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Abstract: This paper examines the impact of advanced technology on both possible changes in workers' skills and wages and the possibility that workers become unemployed due to such technological advancement. Three proxies of advanced technologies are used in the study, ICT, the intensity of robot usage and the value of e-commerce. Our study compares the effects of technological upgrades on labour market outcomes with import penetration, delineating into raw materials, capital goods and final products. Our results show that in Thailand, the impact of advanced technology in pushing workers out of the job market is limited. Instead, it tends to affect the reallocation of workers between skilled and unskilled positions. The results vary among proxies of technology and sectors. It seems that workers in comparatively capital-intensive industries, including the automotive, plastics and chemicals and electronics and machinery sectors are the most affected from technological growth. Our results highlight the diminished negative impact resulting from imports, particularly those of capital goods and raw materials, on employment status and income in comparison to that of technological advancements.

***Keywords*:** Technological Advancement, Import Penetration, Labour Markets

JEL Classification: F16, O30, O53

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1. Introduction

There is a long history of industry being periodically revolutionised by waves of new technology. Clearly, the world is currently experiencing the Fourth Industrial Revolution that allows innovations from the three previous industrial revolutions to become interconnected with each other. In the fourth revolution we have witnessed fundamental advances in technologies, which will radically transform the structure and dynamics of many industries. Industry 4.0 represents the next wave of digital and online transformation as industries are thoroughly remodelled through, for example, ameliorated automation, artificial intelligence, robotics, cloud computing, 3D printing, big data analytics and the internet of things. The advancing technologies tend to enable and facilitate a broad range of business activities related to the storage, processing, distribution, transmission and reproduction of information. However, there are concerns about the impact of such advancing technologies on economic development in both developed and developing countries, especially in the field of labour market outcomes. With such advancing technologies, a wide range of job tasks in many sectors and countries will inevitably become fully or partially automated. This will encompass tasks seen until recently as non-routine, e.g. diagnosing disease from X-rays, facilitating orders in a warehouse or driving cars (Bessen et.al., 2019). Frey and Osborne (2017) and Ford (2015) argue that the pace of technological advancements, especially in terms of automation, artificial intelligence (AI) and robotics, is accelerating, both in developed and developing countries, and the range of jobs affected by such technologies are widening. Autor et al. (2003); Acemoglu and Autor (2011); Acemoglu and Restrepo (2018b) developed a theoretical model showing that with a task-based approach, where the central unit of production involves a task while labour and capital have comparative advantages across different tasks, automation can create displacement effects resulting in both a decline in the demand for labour and wage rates.

Interestingly, so far empirical studies on the impact of cutting-edge technology on labour market outcomes, which are mostly undertaken in developed countries, are mixed. On the one hand, Cirera and Sabetti (2019); Crespi, Tacsir and Perreira (2019); Hou et.al (2019); Mairesse and Wu (2019) and Calvino (2019) using outcome measures from technological advancements show that to some extent, technological advancements help to create product innovation and improve labour market outcomes, including those pertaining to employment and productivity. Moreover, Bartel, Ichiowski and Shaw (2007) studying the impact of new information technologies (IT) showed that the adoption of new IT-support skilled workers improved efficiency in all stages of the production process. On the other hand, Arntz, Gregory and Zierahn (2016), Gaggl and Wright (2017), Acemoglu and Restrepo (2017), and Bessen, et.al (2019) highlight the threats arising from technological leaps. Gaggl and Wright (2017) show that while nonroutine, cognitive tasks are significantly affected by the adoption of ICT, there is only a modest impact when ICT replaces routine, cognitive work. Acemoglu and Restrepo (2017) pointed to the negative effects of robots on employment and wages across commuting zones in the US. Meanwhile, Bessen, et.al (2019) revealed that automation decreases the probability of day work, but not wage rates

In view of the unclear consequences of advanced technology on labour market outcomes, this study aims to examine technological impact in the developing country context with the Thai labour market serving as a case study during 2012-17. This research contributes to the existing literature in three ways. First, while previous studies analysed the impact of advanced technology on labour market outcomes, either employment levels or wages or both, this study examines possible changes in the skills and wages of workers, potentially induced by technological advancements, and the possibility that workers become unemployed due to such changes. Our analysis is conducted in terms of not only the whole manufacturing sector, but also a sector-specific inquiry. Autor and Salomons (2018) argues that advanced technology may only reallocate employment, but not depress the overall demand for labour. In addition, to confirm the effects of technological advancement on wages/income, wage equations at the individual level are performed overtime among workers using the whole manufacturing sector and a sector-specific inquiry.

Secondly, in contrast to other studies technological advancements are proxied by three key variables according to their involvement in supply chains, i.e. inbound (automated e-sourcing), outbound (e-commerce), and internal production (e.g. factory automation/robots) (UNCTAD, 2017) to delineate the relative important effects of technological involvement in supply chains. Both ICT functionality as well as the value of e-commerce at the industry level are used to capture the possible technological involvement in inbound and outbound activities, while industrial robot usage at the industry level is employed to capture the possible impact of technological advancements in internal production. Thirdly, since trade, particularly in terms of import penetration, is another paramount force shaping labour markets, this study compares the effects of technological advancements on labour market outcomes with import penetration. Only a few studies, e.g. Autor, Dorn and Hanson (2015) and Acemoglu and Restrepo (2017) have compared the effects of these two forces, but their work concentrates only on the developed country context. In addition, while previous studies examined the impact of penetration in terms of total imports, this study investigates the phenomenon from the perspective of finished products, capital and raw materials.

The rest of the paper is structured as follows. Section 2 provides a literature survey regarding the impact of technological advancements on labour markets. Section 3 outlines the policy changes in response to industry 4.0 in Thailand and how far technology has progressed to date. Our empirical model and data sources are discussed in Section 4, while Section 5 concerns the empirical results and the last section concludes with key findings and policy inferences.

