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Automation and Productivity: Evidence from Thai Manufacturing Firms

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Abstract

Rapid advances in the automation technology have led to a rise of public interest among researchers and policy makers. In manufacturing, most papers proved that industrial robots and automation is a key enabler to improve firm's competitiveness and the overall growth of country. However, the often referred to picture of this new technology as "job killers" caused by the decoupling of wages and output per worker. Using Thai manufacturing firm-level data, this paper provides empirical evidence that there is a positive relationship between firms adopting automated process and their TFP. However, being in EEC area shows mixed results. We also find that automation investment has positive significant effect on total employment. Furthermore, there is some evidence that automation is driving an increase in demand for skilled workers and has reduced unskilled activities.

Keywords: automation, robots, total factor productivity, labor productivity, employment, skills, firm investment

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1. Introduction

The beginning of the fourth industrial revolution (Industry 4.0) has expanded the possibilities of digital transformation and enhanced the industrial settings through technologies. The technologies behind manufacturing have driven an efficiency in production including artificial intelligence (AI), the adoption of automated and robotic machines, cloud computing, and others. Nowadays, the debate on the effect of robots and automation is flourishing, with the number of studies rising constantly, especially in EU. Researchers focused on the impact of robots and automation on productivity and employment.

We can summarize the approaches used to investigate this research questions in two strands. On the one hand, using an industry data across the country (Graetz & Michaels, 2018; Kromann et al., 2020). On the other hand, looking at firm-level data in specific country (Zator, 2019; Czarnitzki et al., 2022; Eng & Zhang, 2022). However, the most of studies are concentrated in the developed countries, even though the trend of robots and automation adoption has been increasing in the developing countries.

The studies about the advanced technologies effect on productivity indicate that the adoption of robots and automation can raise the productivity and TFP. Nevertheless, the evidence of the effect of robots and automation on employment is ambiguous. Acemoglu et al. (2020) found that firms that adopt robot increased their employment by 10% higher than competitors, while Kim et al. (2019) indicated that there is insignificant effect on employment. Interestingly, Graetz and Michaels (2018) showed that the use of robots can increase the high-skilled workers hour, while low-skilled workers were reduced.

This paper presents evidence on the impact of automation adoption on TFP and employment in Thai manufacturing sector. The data in this study comes from the Office of Industry Economic (OIE) that collect the firm's information on sales, costs of production, and use of automation by sectors. We have data for 22 manufacturing sectors for the 2017-2020 period. Then, we use this dataset to construct firm-level TFP.

The main result of this study is that the use of automation in production process has a positive and significant effect on TFP. Firms who adopt an automation have on average 23% TFP higher than non-automation adopters. However, the results of EEC area aspect are mixed. In the case of employment effect, we find positive significant effect on total employment. Furthermore, the results indicates that firms who use automation tend to employ the more skilled worker but there is reduction in the share of unskilled workers. In line with the adopters in EEC area, we find that the total employment and share of skilled workers is higher than nonadopting firms outside EEC area. The effect of automation on unskilled worker shares are insignificant in case of EEC.

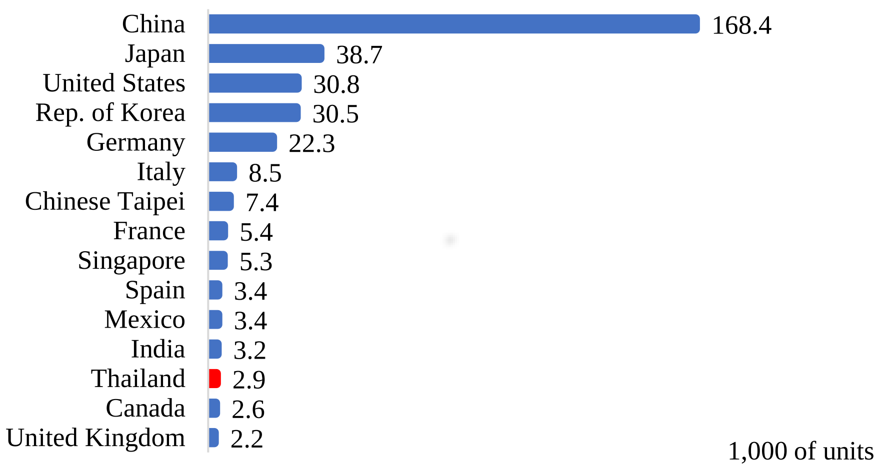
The rest of the paper is organized as follows. Section 2 sheds light on the overview of robot adoption around the world and Thailand. Section 3 contributes a recent literature that investigates the robot and automation effect on productivity and employment. Section 4 presents the empirical framework of total factor productivity (TFP). Section 5 describes the data set and methodology we use. Sector 6 contains the results of our empirical analysis. Finally, Section 7 offers the conclusions and policy recommendations.

2. The adoption of robots and automation in manufacturing: around the world and Thailand

2.1 Robot investment around the world

Over the past decade, there are roughly 3.5 million robots installed in the manufacturing around the world, more than 3 hundred thousand units that installed for each year (IFR, 2022). In 2021, the new robots installed provided a new all-time high of 517,385 units in factory around the world. Asia remains the world's largest market for industries utilizing robotics. China, Japan, and South Korea are among the five major markets along with the United States and Germany. These five countries account for 74% of the global robot installations. Thailand was ranked 13 of 15 world's robot markets with 29,000 units of robot installed in 2020 (see Figure 1).

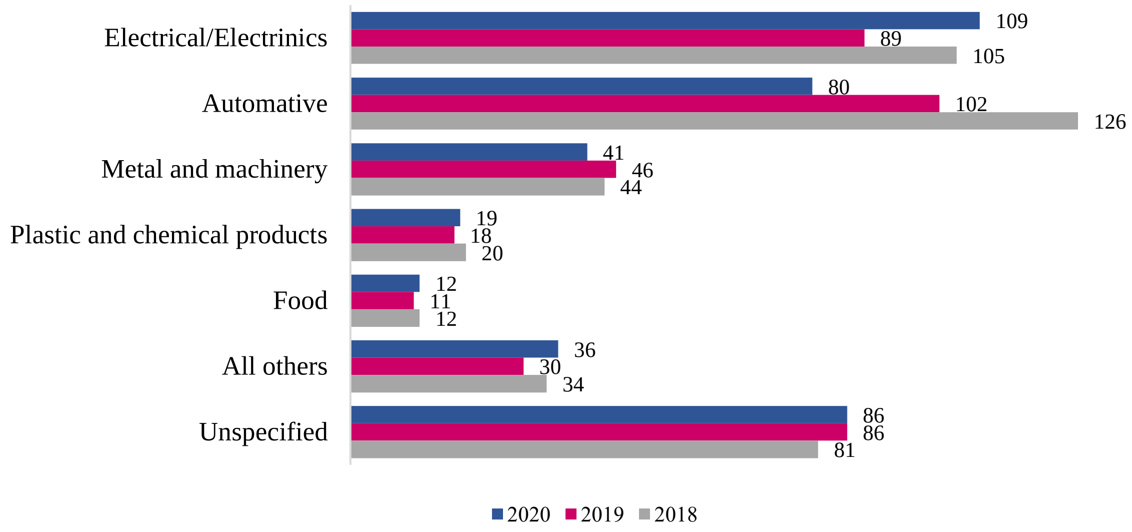
Figure 1: Annual installations of industrial robots of 15 largest markets in 2020



Source: World robotics 2021 reports, IFR (2021).

