bank's STEP Skills Measurement Surveys conducted for several countries with the Thai labour occupational profile. Then, future researches can analyse by weighting the 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 the online tools or conduct a national-scale labour force survey with supports from the 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 (relative to no education/primary)	0.213***	0.171***	0.157***	0.182***
	123.70	71.39	73.84	78.55
Upper secondary education (relative to no education/primary)	0.388***	0.322***	0.353***	0.400***
	223.12	114.59	119.21	105.82
College or higher (relative to no education/primary)	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

Dependent variable: log of hourly earnings	**OLS**	**Q(.25)**	**Q(.50)**	**Q(.75)**
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

Note: LFS 2011Q1-2018Q1. The *t*-statistics are reported in the second row 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 labourers	Crop farm labourers	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	Labourers in mining, construction, manufacturing and transport	Building construction labourers	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).