2. Literature Survey

There is a long history of industries being revolutionised in the face of fresh waves of new technology. With advancing technical capabilities, there are somecome concerns about the impact of such technologies on economic development in both developed and developing countries, especially in the area of labour market outcomes. However, studies concerning such impacts generate mixed findings. On the one hand, some studies show technological advancements, to some extent, help improve labour market outcomes. For example, Beaudry, Doms and Lewis (2006) examined the impact of technology adoption on city-level outcomes, mainly focusing on the abundance of skilled labour and wages during 1980-2000. Herein, skilled labour is defined as workers having at least a four-year college degree or at least some college education. Technology adoption is measured in terms of personal computer (PC) intensity, the number of PCs per employee within each city. Cities that adopt PCs aggressively have a relative abundance of skilled labour and witnessed a significant increase in relative wages. Bartel, Ichiowski and Shaw (2007) studied the impact of new information technology (IT) on the productivity and worker skills within the valve manufacturing context during 1999-2003. Their results revealed that the recruitment of new IT-support skilled workers improved efficiency within all stages of the production process. Meanwhile, the adoption of new IT systems allowed them to shift from mass production to manufacturing more customized valve products.

Cirera and Sabetti (2019) studied the impact of innovation on employment within 53 developing countries during 2013-15. Innovation here is examined in terms of outcome measures, i.e. either product, process or organizational innovation. The study applies the Harrison et.al (2014) format as a base model in which there are two types of products, old and new, which can generate demand. Using a cross-sectional analysis of both manufacturing and services, they show that product innovation increases employment and the effect outweighs any associated job losses due to the cannibalization of old products, particularly in the high-tech manufacturing sector. The impact of process and organizational innovations on employment seem to be negligible. Graetz and Michaels (2018) examined the implications of robot use on labour productivity, total factor productivity, output prices and employment during 1993-2007 across seventeen countries. Their results revealed that robot use contributed positively to both labour and factor productivity growth; thereby lowering output prices. Robots had an insignificant effect on employment across the panel of countries and industries, but they did reduce low-skilled workers' share with total employment. Additionally, the research of Dauth et.al. (2017) indicated a positive impact of robotics on wages, but no impact on total employment.

Crespi, Tacsir and Perreira (2019); Hou et.al (2019) and Mairesse and Wu (2019) also apply a model based on Harrison et.al (2014) in examining the impact of innovation on employment. Crespi, Tacsir and Perreira (2019) applied the model to Chile, Uruguay, Costa Rica and Argentina during 1995-2012, while Hou et.al (2019) concentrated on EU countries and China during 1999-2006 and Mairesse and Wu (2019) on just China during 1999-2006. Note that Mairesse and Wu (2019) extended Harrison et.al (2014) by splitting output into domestic and export, both of which are decomposed further into new and old products. The results of these three papers resemble the findings of Cirera and Sabetti (2019). Calvino (2019) applies different underlying theories of production and competition for Spain during 2004-12 in examining the impact of innovation on employment. As in the previous studies, product innovation was revealed to have a positive effect on employment growth, both with fast-growing and shrinking firms, but the effect of process innovation on employment was insignificant, except in cases involving new production methods or auxiliary processes, such as IT, in which employment growth was stimulated somewhat at the lower end of its conditional distribution. Barbieri, Piva and Vivarelli (2019) use different underlying theories of production and competition for Italy during 1998-2010, but instead of focusing on outcome measures for innovation, they use input, i.e. R&D and innovation expenditure, to represent innovation. In this context innovation tended to have a positive, though rather small, impact on employment.

On the other hand, a number of empirical studies have uncovered details of the negative impact of technological advancements on labour market outcomes. Arntz, Gregory and Zierahn (2016), for example, followed the occupation-based approach proposed by Frey and Osborne (2013), but took into account the heterogeneity of workers' tasks within occupations, to determine the risks of automation in terms of jobs in 21 OECD countries. On average, the threat from technological advances seemed to exist, but the results differed across OECD countries. Gaggl and Wright (2017) studied the effects of information and communication technology (ICT) adoption on employment and wage distribution. ICT adoption was proxied by the number of workers that use a PC and the number of PCs in the workplace. The results showed that nonroutine, cognitive tasks were affected by the adoption of ICT, while there was only a modest impact of ICT with respect to replacing routine, cognitive work.

Bessen, et.al (2019) estimated the impact of automation on individual workers using Dutch micro-data in private non-financial industries during 2000-16. This involved a direct measure of automation at the firm level, i.e. automation costs defined as the costs of third-party automation services, including non-activated purchases of custom software and the costs of new software releases. They showed that automation decreased the probability of day work, which led to a 5-year cumulative wage income loss of about eight percent of one year's earnings, but wage rates were not significantly affected by automation. The impact of automation was more gradual and displaced far fewer workers than mass layoffs. Freya and Osborneb (2017) examined the impact of future computerisation on US labour market outcomes, composed of wages and educational attainment. A Gaussian process was applied to estimate the probability of computerisation for 702 detailed occupations. The author showed that around 47 percent of total US employment was at high risk of computerisation, especially most workers employed in transportation, logistics and office and administrative support workers.

Acemoglu and Restrepo (2017) examined the impact of industrial robots on employment and wages in the US during 1990-2007 on US local labour markets. A model in which robots competed against human labour in the production of different tasks was applied. The results reveal the negative effects of robots on employment and wages across commuting zones. However, the negative impact arising from robots is relatively small due to limited number of robots in the US economy at that time. Autor, Don and Katz (2017) assessed the fall in labour share based on the rise of superstar firms. The U.S. Economic Census data was applied for three decades for the period 1982-2012. The results indicated that technological changes benefit the most productive firms in each industry and lead to a higher concentration of super-star firms, thereby reducing the aggregate labour share. The decline in labour share is driven mainly by between firm reallocation, rather than a fall in labour share within firms..

However, there are some studies arguing the impact of technological advancement on labour market is unclear depending on the prevailing conditions in labour markets and particular production structures. Acemoglu and Restrepo (2018a, 2018b, 2019) developed a conceptual framework to understand how machines replace human labour and how employment and wages are affected. Their model involved a task-based framework where automation is represented as the expansion of the set of tasks that can be performed by capital and replace labour. In addition to automation, the model encompassed another type of technological change, which captured a greater degree of complexity than considering only existing tasks. It was assumed that labour tends to have more comparative advantage in these new tasks than automation. In the short run, the displacement effect in which automation is able to replace labour could occurred, thereby depressing demand for labour and wages. However, in the long run, since labour has a comparative advantage over automation, if the creation of new tasks continues employment and labour share are able to remain stable even in the face of rapid automation. Acemoglu and Restrepo (2018b) clearly argued that the presence of the displacement effect may eventually counteract any reduction in the demand for labour due to the effect of three channels, namely productivity, capital accumulation and the expansion of automation. Meanwhile, Acemoglu and Restrepo (2019) illustrated that productivity improvement in non-automated tasks induced by automation technology and the reinstatement effect, in which technology creates new tasks reinstating labour into a broader range of tasks, was able to counterbalance any displacement effect.