Recent changes in the trends of automation and robotics have been shifted the ranking in terms of the industries with the highest concentration of robots. The electronics and automotive industries were the largest robot adopters with a share of 30% of total supply (IFR. 2018). Figure 2 shows the electrical/electronics sector replaced the automotive sector as the most importance customer for industry using robots in 2020. According to COVID-19 pandemic, the demand for electronic devices has rapidly increased. Although the industry faced the supply disruption from factor closures and labor shortages in China, but the electronics industry will continue to grow since the online education and working from home has become an option during the pandemic. Meanwhile the automotive industry was hit hard with a 16% drop in production of automation industry from the shutdowns of a large parts and its many suppliers during the COVID pandemic (OICA, 2020).

Figure 2: Annual installations of industrial robots by industry in 2020



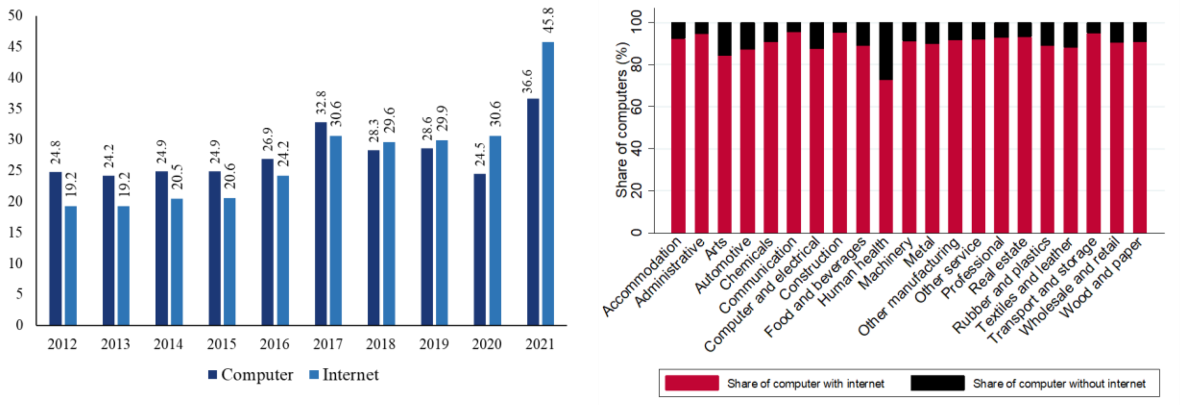
Source: World robotics 2021 reports, IFR (2021).

2.2 Firm investment in automation in Thailand

To cross over the middle-income trap (MIT) and transform the country into an innovative and value-added industry, the Thai government has been reformed the manufacturing sector through the economic model of Thailand 4.0 which mainly focuses on technology and innovation. The targets of the 20-year economic reform (2017-2036) consist of GDP growth grows 4.5% per year, investment increases in 10% per year on average, export value expands 8% per year, TFP growth increase 2% per year, and having the number of new warriors 4.0 of 150,000 people (OIE, 2016).

Before jump into the Thailand 4.0 era, Thailand has been attempting to develop the digital infrastructure during the digitization era. The internet penetration rate of establishments in Thailand has been growing over the past decade (Figure 3 (panel a)). Share of total number of computers with internet by sector during 2016-2020 greater than 80% in almost sectors (Figure 3 (panel b)). Hence, it believes that the fundamentals of growing internet penetration and ICT usage would continue to drive healthy growth and important infrastructure for transforming to the automation usage era.

Figure 3: Development of digitization in Thailand



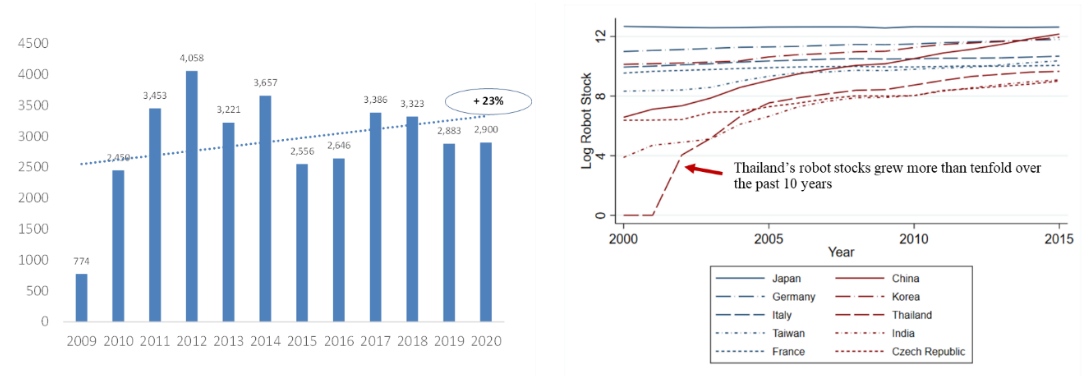
(a) Percentage and number of establishments using internet and computer (2012-2021)

(b) Share of internet usage in the total number of computers by sector on average (2016-2020)

Source: ICT data from NSO (2021), calculated by authors.

As mentioned, Thailand ranked as the 13th largest of robot market in 2020. The rise of robots partly results from the decline in robot prices and facing the labor shortage problem that tends to become more severe because of the aging society. The International Federation of Robotics (IFR) reported the trend of robot installation in Thai factories has increased by an average of 23% over the past 10 years, and the rate is exponentially fast compared to abroad (see Figure 4 panel (a) and (b)).

Figure 4: The number of installation of robots in Thailand and robot comparison across country



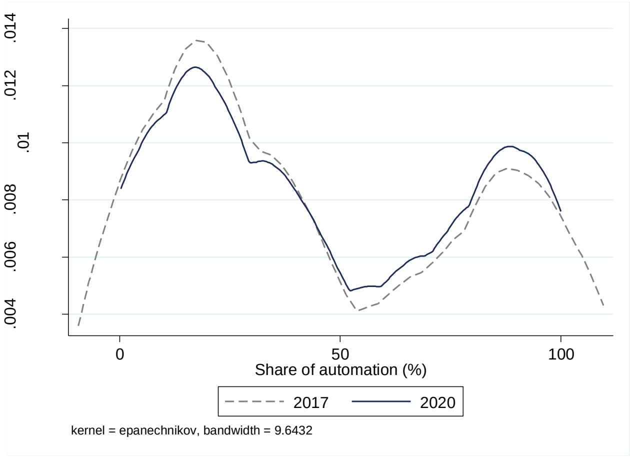
(a) Annual installation of industrial robot in Thailand (units)

(b) Robot diffution in top five developed and developing economies

Source: (a) IFR (2020) and (b) DeStefano and Timmis (2021)

For automation adoption, Thailand's productivity, and industries performance annual survey, conducted by OIE provided us the interesting facts about automation adoption in Thai manufacturing. Figure 5 revealed the overall investment in automation and robotics in Thailand has not changed much. The distribution of firm-level automation shares in 2017 and 2020 still have not very high investments in robots and the difference between factories is quite high. The automation share on average was 45.81% in 2017 and 47.16% in 2020.

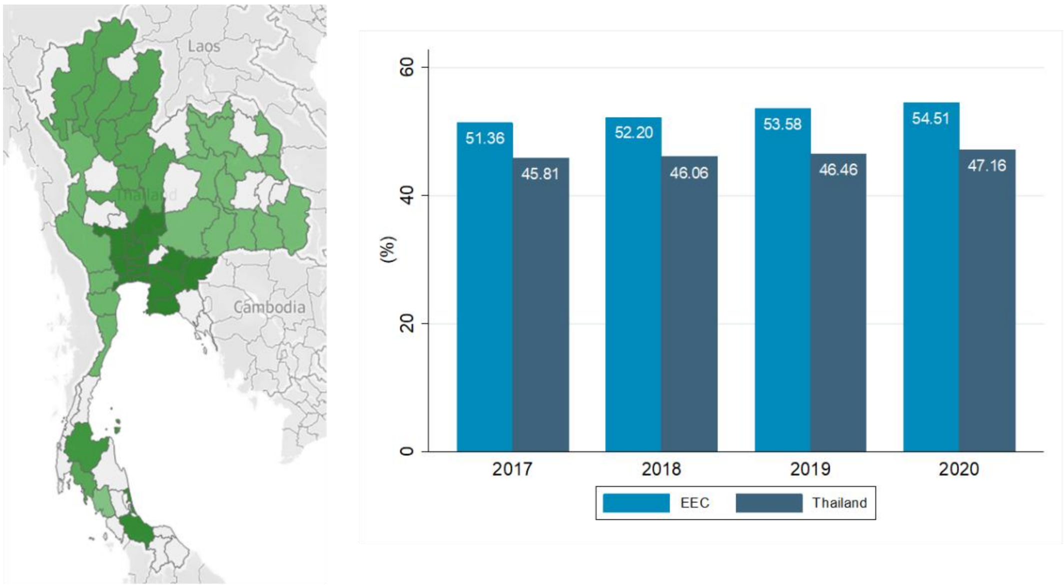
Figure 5: Distribution of share of automation machines in Thai manufacturing



Source: OIE (2020). Calculated by authors.

There is the difference of robotics and automation across areas. Figure 5 shows the areas that are important bases for industrial production such as the central and eastern regions, especially the three provinces in the Eastern Special Development Zone (EEC), have a higher proportion of automation use than other areas. This is partly due to the readiness of information technology infrastructure and government support measures in these strategic areas.

Figure 5: The proportion of robot and automation adoption through automation share across areas in Thailand

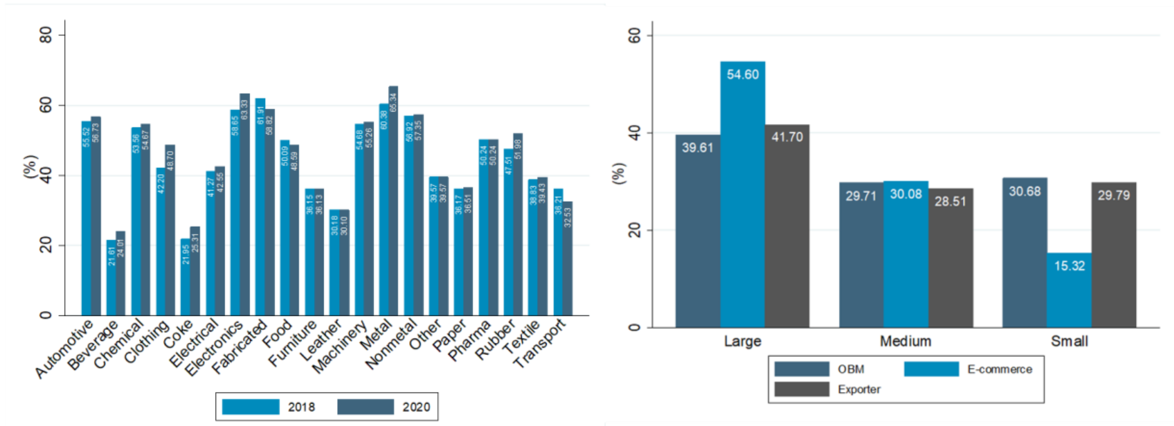


Source: OIE (2020). Calculated by authors.

When we consider at sector level, the investments in robotics and automation vary according to the type of industry and the nature of the plant. Panel (a) of Figure 6 shows the top 5 sectors with the highest proportion of robots which comprise the electrical and electronics, automotive, metal and machinery industries, in line with the world's robot investment from IFR.

In addition, the proportion of reliance on automation in factories also depends on their firm characteristics. Panel (b) of Figure 6 presents the large firm use automation more than SMEs. Making your own brand (original brand manufacturing: OBM) or a firm who is exporter or relies on online sales (E-commerce) tends to have a higher proportion of automation adoption than non-automation adopters.

Figure 6: Share of automation adoption by sector and characteristics of automation adopter



(a) Share of automation adoption by sector (b) Characteristics of manufacturing firms by size

Source: OIE (2020). Calculated by authors.

3. Literature Review

3.1 Displaces or reinstates employment?

There are two strands of research about the impact of robots and automation adoption on employment. First, the usage of automation and robot can provide the displacement effect and reinstatement effect at the same time. Acemoglu and Restrepo (2019) studied the effects of different technologies on labor demand based on a task-based model. The results indicated that the task of production was reduced by the robots and automation adoption. In contrast, the creation of new tasks related to robot implementation has also increased the labor demand. Some studies found that automation will increase the job opportunity for skilled workers, but reduce the demand of unskilled workers (Acemoglu & Autor, 2011; Graetz & Michaels, 2018; Zator, 2019; and Tang, et al., 2021)

Second, the automation technologies provide a negative effect on employment. Autor and Salomons (2018) investigated the impact of automation on employment in the industry level. They suggested that automation displaced employment and reduced labor share. This result was the same as they found in the case of the impact of AI on productivity and employment. The main reason was that these new technologies significantly increase firm productivity. Moreover, the study of Acemoglu and Restrepo (2020) which studied the effect of robots in U.S. local labor market showed that adding robot adoption reduced employment by 0.18-0.34%.

3.2 Effect of automation on productivity and employment

To evaluate the effect of technological change (robots and automation) on productivity and TFP, there is growing evidence that focus on this issue. Most studies investigated the adoption of robots and automation and their impacts on both productivity and employment. ln Europe, several papers focus mainly on cross country analysis. Graetz and Michaels (2018) investigated the impact of robot adoption on labor productivity, TFP and employment in 17 EU countries. The study found that the robot adoption raised labor productivity and TFP about 0.36 and 0.26 percentage points, respectively. For employment, the share of hour worked in high-skilled worker has increased by 1.22 percentage points, while low-skilled workers were reduced by 3.4 percentage points. Moreover, Kromann et al. (2020) investigated the effects of automation on TFP and employment by using the industry-level panel data. They found that the automated-intensity industries have a positive effect on TFP and employment.

Nevertheless, there is the evidence that the application of robots may reduce TFP in the short term. Aghion et al. (2018), studied the theoretical mechanism of the effect of robot adoption on TFP. In short run, the replacing of unskilled workers by automation machines can take a lot of time for automation to exert its production efficiency fully. Therefore, the efficiency at this stage is not high. When the middle- and high-skilled workers can match with the automated machinery, then the efficiency of production process will increase in the long run. In line with the study of Du and Lin (2022), investigated the spatial effects of robot adoption on TFP between local and adjacent areas. They found that the effect of robot adoption on TFP in local area has the U-shape. At the first stage, skilled worker who replaced by robots in local area have moved to neighboring area, this may temporarily increase their production in adjacent area and decrease in local area. Then, the local area will increase their production efficiency faster than the neighboring area afterwards.

In case of study by country in EU, Zator (2019) investigated the impact of digitization and automation on productivity and employment in Germany during 2005-2015. The results showed that the adoption of automation is associated with an increase in labor productivity by 81%. On the other hand, automaton reduced the employment growth by 36%, but increased the high-skilled worker by 5.7%. In line with Czarnitzki et al. (2022) who studied the effect of AI on firm-level productivity in Germany. The results indicated that the use of AI has positive and significant effects on firm productivity by 6%. Acemoglu et al. (2020), who studied the impact of robot adoption on productivity and employment in French manufacturing, showed that robot adoption increased the labor productivity and TFP by 9% and 2% respectively. The employment increased by robot adoption 10%. And Koch et al. (2021) studied the effect of robot adoption on productivity and employment in Spanish manufacturing firms. The results provided that the adoption of robot generated the output gains 20-25% and led to grow in total employment by 5% with high-skilled workers 6% and low-skilled workers 8%.