Autor and Salomons (2018) examined the impact of technological progress on aggregate employment and labour share at the industry level by considering both direct and indirect effects. They argue that technological innovations replace workers with machines. However, aggregate labour demand may not be reduced from such capital-labour substitution. Three countervailing responses could occur to eventually stimulate more demand, including inter-industry demand linkages, between-industry compositional changes and an increase in final demand. Harmonized cross-country and cross-industry data covering 19 countries in OECD, were studied for the period 1970-2007 Dauth et.al (2018) using data from German labour market during 1994-2014, showed that job losses induced by robot adoption in the manufacturing sector were offset by gains in the business service sector. This study also looked at the impact of robots on individual workers and revealed that the risks arising from the displacement effect were minimal for incumbent manufacturing workers, but high for young labour market entrants. The incumbent manufacturing workers tended to either stay with their original employer or switch occupations at their original workplace.

Interestingly, there are few studies (e.g. Autor, Dorn and Hanson, 2015 and Acemoglu and Restrepo, 2017) comparing the impact of technological advancements with those of imports. In fact, recently both technology and trade have become recognised as two important sources shaping labour markets, especially in developed countries. In terms of trade, it is argued that commercial exchange with lower-wage countries tends to depress wages and employment in the industries, occupations and regions exposed to import penetration (Autor, Dorn and Hanson, 2015). Autor, Dorn and Hanson (2015) examined the impact of technological change and trade on the US labour market within 722 commuting zones (CZs). Their results showed that trade competition, especially from Chinese imports, leads to a noticeable decline in manufacturing employment across all major occupation groups, including managerial, professional and technical. In particular, workers without a college education are greatly affected. The impact of technological changes seems to be negligible on overall employment. However, the changes create substantial shifts in occupational composition within sectors, from routine task-intensive production and clerical occupations to manual task-intensive work. The Acemoglu and Restrepo (2017) study mentioned earlier also supported the findings of Autor, Dorn and Hanson (2015) in that the impact of imports from lower-wage countries, China and Mexico, on employment and wages are relatively larger than those of technological advancement.

3. Technological Advancements in Thailand

Many countries, including Thailand, have embarked on formulating and implementing Industry 4.0 policies. The Thai government has been engaged in formulating Industry 4.0 since 2016 in order to transform the nation into a value-based economy. To do so, the policy package involved represents a combination of incorporating tested and proven industrial strategies and adopting an economic corridor framework wherein agents are efficiently connected along a defined geography.[1] In the former, ten newly targeted industries were selected to hopefully serve as novel and more sustainable growth engines. These ten industries were equally divided into two segments, five S-curved and five new S-curved sectors. The five S-curved industries included new-generation automotive, smart electronics, affluent, medical and wellness tourism, agriculture and biotechnology, and food for the future. The five new S-curved industries comprised manufacturing robotics, medical hub activities, aviation and logistics, biofuel and biochemicals and digital. In the latter, the Eastern Economic Corridor (EEC) - the newest special economic zone - was established in 2017 to help achieve the industrial transformation under Thailand 4.0. The EEC straddles three eastern provinces of Thailand – Chonburi, Rayong, and Chachoengsao – located off the Gulf of Thailand. It covers a total area of 13,285 square kilometers. The government aims to complete the EEC by 2021, turning these provinces into a hub for technological manufacturing and services with strong connectivity to its ASEAN neighbors by land, sea and air.[2]

Incentives through the Board of Investment have been granted to support Thailand moving towards industry 4.0. The BOI investment promotion plan (2015-2021) was amended in 2014. The incentives provided by BOI for the newly targeted industries comprise a combination of two sub-incentive schemes, activity-based and merit-based. With the former, a list of activities is divided into seven categories (A*, A1-A4 and B1-B2), according to their involvement in technology and innovation. A* for example refers to activities classified as support targeted technology, i.e. nanotech, biotech, advanced material and digital, A1 refers to knowledge-based activities focusing on R&D and design, and A2 represents incentives for infrastructure activities using advanced technology to create value-added results. For the latter, additional incentives are stipulated when activities add additional value to the economy in three areas, namely competitiveness and enhancements, together with decentralization and industrial area developments. Incentives for investors are in the form of corporate income tax (CIT)

[1] See Brunner (2013) discussing the concept of economic corridors.

[2] To enhance connectivity within as well to the EEC, the Thai government have invested heavily in infrastructure to enhance the connectivity of these three provinces with the rest of the world. Total infrastructure investment amounting to $43bn of investments will be channeled into the EEC by 2021. These investments will come from state funds, FDI and through infrastructure development under a public-private partnership framework, e.g. expanding the Laem Chabang seaport (Laem Chabang Phase 3) with the goal of transforming it into the marine hub of South East Asia. This could establish sea routes from the eastern provinces of Thailand to Myanmar's on-going Dawei deep-sea port project, Cambodia's Sihanoukville port, and Vietnam's Vung Tau port (US$2.5 billion).

exemption (the maximum is up to 13 years)[3], exemption from import duties on machinery and raw materials used in R&D and/or exports, and non-tax incentives, such as access to long-term land leases and working visas. It can be argued that the incentives provided by the BOI in Thailand represent the most generous package in Southeast Asia.[4]

ICT adoption is a key factor in harnessing the benefits of Industry 4.0. The first plan introduced the Thai *National IT policy* (1996-2000) in the mid-1990s intended to promote the use of ICT at the national level. Since then, a number of national-level plans have been launched, including the Thailand Information and Communication Technology (ICT) Policy Framework (2001-10), the National Broadband Policy (2009), the Information and Communication Technology Policy Framework (2011-2020), the Universal Service Obligation (USO) Master Plan for Provision of Basic Telecommunication Services (2012-14), and more recently, the Digital Thailand Plan (2016). The 2016 plan involved five main elements, (i) investing in hard ICT-related infrastructure, (ii) e-government services, (iii) soft infrastructure (e.g. cybersecurity, the amendment of existing laws and regulations), (iv) digital economy promotion (e.g. e-commerce, software industry, digital marketing), and (v) digital society and knowledge. After the establishment of the EEC in 2017, foreign direct investment increased in Thailand, but mostly in the form of mergers and acquisitions, instead of Greenfield investment (Jongwanich et.al., 2020).