For Asia, Tang et al. (2021) identified the causal relation between robot adoption and employment in China. The findings indicated that robot adoption increased the share of high-skilled workers by 42%, while the impact on share of low-skilled worker was insignificant. Kim et al. (2019) studied the effect of factory smartization on productivity and employment in Korean manufacturing. The results indicated that smart factories generated the productivity gains 9.1 percentage points. In the case of employment, they found that pure automation was likely to curtail labor demand while full smartization is not. While Eng and Zhang (2022) focused on the impact of automation adoption on labor productivity, TFP, and employment in Indonesia. The results indicated that the use of automation provide the positive effect in both TFP and employment.

For Thailand, the empirical study on the effect of automation on economic aspects (such as productivity or TFP) and employment is still scant and very recent. Similarly, there is the ground study of the use of broadband effect on TFP in Thai manufacturing revealing that broadband adoption can raise productivity by 23% to 54% (Nakavachara, 2020). Recent study of Jongwanich et al. (2022) indicated that use of ICT tends to affect the reallocation of workers between skilled and unskilled positions.

Our paper is the first attempt in the analysis of impact of automation adoption on productivity and employment in Thailand at firm-level data. We use a panel data set of Thailand manufacturing firms from the annual survey on Factory Operations Information Form (Ror. Ngor. 9) over a 4-year period (2017-2020). According to the former literatures is that this dataset provides us an explicit information on automation adoption. Therefore, we can provide the causal evidence on the following questions: (1) What is the impact of automation adoption on firm-level TFP? and (2) What is the impact of automation adoption on employment?

4. Empirical Framework

In the literatures on production function, it is common to use traditional productivity estimates to obtain the residual (TFP) from OLS estimation. However, the coefficients on variable inputs (K and L) from OLS estimates will be biased upward because of the endogeneity. An alternative approach to remedy the bias of coefficients is using the instrumental variable (IV) as the independent variable in production function. Considering the appropriate IV is that instruments need to be correlated with the endogenous regressors (inputs) and uncorrelated with the error term.

There are different approaches have been suggested to alleviate the endogeneity. The notable example is Olley and Pekes (1996). They used an investment as an instrument to proxy for productivity. Then, there are the studies that refined this approach by Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2015), using the intermediate inputs (material in this study). Moreover, Wooldridge (2009) extended the Levinsohn and Petrin estimator by implementing an estimation setting within a system generalized method of moments (GMM) econometric framework, which a single step and the appropriate moment conditions can be proposed (Rovigatti & Mollisi, 2018).

In this study we employ a modification to the Wooldridge (WRDG) estimator to calculate total factor productivity at firm level using a Cobb-Douglas production function. Formally, the production function (f) describes the relations between a firm's output (Y) and TFP combined with a set of inputs. Output is measured by value added which defined as the sales minus the cost of production and operating cost including wages, interest paid, depreciation, and rent. Following the total factor productivity (A) and a set of inputs consist of capital (K), labor (L). The production function for firm i in period t is defined as equation (1):

$$Y_{it} = f(A_{it}, K_{it}, L_{it}) \text{ with } i = 1,2, \dots, N. \quad (1)$$

We can rewrite equation (1) in terms of the functional form of the Cobb-Douglas as equation (2):

$$Y_{it} = A_{it} K_{it}^{\beta k} L_{it}^{\beta L}, \quad (2)$$

or, taking the natural logarithm as shown in equation (3),

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it}. \quad (3)$$

Where ω_{it} is the total factor productivity (TFP). The error term ε_{it} can be decomposed into υ_{it} is the observable productivity of firms and η_{it} is the unobservable component where $\varepsilon_{it} = \upsilon_{it} + \eta_{it}$. Based on Levinsohn and Petrin (LP) model, they concerned a simultaneity problem between inputs and productivity shocks. Thus, they used intermediate inputs (m_{it}) as a proxy of unobserved productivity. In this case we can employ the energy cost as intermediate inputs that firms report in our data. This implies that the intermediate input is expressed in terms of capital and productivity, $\upsilon_{it} = m_{it}(k_{it}, \omega_{it})$.

Using monotonicity condition, the intermediate input (energy) is strictly increasing in productivity and are also invertible as $\omega_{it} = \upsilon_t(k_{it}, m_{it})$ where $h_t(.) = \upsilon_t^{-1}(.)$. The equation (3) becomes:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + h_t(m_{it}, k_{it}) + \eta_{it}. \quad (4)$$

The LP assumption restricted the productivity dynamics in which firm choice at time t does not impact the profits in the future. Hence, Wooldridge implemented GMM approach that assumed orthogonality between productivity shocks and current values of the state variables as well as between productivity shocks and the firm realizes on the capital and intermediate input in the past, $\upsilon_{it} = f[h_t(k_{it-1}, m_{it-1})]$. Therefore, the equation (4) transformed as shown in equation (5):

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + f[h_t(k_{it-1}, m_{it-1})] + \eta_{it}. \quad (5)$$

5. Data and Methodology

Our main source of data on automation adoption is from the annual survey on Thailand's productivity and industries performance, also known as "Factory Operations Information Form or Ror. Ngor. 9", conducted by the Office of Industrial Economics (OIE). The Ror. Ngor. 9 was designed as a panel survey and conducted among a sample of 2,500-3,000 business operators in the manufacturing sector in every year. The survey covers 22 sectors at 2 digits which classified following TSIC NSO Revised Version 2009 and contains important information on firm-level balance sheet such as sales, costs of production and administration, assets, debts, employment, and characteristics of production types[1] and distribution channel through E-commerce.

Now, it is worthwhile to describe more in detail the set of variables we employ in the empirical analysis. The study utilized the dataset of the Ror. Ngor. 9 during 2017-2020. Originally, there were 12,792 observations but after cleaning process, about 5,062 observations were remained[2]. To identify a comparison group between datasets that were used and dropped, this study needs to test whether there is the different between two group of datasets. The results show that the differences of mean in set of variables between two datasets is different from zero[3]. There is limitation of the data with missing data problem in terms of missing at random. We suggest the future studies to handle the limitations of missing data by any technique or using more complete dataset which would be the first-best choice. Therefore, the dataset that we employ in this study is currently the second-best option. All variables were deflated by using the producer price index (PPI) at two-digit sectors. Table 1 provides descriptive statistics by automation adopters and non-automation adopters.

5.1 Automation variables

Since 2017, the questionnaire included the question on automation adoption. To capture technology and innovation data firms were asked whether they adopt and invest the automation machinery[4] in the production process (calculated by the values of automation machinery to the net of machinery and equipment values (%)). Any firm that has adopted the automation machinery is considered as an

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[1] The survey classifies the distribution channel of sales by production types. There are three types as followings: (1) Original Equipment Manufacturer (OEM), (2) Original Design Manufacturer (ODM), and (3) Original Bran Manufacturer (OBM).

[2] 7,730 observations were dropped due to three causes: (1) there were 4 sectors (TSIC 12, 16, 18, and 33) dropped since the observation less than 50 observations, (2) 50% of the observations were not reported their employment, and (3) Outliers were removed through the following procedure: sales, capital, and employment are first log-transformed, then trimmed at plus and minus three standard deviations from the means. After calculating the value added, firms with negative value added were dropped.

[3] As the 50% of observations were dropped, we use the independent group t-test to test whether the mean difference between two datasets is zero or not. The results indicate that the average characteristics of used and dropped datasets are different. The p-value of the variables are mostly less than 0.05 showing that the two datasets are not the same.

[4] Automation machinery in this survey is considered as firms who employ the fully automation, robots, and semi automation in the production process.

automation adopter. Table 1 shows the panel sample contains 5,062 firms and 1,608 can be classified as automation adopters (31.77%) which has the automation share about 46.87% on average.

5.2 Endogeneity of automation adoption

The impact of automation on TFP can be biased due to an endogeneity problem on the decision to employ the automation machinery. Firstly, firms could decide to use automation because of higher productivity or a firm with higher productivity level might drive the decision to adopt an automation (reverse causality). Secondly, the omitted variables could lead to the biased estimator because the unobserved variables cannot include in the estimated specification but correlated with the automation adoption (omitted variable).

Therefore, we need an instrument variable (IV) that correlated with automation adoption, but not with unobserved productivity shocks to address this issue. In this study, we use (1) automation group as the proportion of firms in the same group that have automation adoption. We first define firms in the same group as belonging to the same size, industry (two-digits), and region[5]. Given the high proportion of automation adoption at the same group may induce the focal firm to also employs automation. However, they should not depend on the firm-level decision to employ the automation. Another IV that we use is (2) the automation shares in the previous year. The concept behind the instrument is that previous share of automation can explain the current share but is not related with shocks to productivity in the current period. Assuming shocks are not too long-lived. In other words, preciseness of the instruments requires the lagged in automation shares are not related to the disturbance term.

5.3 Descriptive statistics

We generally observe that firms which adopt the automation machinery in production process, are larger in several dimensions, for example, sales, export, capital, and employment compared to non-adopters. For instance, the average automation adopter realized sales about 4,948.45 million Baht and employs 446 employees. For non-automation adopters, sales are about 2,570.00 million Baht and 286 employees. In case of share of workers, the automation adopters have higher skilled worker share than non-automation adopters by 35.73 and 31.45 percent respectively. While non-automation adopters have higher unskilled worker share than automation adopters by 68.42 and 63.95 percent respectively. Table 1, we present the descriptive statistics by automation adopters and non-automation adopters. The dependent, key independent, and control variables will be used in the empirical analyses in section 6.

[5] The automation group is partitioned into k groups. For each group, firm i ($i = 1,2, \ldots, N$) is excluded and the remaining $N - 1$ firms are calculated at time t-1.

Table 1: Descriptive statistics by automation adopters and non-automation adopters

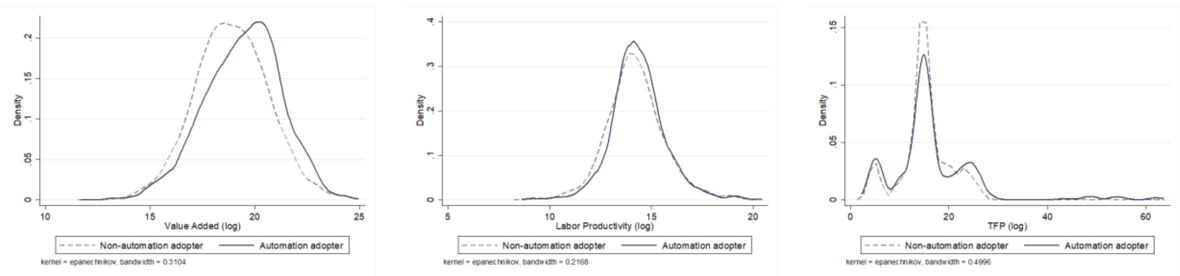
Variable	Automation adopters (1,608 obs.)				Non-automation adopters (3,454 obs.)			
	Mean	Std.dev.	Min	Max	Mean	Std.dev.	Min	Max
Dependent variables								
TFP (log)	16.62	9.03	2.29	63.57	15.30	5.52	1.86	63.29
Employment (log)	5.08	1.48	0.00	9.14	4.68	1.47	0.00	8.84
Share of skilled workers (log)	3.15	1.12	2.04	4.61	3.04	1.12	1.53	4.61
Share of unskilled workers (log)	4.05	0.85	1.71	4.61	4.17	0.69	0.51	4.61
Key independent variable								
Automation adoption (D)	1.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00
Control variables								
Sales (log)	20.24	2.00	14.11	26.64	20.02	1.83	11.24	26.06
Average wage (log)	12.75	1.18	4.89	17.81	12.69	1.31	3.87	18.58
Export intensity (log)	0.18	0.25	0.00	0.78	0.09	0.19	0.00	0.78
Skill intensity (log)	0.28	0.23	0.00	0.69	0.25	0.22	0.00	0.69
Capital intensity (log)	1.56	0.95	0.00	9.55	1.71	0.99	0.00	12.97
E-commerce (D)	0.11	0.31	0.00	1.00	0.05	0.21	0.00	1.00
R&D (D)	0.21	0.41	0.00	1.00	0.09	0.29	0.00	1.00

Notes: D is dummy variable.

Source: OIE (2020).

Before analyzing automation adoption in our empirical analysis, we provide some evidence on the relationship between output (value added, labor productivity, TFP), and automation adoption. Figure 7 shows the distribution of value added, labor productivity, and TFP (deflated and in logs) for automation adopters and non-automation adopters. The figure reveals that the distribution of automation adopters (solid line) clearly dominates the distribution of non-automation adopters (dashed line).

Figure 7: Distributions of value added, labor productivity, and TFP for automation adopters versus non-adopters



(a) Value added (b) Labor productivity (c) TFP

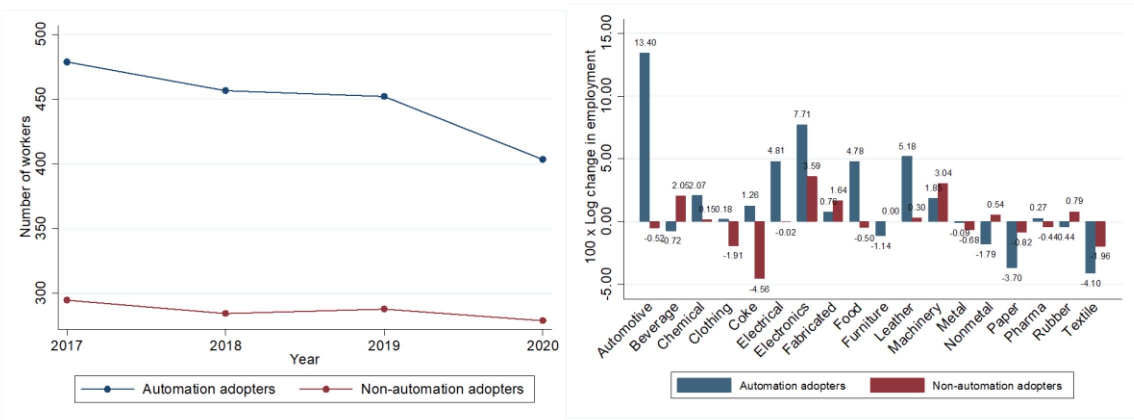
Note: Labor productivity based on value added per employment.

Source: OIE (2020). Calculated by authors.

In case of employment, Panel (a) of Figure 8 provides an indication that the adoption of automation is heterogeneous across firms. Those firms who adopt the automation have the number of jobs around 1.6

times higher than non-adopters. Interestingly, however, employment of both adopted and non-adopted firms gradually declined in the recent years but automation adopters' employment dropped dramatically during the spread of COVID-19 pandemic. At the same time, panel (b) shows the change in employment (in log) between 2017-2019[6] for both groups. Automation adopters are likely to expand their employment in almost sectors when compared to non-automation adopters, especially in high technology intensity sectors such as automotive, electronics and electrical industries.