So far, Thailand has shown progress in technological advancements along with manufacturing supply chains, which could be divided into three key areas, inbound (automated e-sourcing), outbound (e-commerce), and internal production (industrial robot usage) (UNCTAD, 2017). However, progress tends to be concentrated in particular industries. To delineate the relative importance of effects of the technological involvement in supply chains, ICT usage as well as the value of e-commerce usage at the industry level are applied to proxy the possible technological involvement in inbound and outbound activities, while industrial robot usage at the industry level is employed to capture advancements in internal production. Figure 1 reflects ICT usage per worker by industry in Thailand in 2012 and 2017. The figure

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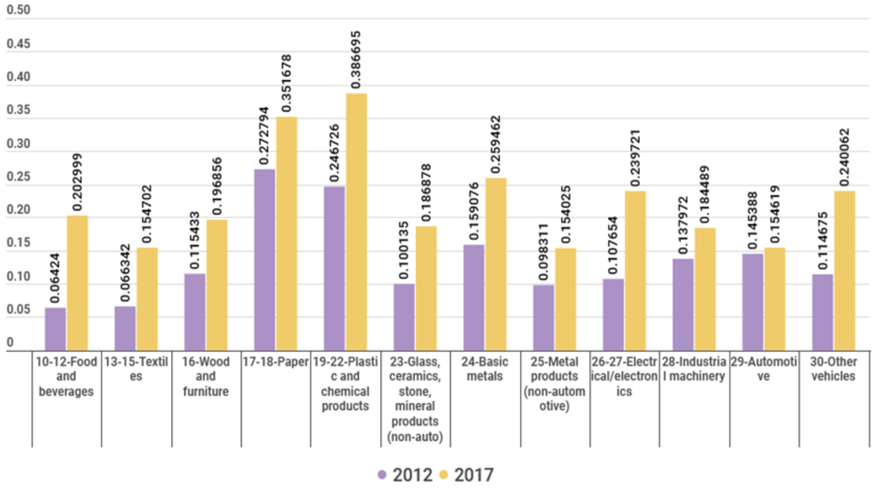
[3] Note that under the Competitiveness Enhancement Act, section 24, CIT exemption for targeted industries could be extended to 15 years, based on the judgment of the Board of Investment.

[4] In addition to the BOI incentives, the government committed itself to infrastructure investment projects in the EEC area. This includes launching a third international airport (U- Tapao), expanding the Laem Chabang seaport (Laem Chabang Phase 3), extending the communications network (high-speed trains, double-track railways, highways) in the EEC area, representing a total investment of $ 43 billion between 2019 and 2025. See a detailed discussion in Jongwanich et al. (2019).

indicates a significant improvement in ICT usage in all industries over the past five years, except in the automotive sector where ICT usage remained relatively stable. However, ICT usage exceeding 0.25 was revealed in four industries, namely plastics and chemicals, paper, basic metals and electronics. In terms of the automotive sector, this could be due to the nature of the industry wherein the development of technology is more concentrated in internal production so ICT usage remained relatively stable.

Figure 1: The use of ICT, by industry



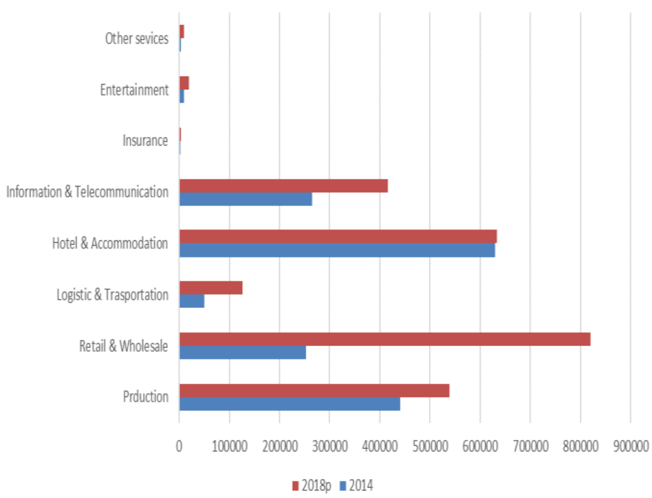
Note: The use of ICT is measured by value of ICT used per workers
Source: National Statistical Office (NSO)

The use of e-commerce in the manufacturing sector expanded during 2014-17, but its value was far lower than that of the service sector, especially compared to retail and wholesale and hotels and accommodation (Figure 2A). In the manufacturing sector, paper; wood and furniture; plastics; apparel and textiles tended to increasingly use e-commerce. In contrast, due to nature of the industry where direct buying is still crucial, the usage of e-commerce in automotive; electronics; electrical appliances and machines were relatively low and stable. E-commerce was predominately utilized in the manufacturing sector in the form of Business to Business (B2B) models at around 91 percent, while nine percent was in the form of Business to Consumer (B2C). Business enterprises took the lead in utilizing the benefits from the emergence of e-commerce, at around 95 percent of total e-commerce users, with only five percent being SMEs. This contrasts with the service sector where most of the users were SMEs in the form of B2C.