Figure 8: Firm employment and change in employment of automation adopters versus non-adopters



(a) Average firm employment

(b) Change in employment between 2017-2019

Source: OIE (2020). Calculated by authors.

5.4 Methodology

We next move to investigate the automation adoption effect through the regression analysis. The baseline regression in this study estimates the following equation (6):

$$TFP_{it} = \beta_0 + \beta_1 Automation_{\,i,t-1} + \beta_2 Firm\ control_{i,t-1} + S_j + \varepsilon_{it}, \qquad (6)$$

where TFP_{it} represents the natural logarithm of total factor productivity of firm i at time t. $Automation_{\,i,t-1}$ denotes the variables of interest: automation adoption is a 0/1 indicator variable for automation adoption in the production process of firm i at time $t-1$ and zero is otherwise. For the set of firm control variables, we focus on six variables which represents in lag term ($t-1$): (1) firm's size is the dummy variable of number of employees following OSMEP definition[7], (2) e-commerce is a 0/1 indicator variable for firm who has sale channel through e-commerce and zero is otherwise, (3) R&D is a 0/1 indicator variable for firm involved in R&D and zero is otherwise, (4) export intensity is the

[6] We calculated the change in employment between 2017-2019 to investigate the impact of automation adoption before the pandemic.

[7] Office of Small and Medium Enterprise Promotion (OSMEP) classifies the firm' size in manufacturing by employment as follows: (1) small enterprise employs fewer than 50 people, (2) medium enterprise employs 51 to 200 people, and (3) large enterprise employs 201 or more people.

share of exports in total sales (in log), (5) skill intensity is the share of skilled worker in total employment (in log), and (6) capital intensity is the share of fixed asset in labor cost (in log). S_j denotes the year fixed effect and industry fixed effects at two-digit level and ε_{it} is the usual error term.

For the control variables used through this analysis, we introduce the factor intensity variables to time varying industry specific factors in the model. These variables include the firm's capital intensity, export intensity, and skill intensity (all in logs). Skill intensity can be used as a proxy for the complexity of the production process which determines firm's automation adoption. We expect that firms are likely to use automation in the production process when they have high share of skilled workers. Moreover, the share of unskilled workers should be reduced due to the displacement effect. The globalization variable we implement is the export intensity because the higher productive exporters have stronger incentives to adopt automation for reducing the production costs and scaling up to a larger volume of sales in domestic and oversea. For the capital intensity, we use as a proxy of how much capital employed in the provision of manufacturing goods, as they reflect the utilization of fixed assets per labor cost in the production process. Furthermore, we control for e-commerce distribution and R&D expenses. Some evidence indicates that firm with e-commerce or invest in R&D are likely to be more knowledgeable and innovative (Kinda, 2019).

In our analysis, to avoid the endogeneity problem, we, firstly, use the lagged explanatory variables to alleviate the causal identification[8]. Second, we applied the instrument variable (IV) technique to manage the endogeneity bias. By introducing additional variable, "automation group", as mentioned above which is correlated with the suspect endogenous variable $Automation\ adoption_{i,t-1}$ but not with ε_{it}. The IV estimator is analogous to a two-stage least square (2SLS) approach: in the first stage $Automation\ adoption_{i,t-1}$ is regressed on an instrument; second one, the fitted values $\widehat{Automation\ adoption}_{i,t-1}$ is used in the TFP equation, as $E(\widehat{Automation\ adoption}_{i,t-1}.\varepsilon_{i,t-}) = 0$.

For investigating the automation effect on employment, the baseline regression is as shown in the equation (7):

$$EMP_{it} = \beta_0 + \beta_1 Automation_{i,t-1} + \beta_2 Firm\ control_{i,t-1} + S_j + \varepsilon_{it} \qquad (7)$$

where EMP_{it} denotes the related various measures of worker in log form: (1) total employment, (2) share of skilled workers, and (3) share of unskilled workers[9] of firm i at time t. $Automation_{\ i,t-1}$ represents the variables of interest: Automation adoption is a 0/1 indicator variable for automation adoption in the production process of firm i at time $t-1$ and zero otherwise and. The set of firm control

[8] We are careful not to claim that use of lagged explanatory variables, especially automation adoption, can get rid of a causality problem.

[9] According to Ror. Ngor. 9, the skilled worker defined as skilled staffs or experts who operate in the factory area. Conversely, the unskilled worker refers to staffs that require relatively little or no training or experience for the work performed and working in the factory area.

variables consist of sales, average wage (wage bill divided by total employment), export intensity, skill intensity, and capital intensity (all in logarithmic form). We also control for e-commerce and R&D as dummy variables. S_j denotes the year fixed effect and industry fixed effects at two-digit level and ε_{it} is the usual error term. For the treatment of endogeneity problem, we also implemented the 2SLS with instrument (adoption group) as the same with productivity analysis.

6. Empirical Results

6.1 Automation adoption and productivity

We begin our empirical analysis by investigating how automation affects the TFP at the firm level. Our baseline results are provided in Table 2. The table contains a set of OLS regressions starting with a parsimonious specification and adding the various controls sequentially. Columns (1)-(4) show the relationship between TFP and automation adoption. The main results are positive and statistically significant. The estimated coefficients of automation adoption range from 0.17 to 0.47. Thus, firms who adopt automation in the previous year, the associated increase in TFP equals 18.89% to 59.68[10]% compared to non-automation adopters.

The relationships between TFP and several control variables are significant and show the expected direction. First, firms who spent more on R&D have 23.37% to 26.36% higher TFP. The firm's export status is positive and significant, for 1% increase in export shares, the associated increase in the TFP equals 0.69% to 0.75%. Exporting firms tend to invest more in new technologies due to high competition on the international markets (Yasar & Nelson, 2003; Abor, 2011). Skill intensity enters positively and significantly, 1% increase in skilled labor shares, the associated increase in the TFP equals 0.84% to 0.88%. Capital intensity is also correlated with TFP. We find that 1% increase in the share of fixed asset in labor cost can raise TFP by 0.09%. In the other hand, firms involved in e-commerce do not yield the statistical significance result.

Usage of technology also varies by geographical area, even after controlling for the factor intensities. In this case, we assign the case of firm who adopt an automation in EEC area as a reference group. Therefore, columns (5) to (8) can provide three cases as follows: firstly, we find that firms adopt automation in EEC have on average 10.52% to 39.43% (at the 10% significance level) higher TFP in the following year compared to the non-automation adopters outside EEC area; secondly, the automation adopters in EEC area are lower than in TFP on average 26.87% to 71.60% compared to the adopters outside EEC area; and lastly, the automation adopters in EEC area have on average 8.37% to 16.18% lower TFP compared to the nonadopters in EEC area as shown in columns (5) to (8).

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[10] Our variable of interest is automation adoption which is dummy variable and TFP in log term. Thus, the interpreted coefficient is equal to $(exp^{\beta} - 1) * 100$.

Table 2: Automation adoption and TFP: Ordinary Least Squares

Dependent variable: TFP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Automation adoption (1/0)	0.468***	0.197***	0.174***	0.173***	0.540***	0.263***	0.243***	0.238***
	(0.0542)	(0.0500)	(0.0493)	(0.0523)	(0.0638)	(0.0570)	(0.0562)	(0.0561)
EEC					0.0804	0.117	0.150*	0.133*
					(0.0712)	(0.0644)	(0.0642)	(0.0647)
Automation adoption x EEC					-0.288*	-0.273*	-0.292*	-0.271*
					(0.131)	(0.118)	(0.117)	(0.116)
Medium (51-200 workers)		0.522***	0.550***	0.550***		0.525***	0.555***	0.555***
		(0.0563)	(0.0568)	(0.0581)		(0.0565)	(0.0570)	(0.0570)
Large (> 200 workers)		1.435***	1.483***	1.478***		1.435***	1.486***	1.481***
		(0.0628)	(0.0632)	(0.0590)		(0.0625)	(0.0630)	(0.0627)
E-commerce (1/0)		-0.0188	0.0148	0.0281		-0.0313	0.00211	0.0155
		(0.0862)	(0.0839)	(0.0875)		(0.0863)	(0.0839)	(0.0832)
R&D (1/0)		0.234**	0.210**	0.217**		0.233**	0.208**	0.215**
		(0.0720)	(0.0694)	(0.0674)		(0.0720)	(0.0695)	(0.0693)
Export intensity		0.698***	0.691***	0.749***		0.701***	0.693***	0.747***
		(0.0931)	(0.0917)	(0.112)		(0.0939)	(0.0923)	(0.0939)
Skill intensity			0.880***	0.836***			0.891***	0.848***
			(0.115)	(0.105)			(0.114)	(0.112)
Capital intensity				0.0865***				0.0819**
				(0.0251)				(0.0285)
Constant	14.75***	13.97***	13.79***	13.63***	14.73***	13.95***	13.76***	13.61***
	(0.0722)	(0.0751)	(0.0786)	(0.0936)	(0.0733)	(0.0768)	(0.0800)	(0.0978)
Year (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,702	3,702	3,702	3,702	3,702	3,702	3,702	3,702
R-squared	0.953	0.961	0.962	0.962	0.953	0.961	0.962	0.962

Note: The dependent variable is the log of TFP. Main interest of variable is automation adoption. Control variables consist of e-commerce, R&D, export intensity, skill intensity, capital intensity which represents in lag term (t-1). Also, firm's size, industry fixed effect (two-digits) and year fixed effect. All factor intensity variables plus one before taking logs to keep zero observations. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6.2 Robustness checks

We then verify the results by examining the robustness checks. In the baseline models, the observations have been given the same weight in every sub-sample industry. Therefore, a small sector in terms of a small value added, such as textiles, furniture, pharma, and leather[11], carries as much importance for the coefficients as a larger sector with a large value added, such as food, automotive, chemical, electronics, and metal[12]. An alternative approach would be estimated to our model using weighted least squares (WLS), where the weights are the value added and labor input by sectors.

[11] These sectors provide the share of value added < 1% in 2020 (Ror.Ngo.9).
[12] These sectors provide the rage of value added from 5-13% in 2020 (Ror.Ngo.9).

WLS is employed in Table 3, columns (2) to (4) for baseline and columns (6) to (8) for the interaction term of automation adoption and EEC area. In columns (2) and (6), we weight the regressions using the log of value added, columns (3) and (7) employed the log of the wage bill as weights, whereas in columns (4) and (8) the log of total employment is weighted. We also estimate the OLS specification from column (4) in Table 2 as shown in columns (1) and (5). The magnitude of coefficients in all specifications are relative to baseline regression. This evidence supports that the baseline estimations were not driven by small sectors. In particular, the coefficient of the automation adoption is positive and strongly significant in all columns.

Table 3: Automation adoption and TFP: alternative estimation methods

Dependent variable: TFP	OLS	WLS-VA	WLS-Wage	WLS-EMP	OLS	WLS-VA	WLS-Wage	WLS-EMP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Automation adoption (1/0)	0.173***	0.173***	0.172***	0.183***	0.238***	0.240***	0.241***	0.253***
	(0.0523)	(0.0496)	(0.0497)	(0.0493)	(0.0561)	(0.0564)	(0.0564)	(0.0561)
EEC					0.133*	0.136*	0.138*	0.142*
					(0.0647)	(0.0653)	(0.0662)	(0.0649)
EEC x Automation adoption					-0.271*	-0.281*	-0.287*	-0.294*
					(0.116)	(0.117)	(0.116)	(0.115)
Constant	13.63***	13.64***	13.65***	13.61***	13.61***	13.62***	13.63***	13.59***
	(0.0936)	(0.0975)	(0.0981)	(0.0977)	(0.0978)	(0.0984)	(0.0986)	(0.0982)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,702	3,702	3,702	3,702	3,702	3,702	3,702	3,702
R-squared	0.962	0.962	0.962	0.962	0.962	0.962	0.962	0.962

Note: The dependent variable is the log of TFP. Main interest of variable is automation adoption. Control variables consist of e-commerce, R&D, export intensity, skill intensity, capital intensity which represents in lag term (t-1). Also, firm's size, industry fixed effect (two-digits) and year fixed effect. All factor intensity variables plus one before taking logs to keep zero observations. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6.3 Instrumental-variable estimations

Even through the baseline regressions in Tables 2 and 3 indicate a positive correlation between automation adoption and TFP when controlling for labor, capital, weighted across sectors. As we mentioned earlier the reverse causality of the automation adoption on TFP is still a trivial concern. The risk that unobserved shocks to TFP will affect input choices (including automation adoption) can occur. For example, some sectors are hit hard by positive shocks during the observed period tend to invest more in an automation. The result in this case leads to the upward biased of the coefficient of the automation adoption.

To mitigate these concerns, we use two instrument variables consist of automation group and automation shares in the previous year. The idea behind these IV we have already described in section

5.2. The instrument variable approach we use is the two-stage least squares (2SLS) to confirm the baseline results.

Table 4 presents the IV results. The table shows that positive results still hold, when we address the endogeneity of automation adoption by using automation group and automation shares $(t-1)$ as instrument variables. A first stage of F-test shows that two IV indicators are statistically significant. This implies that the instrument is not weak for automation adoption. In columns (2) to (4) show that firms who adopt an automation provide TFP in the following year, on average 22.51% to 22.63% more than non-automation adopters.

According to a reference group by firms who adopt the automation in EEC area, there are three cases in this regression model. Firstly, firms who are automation adopter in EEC area have around 12.19% to 12.41% higher TFP compared to non-automation adopters outside the EEC area. Secondly, the adopters in EEC area have on average 32.18% to 33.11% lower TFP compared to firms who adopt outside EEC area. Lastly, automation adopters in EEC area are lower in TFP around 15.37% to 15.60% compared to non-automation adopters in EEC area as shown in columns (6) to (8).

Table 4: Automation adoption and TFP: Instrumental variable approach

Dependent variable: TFP	OLS (1)	IV-2SLS (2)	IV-2SLS (3)	IV-2SLS (4)	OLS (5)	IV-2SLS (6)	IV-2SLS (7)	IV-2SLS (8)
Automation adoption (1/0)	0.173***	0.204	0.203***	0.203***	0.238***	0.279	0.286***	0.285***
	(0.0494)	(0.156)	(0.0597)	(0.0584)	(0.0561)	(0.224)	(0.0773)	(0.0764)
EEC					0.133*	0.143	0.145*	0.145*
					(0.0647)	(0.0732)	(0.0680)	(0.0664)
EEC x Automation adoption					-0.271*	-0.307	-0.314*	-0.313*
					(0.116)	(0.230)	(0.133)	(0.133)
Constant	13.63***	13.52***	13.52***	13.52***	13.61***	13.49***	13.49***	13.49***
	(0.0972)	(0.0927)	(0.0906)	(0.0907)	(0.0978)	(0.0971)	(0.0918)	(0.0920)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,702	3,702	3,702	3,702	3,702	3,702	3,702	3,702
R-squared	0.969	0.968	0.969	0.969	0.969	0.966	0.969	0.969
First stage for automation adoption								
IV1: Automation group	-	0.954***	-	0.490***	-	0.728***	-	0.439***
	-	(0.031)	-	(0.030)	-	(0.030)	-	(0.028)
IV2: Automation shares (t-1)	-	-	0.011***	0.011***	-	-	0.010***	0.010***
	-	-	(0.0002)	(0.0002)	-	-	(0.0002)	(0.0002)
F-stat for the joint sig. of the IV	-	922.475	5841.24	2959.02	-	602.57	3859.70	1940.94
Number of IV	-	1	1	2	-	1	1	2