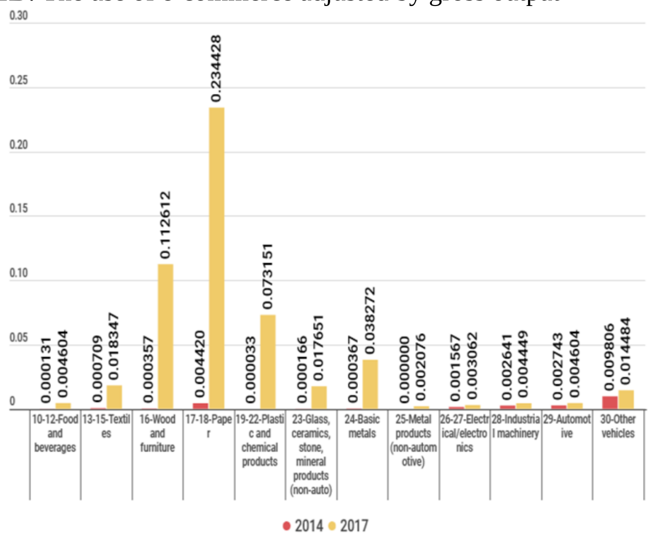
With respect to industrial robot usage, the intensity of robot use, measured by the operational stock of robots per worker, increased in Thailand between 2012 and 2017, but such an increase was concentrated only in three industries, the automotive sector, electronics and electrical appliances, and plastics and chemical products. With metals and food, the use of robots increased in 2017 but the absolute value of the operational stock of robots stayed relatively low, compared to the automotive and electronics sectors. A surge in the robot usage in the industries mentioned earlier in Thailand was in line with the trend in the global economy (World Robotics, 2019). However, in comparison to Korea and Singapore, the intensity of robot usage in Thailand was far lower, especially in the automotive and electronics sectors.

Figure 2: The use of e-commerce in Thailand

2A. The value of e-commerce by industries



2B. The use of e-commerce adjusted by gross output

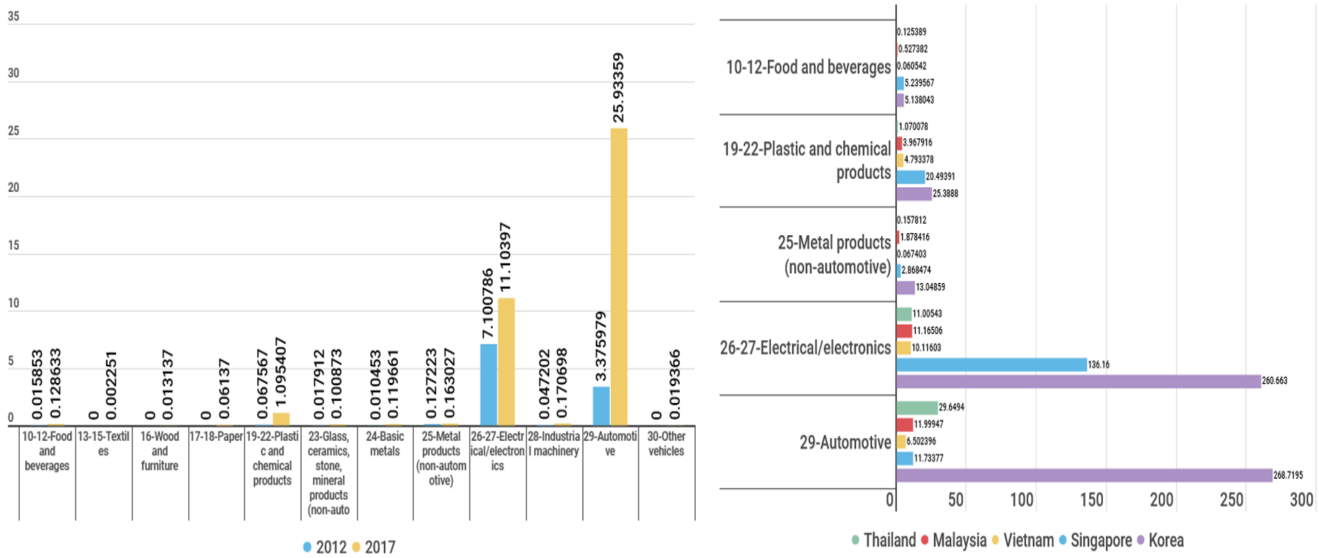


Source: Electronic Transactions Development Agency (ETDA) and Office of the National Economic and Social Development Council

Figure 3: Intensity of robot usage in Thailand

3A. Intensity of robot use in Thailand

3B. Intensity of robot use in Thailand and other Asian countries in 2017



Note: Figure 3A shows intensity of robot usage in Thailand, measured by operational stock of robots per worker, while figure 3b presents intensity of robot usage in Thailand and other Asian countries in 2017
Source: International Federation of Robotics (IFR) and National Statistical Office (NSO)

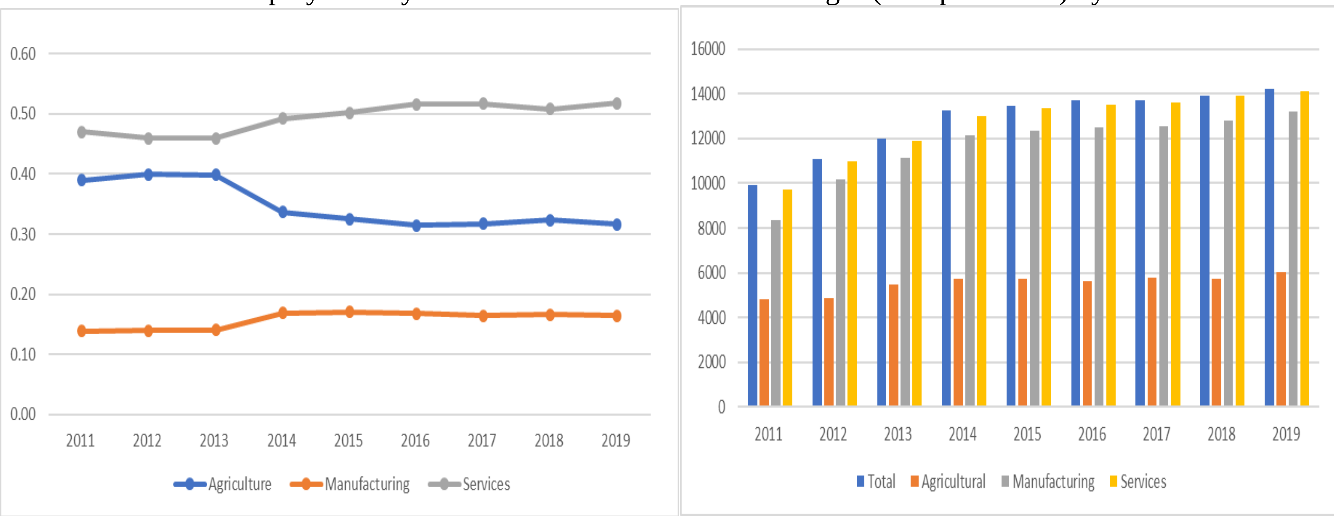
When employment and wages in Thailand are considered, Figure 4 shows that the share of employment to total employment in the manufacturing sector remained relatively stable at around 17 percent during 2014-19, while the share of employment in service sectors had increased to around 52 percent since 2014, from around 47 percent in 2011. With the agriculture sector, the share of employment declined significantly from 40 percent in 2013 to around 32 percent in 2019. Using a labour force survey in which fifty percent of samples at time t-1 are matched exactly with those at time t, we are able to construct two-year panel data, allowing us to show that most of the workers moving to the service sector are from the agriculture sector.[5] On average wages, measured by baht per month, in the manufacturing and service sectors increased sharply in 2011-2014 before appreciating gradually in 2015-19. In contrast, wages in agriculture remained relatively low and stable post-2011. In the service and manufacturing sectors the wage rate was around twice that of agriculture. Agriculture is the only sector in which the wage rate in some years, e.g. 2015 and 2018, was adjusted lower than headline inflation.

[5] Note that in this study, we consider only workers in manufacturing sector due to data limitation in technological advancement.

Figure 4: Employment and wages in Thailand, by industry

4A. Share of employment by sector

4B. Wages (baht per month) by sector



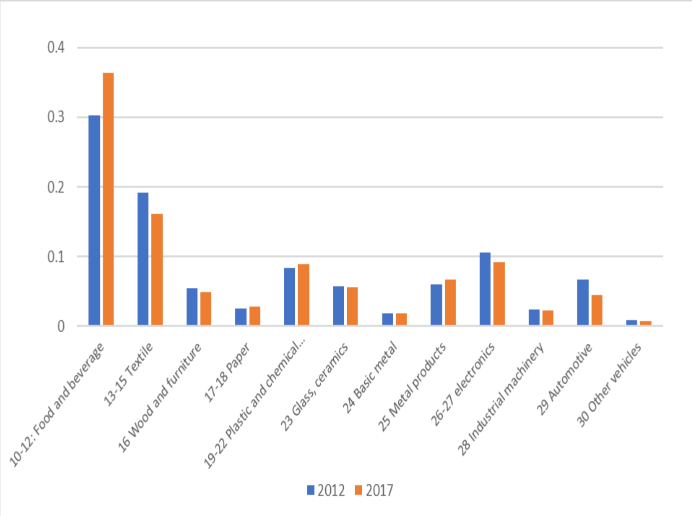
Source: National Statistical Office

In the manufacturing sector, more than 30 percent of workers worked in food and beverage, followed by clothing and textiles, electronics, and plastics and chemicals. Comparing 2012 and 2017, employment increased noticeably in the food sector, while a declining trend was observed in some sectors, including clothing and textiles, automotive and electronics. In other sectors, employment during these two periods remained relatively stable. The picture for wage is different in that sectors with a relatively lower share of labour e.g. automotive, plastics and chemicals, papers and electronics, tended to offer higher wages. In the clothing and textiles and food sectors workers received lower wages (as well as net income)[6], while workers in automotive, plastic and chemicals, and paper were paid the highest. Due to different patterns concerning wages and employment, this study examines the reallocation of workers along with wage changes (see empirical model in the next section).

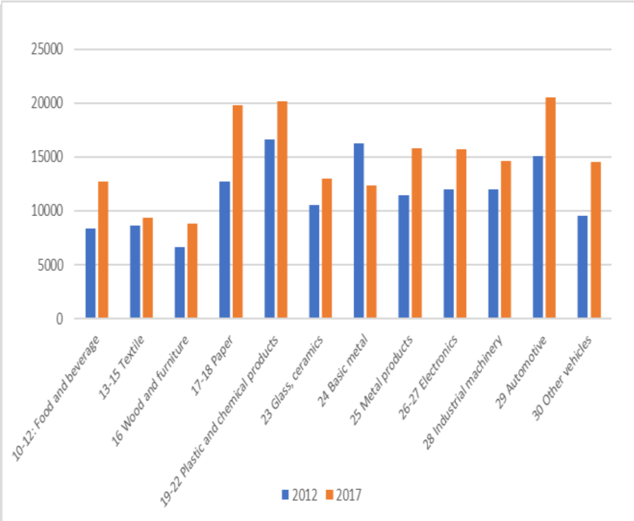
[6] Note that net income refers to wages and other benefits for workers, including overtime payments and bonuses.

Figure 5: Employment and wages in the Thai manufacturing sector

5A. Share of employment by sector



5B. Wages (baht per month) by sector



Source: Labour Force Survey, National Statistical Office

4. Empirical Model and Data Sources

4.1 Empirical Model

The empirical models applied in this study are based on the framework developed by Acemoglu and Restrepo (2018b) where the central unit of production is a task, and labour and capital have comparative advantages across different tasks. An example of a task-based approach can be found in textile production. This necessitates many tasks, including the production of fibre, yarn and fabric, pre-treatment, dyeing and printing, as well as design, marketing and retailing (see Acemoglu and Restrepo, 2018b). In each task, labour involves different comparative advantages, e.g. (skilled) labour tends to have more comparative advantages than capital in design and marketing. With a task-based framework, automation could substitute labour in task and reduce demand for labour and wages, the so-called displacement effect. This is different from applying a factor-augmenting technology framework wherein general labour demand is expanded along with productivity improvement, except in the case where elasticity of substitution between capital and labour is small. However, as argued by Acemoglu and Restrepo (2018b), demand for labour may eventually not reduce the displacement effect when productivity improvement in a subset of tasks induces more demand for labour in non-automated tasks, if technology advancements increase the capital intensity of production, and if the deepening of automation leads to the intensification of the productive use of machines stimulating more demand for labour.