Note: The dependent variable is the log of TFP. Main interest of variable is automation adoption. Control variables consist of e-commerce, R&D, export intensity, skill intensity, capital intensity which represents in lag term (t-1). Also, firm's size, industry fixed effect (two-digits) and year fixed effect. All factor intensity variables plus one before taking logs to keep zero observations. Instrument variable is the adoption group and lag of automation shares. Endogenous variable is the automation adoption. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In sum, the instrument variables that we employed indicate that the coefficients associated with automation adoption with IV approach are of similar magnitude as the OLS and WLS approaches. Also, the instrumental variables are not weak. This suggests that endogeneity through measurement errors exists in this case. Thus, we apply the results of IV estimate to reduce the bias of coefficients in the OLS estimates due to endogeneity problem.

6.4 Automation adoption and employment

We next turn to our second question on how did automation affect firm's employment? This section, therefore, devoted to investigating the relationship between the use of automation and employment. All regressions are carried out using OLS with year and sector fixed effects, and 2SLS in Table 5.

We use the number of total employment and share of skilled and unskilled workers in logs as our dependent variables. Columns (1) to (3) in panels (A) of Table 5 show the OLS estimates. The results indicate that the numbers of total employment and share of skilled workers in automation adopters significantly increases by 13.66% and 8.93%, respectively, relative to non-automation adopters. While the changes for share of unskilled workers are insignificant. On the other hand, we find that total employment, share of skilled and unskilled workers are insignificant for automation adopters in EEC.

Columns (4) to (6) of panel (B) display the IV-2SLS estimation. We find positive significant relationship between the use of automation and overall employment which increases by 116.41%. When we focus on the share of skilled and unskilled workers, automation adopters would like to employ more skilled workers (share of skilled workers increased by 55.73%) but decrease the demand for unskilled workers (share of unskilled workers decreased by 12.80%) compared to non-automation adopters. In overall, these results imply that automation adoption causes skill-biased development in firm's employment structure in Thai manufacturing firms (Tang, et al., 2021). For the adopters in EEC area, the results indicate that the automation adopters in EEC tend to have a higher total employment and share of skilled workers than non-automation adopters outside EEC by 54.19% and 14.84%, respectively. However, we find no significant relationship between automation usage and share of unskilled workers.

Table 5: Automation adoption and Employment: OLS and Instrumental variable approaches

	Employment	Share of skilled workers	Share of unskilled workers	Employment	Share of skilled workers	Share of unskilled workers
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Automation adoption (1/0)	0.128***	0.0855*	-0.0121	0.128***	0.0675	0.00527
	(0.0245)	(0.0430)	(0.0312)	(0.0286)	(0.0468)	(0.0344)
EEC				-0.0271	-0.253***	0.0915*
				(0.0306)	(0.0560)	(0.0364)
EEC x Automation adoption				0.00452	0.108	-0.0803
				(0.0488)	(0.0923)	(0.0660)
Observations	3,702	3,401	3,400	3,702	3,401	3,400
R-squared	0.832	0.152	0.134	0.832	0.158	0.136
B. IV-2SLS						
Automation adoption (1/0)	0.772***	0.443***	-0.137*	1.045***	0.657***	-0.192*
	(0.0745)	(0.120)	(0.0670)	(0.107)	(0.169)	(0.0930)
EEC				0.206***	-0.0956	0.0416
				(0.0410)	(0.0707)	(0.0432)
EEC x Automation adoption				-0.818***	-0.423*	0.0977
				(0.106)	(0.176)	(0.106)
First stage for automation adoption						
IV: Automation group	0.933***	0.941***	0.952***	0.704***	0.714***	0.707***
	(0.031)	(0.032)	(0.031)	(0.030)	(0.031)	(0.031)
F-stat for the joint sig. of the IV	922.57	865.03	857.87	568.98	525.75	515.16
Wooldridge's score test for endogeneity	82.300***	10.490***	3.661*	83.860***	14.681***	4.597*
Observations	3,702	3,401	3,400	3,702	3,401	3,400
R-squared	0.798	0.133	0.129	0.779	0.118	0.127
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year (FE)	Yes	Yes	Yes	Yes	Yes	Yes
Industry (FE)	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the employment, share of skilled and unskilled workers (all in log). Main interest of variable is automation adoption. Control variables consist of log of sales, log of average wage, e-commerce, R&D, export intensity, skill intensity, capital intensity which represents in lag term (t-1). Also, the industry fixed effect (two-digits) and year fixed effect. All factor intensity variables plus one before taking logs to keep zero observations. Instrument variables are the adoption group. Endogenous variable is the automation adoption. Wooldridge's score test does reject the null hypothesis that automation adoption is exogenous at conventional significance levels. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Lastly, the IV-2SLS estimators indicate that the coefficient associated with automation adoption is higher than OLS approach. Furthermore, Wooldridge's score test cannot accept that automation adoption is an exogenous, suggesting that the endogeneity holds for automation adoption. Therefore, we apply the results of IV estimate to avoid the bias of coefficients in OLS due to endogeneity problem.

7. Conclusions and Policy Implications

In this paper we present new evidence on the role of automation for TFP and employment at firm level in manufacturing sector. Using our panel data covering 22 manufacturing sectors over 2017-2020, we find that automation adopters can raise TFP by an average of 23%. The results also highlight that firms who use automation in EEC area have 12% higher TFP than nonadopters outside EEC. These estimates are robust to the use of an instrumental variable approach.

Nevertheless, some evidence indicates that adopters in EEC area provide the lower TFP than firms who adopt automation outside EEC area and nonadopters who operate in EEC area. Following Aghion et al. (2018), there are two effects of the industrial robot adoption on TFP. On the one hand, firms can suffer from the increases in costs for utilize the robots and decrease profit margins, especially firms in EEC area that may have more incentive to invest in high-level technology than outside EEC to obtain the investment incentive packages. It may reduce the TFP in the short term. On the other hand, the use of robotization will improve TFP and increase profit margin in the long run.

Acemoglu and Restrepo (2019) studied the effects of different technologies on labor demand based on a task-based model. The results indicated that the task of production was reduced by the robots and automation adoption. In contrast, the creation of new tasks related to robot implementation has also increased the labor demand. Some studies found that automation will increase the job opportunity for skilled workers, but reduce the demand of unskilled workers

Finally, there is no evidence for supporting the displacement effect in total employment due to automation adoption. The automation technologies provide a positive effect on total employment. In contrast, there is some evidence that the use of automation causes skill-biased development in firm's employment structure by increasing the share of skilled workers and decreasing the unskilled worker shares. Whereas automation adoption in EEC did increase the share of skilled workers to support the automation acceleration in the area. These results support the idea of Acemoglu (2019) that some tasks will be replaced by automation technologies while some new tasks are reinstated from those technologies as well.

Our findings suggest that automation adoption potentially raise TFP growth in Thailand supporting the government target to achieve the high-income country in 2037. Moreover, the rise of automations also creates more jobs for skilled workers in manufacturing sector but tends to affect the unskilled workers in losing a job. Therefore, government and companies must focus on providing the right skills and demand-driven education to current and future workers to ensure a continuation of the non-negative impact of automation on employment. Hence, there is plenty of room for further automation adoption to drive economic growth and make opportunity of manufacturing jobs more in the future.

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