To examine the impact of technological advancement on job displacement and possible skill reallocation in the manufacturing sector, an equation examining the probability of being employed, unemployed, or changing jobs/skills induced by technological advancement is employed. It is possible that technological advancements could change employment status, from being employed to unemployed (and vice versa), from being employed in one task/job to another job, or alternatively a continuance of the status quo. In terms of changing task/job, workers can change skills in both directions, i.e. from skilled to unskilled and vice versa. While there is no guarantee that changing jobs/tasks results in higher wages/income, this study incorporates the aspect of wages/income adjustment to be analysed simultaneously with skill changes. Eight possible scenarios could occur from technological advancement when both employment status and wages/income are considered together, namely (1) workers who are employed at the same task/job and wages/income becomes higher; (2) workers employed at the same task/job, but wages/income is lower (or unchanged); (3) workers changing skills, from unskilled to skilled task/job, and wages/income is higher; (4) workers changing skills, from unskilled to skilled task/job, but wages/income becomes lower (or unchanged); (5) workers changing skills, from skilled to unskilled, but wages/income is higher; (6) workers changing skills, from skilled to unskilled, and wages/income is lower (unchanged); (7) workers who become unemployed and (8) workers who move from unemployed to employed. The eight possible scenarios are constructed from the Thai labour force survey (National Statistical Office, NSO), which is described in detail in section 4.2.

Note that technological advancements in this study are proxied by three key aspects according to their involvement in manufacturing supply chains, i.e. inbound (automated e-sourcing), outbound (e-commerce), and internal production (e.g. factory automation) (UNCTAD, 2017) to delineate the relative importance of the effects of technology involvements in supply chains on the labour market. As mentioned in the analytical framework, trade represents another important variable, which can shape labour markets. Import penetration, both in terms of finished, capital and raw materials, is included in our analysis to compare its effects on possible skill and wage adjustments. Equation (1) shows the variables included in examining the probability of being employed, unemployed, or changing jobs/skills as follows.

$$EmployS_{i,j_t,t} = \alpha_0 + \alpha_1 Technology_{j_{t-1},t-1} + \alpha_2 IMpen_{j_{t-1},t-1} + \alpha_3 IControl_{i,j_{t-1},t-1} + \eta_{i,j,t} + \varepsilon_{i,j,t} \qquad (1)$$

where $EmployS_{i,j_t,t}$ is the employment status of individual i, in sector j at time t. To derive $EmployS_{i,j_t,t}$ at time t, the employment status of individual i is compared between two periods to ascertain whether at time t workers change skills/tasks from period t-1. To determine workers' skills/tasks, the job position and wages/total income provided in the labour force survey are applied (See section 4.2). As mentioned earlier, there are eight possible scenarios for identifying changes in the employment status of individual workers as follows:

$EmployS_{i,j_t,t}$ = 1 for workers employed at the same task/job and wages/income becomes higher

$EmployS_{i,j_t,t}$ = 2 for workers employed at the same task/job, but wages/income is lower (or unchanged)

$EmployS_{i,j_t,t}$ = 3 for workers changing skills, from unskilled to skilled task/job, and wages/income is higher

$EmployS_{i,j_t,t}$ = 4 for workers changing skills, from unskilled to skilled task/job, but wages/income becomes lower (or unchanged)

$EmployS_{i,j_t,t}$ = 5 for workers changing skills, from skilled to unskilled, but wages/income is higher

$EmployS_{i,j_t,t}$ = 6 for workers changing skills, from skilled to unskilled, and wages/income is lower (unchanged)

$EmployS_{i,j_t,t}$ = 7 for workers who become unemployed, and

$EmployS_{i,j_t,t}$ = 8 for workers who move from unemployed to employed.

$Technology_{j_{t-1},t-1}$ represents the technological advancement in industry j at time t-1. Since changing job position between time t-1 and t would be influenced by technological advancement at time t-1, we employ lag values of three proxies to represent technological advancement along the manufacturing supply chains. The three proxies are composed of:

(1) $ICTUSE_{j_{t-1},t-1}$ = ICT usage per worker in sector j_{t-1} at time t-1

(2) $ecommerce_{j_{t-1},t-1}$ = value of e-commerce as a percent of GDP in sector j_{t-1} at time t-1

(3) $robot_{j_{t-1},t-1}$ = intensity of industrial robot usage (operational stock of robots per worker) in sector j at time t-1

Note that once workers move to new tasks at time t, the new tasks might not be in the same industry as those at time t-1. In other words, industry *j* and industry j_{t-1} could be different. The endogeneity problem is redressed by employing lag values of technological advancement.

$IMpen_{j_{t-1},t-1}$ is import penetration in industry j_{t-1} at time t-1. Import penetration is measured by the share of imports at industry j to GDP.[7] Import penetration is further divided into finished products ($IMpen\_finish_{j_{t-1},t-1}$), capital ($IMpen\_cap_{j_{t-1},t-1}$) and raw materials ($IMpen\_raw_{j_{t-1},t-1}$)

$IControl_{j_{t-1},t-1}$ is the control variables for individual workers i in industry j_{t-1} at time t This includes age, gender and education.

$\eta_{i,j,t}$ is an unobserved industry-specific effect and $\varepsilon_{i,j,t}$ is the error term

The impact of advanced technology and import penetration are examined by sector. Five key sectors in Thailand are investigated, namely food and beverage, clothing and textiles, plastics and chemicals, electronics and machinery and automotive sectors. To identify such impacts, interaction terms between the proxies of technology/import penetration and industry-dummy variables are introduced in the model, as in equation (2):

$$\begin{aligned} EmployS_{i,j_t,t} = {} & \alpha_0 + \alpha_1 Technology_{j_{t-1},t-1} + \alpha_2 IMpen_{j_{t-1},t-1} + \alpha_3 \left(Technology_{j_{t-1},t-1} \cdot DumINDUS_{j_{t-1},t-1} \right) \\ & + \alpha_4 \left(Mpen_{j_{t-1},t-1} \cdot DumINDUS_{j_{t-1},t-1} \right) + \alpha_5 IControl_{i,j_{t-1},t-1} + \eta_{i,j,t} + \varepsilon_{i,j,t} \end{aligned} \tag{2}$$

where $DumINDUS_{j_{t-1},t-1}$ are industry-dummy variables, composing the five key sectors as mentioned earlier, food and beverage (*dumfood*), clothing and textiles (*dumcloth*), plastics and chemicals (*dumplas*), electronics and machinery (*dumelec*) and automotive (*dumauto*) sectors.

As discussed in section 4.2, due to the process of data collection in the labour force survey, around half of observations from the survey are used to conduct $EmployS_{i,j_t,t}$. To ensure the impacts of technological advancement on labour outcome, especially wage/total income, we conduct another equation examining impacts of technological advancement on individual wage/income by using the whole observations in manufacturing sector.[8] Equation

[7] The results are robust, though we measure import penetration as the share of import at industry j_{t-1} to total supply (GDP and imports)

[8] We conduct impacts of technological advancement on employment also by specifying dummy variable, which equals to 1 if workers are employed and 0 otherwise. The results are similar to those in equation (1) when half of the observations are used. We do not examine effects of employment at industry level due to data limitation, especially when we try to control for industry specific effects (through including industrial dummy variables) and using two-stage least square to redress endogeneity problem.

(3) shows wage/income equation, which could be affected by technological advancement and import penetration.

$$wage_{i,j,t} = \alpha_0 + \alpha_1 Technology_{j,t} + \alpha_2 IMpen_{j,t} + \alpha_3 IControl_{i,j,t} + \eta_{j,t} + \varepsilon_{j,t} \qquad (3)$$

where $wage_{i,j,t}$ is wage (measured by baht per month) of worker i in sector j at time t. Since we control for year fixed effect, nominal instead of real wage (nominal wage adjusted by consumer prices) is employed. In this study, we employ both wage and total income, which is wage plus overtime payments and bonus. As discussed in section 4.2, we also use lag value of technology and import penetration to examine such impacts on wage. The results are similar to those when current value (time t) of technology and import penetration are employed.

4.2 Data and Methodology

The Thai labour force survey, from the National Statistical Office (NSO), during 2012-17 is used to construct employment status ($EmployS_{i,j_t,t}$). Although NSO conducts a labour force survey every quarter, our analysis is performed as an annual calculation due to the data collection of our technology variables.[9] To avoid the overestimation of employment arising from temporary workers, in either the manufacturing or service sectors, information from the third quarter of the labour force survey, i.e. during the harvest season, is utilized. The process of data collection in the labour force survey allows us to examine the status of workers between period t and period t-1. Table 1 shows how observations are included in the Thai labour force survey.

Table 1: Observations included in the Thai labour force survey

		Sampling	Sampling (around 40-50%)					
2012	Q3	1C	2C					
2013	Q3		2C	3C				
2014	Q3			3C	4C			
2015	Q3				4C	5C		
2016	Q3					5C	6C	
2017	Q3						6C	7C

Source: Authors adoption from the Thai labour force survey

[9] Note that the sampling method for each quarter is similar to that of the method done on an annual basis, i.e. only half of the observations in the current quarter (e.g. 2nd quarter) are matched with the previous quarter (1st quarter).

From table 1, the NSO divides samples in the labour force survey into two groups, e.g. 1C and 2C in 2012Q3, and 2C and 3C in 2013Q3. For every year, around fifty percent of the samples in the labour force survey at time t-1 are matched precisely with those at time t. In 2012Q3, the group of people in 2C are the same as in 2013Q3, and the group in 3C in 2013Q3 is the same as in 2014Q3. Thus, from the survey we have a two-year panel which can be used to determine whether a worker changes job from skilled to unskilled position or vice versa, or from employed to unemployed, or vice versa, or is employed/unemployed and maintaining the status quo. As mentioned earlier, along with changing employment status, we look at how wages/income is adjusted over the two-year panel. Note that in the construction of employment status and wages/income changes, we exclude workers who are not in the labour force, such as persons who are studying, disabled, or older than 75 and workers who do not specify their wages and other income. Due to data limitations concerning technology variables, our analysis focuses only on the manufacturing sector (Thailand Standard of Industrial Classification, TSIC 10-32), excluding agriculture and service sectors.

From the labour force survey, to determine changing position from skilled to unskilled workers, or vice versa, we use the job positions provided in the labour force survey. There are eight principal positions in each industry classified in the survey, (1) executive manager; (2) manager; (3) professional; (4) associate professional; (5) technician; (6) service and sales workers; (7) clerical support workers; (8) basic jobs (See table 2). If a worker moves in an ascending order, e.g. from services and sales workers to technicians, or to becoming an associate professional, we classify that as changing from unskilled to skilled employment. By contrast, if a worker changes a position in a descending direction, e.g. from an associate professional to a technician or services and sales worker, we classify that as changing from skilled to unskilled employment. As mentioned in the previous section, we use only job position and wages/total income to be the criteria to construct $EmployS_{i,j_t,t}$. Thus, a worker classified as relatively unskilled in one industry can become more skilled within the same industry or in another industry. Workers who are employed, but do not change positional status are classified as employed and representing the status quo, i.e. $EmployS_{i,j_t,t}$ = 1 or 2 depending on the wages/income of such workers. In contrast, if workers change status from employed at time t-1 to unemployed at time t, we classify them as $EmployS_{i,j_t,t}$ = 7 and vice versa, we classify those workers as $EmployS_{i,j_t,t}$ = 8.

Table 2: Occupation codes used to define employment status

Changing skills		Occupation code	Skilled to unskilled	unskilled to skilled
1	Executive Manager	1111-1120		
2	Manager	1211-1439		
3	Professional	2111-2659		
4	Associate professional	3111-3522		
5	Technician	6111-8350		
6	Service and sales workers	5111-5419		
7	Clerical support work	4110-4419		
8	Basic jobs	9111-9629		

Source: The Thai labour force survey

Table 3 shows the frequency of employment status and distribution of workers among eight categories (*EmployS*i,j,t) during 2012-17. From the table, it can be observed that *EmployS*i,j,t = 2 has the highest frequency, followed by *EmployS*i,j,t = 1. This indicates that in the manufacturing sector most workers were employed in the same position and income level during the two-year panel, on average amounting to around 50 percent of total observations. This is not surprising as our panel is short. In fact, without data limitation, it would be better to construct *EmployS*i,j,t using a long period of panel data collection as normally changing position takes time. However, since the technology involved in moving the country towards Industry 4.0 such as robots/automation could create a possible disruptive impact on labour market outcomes, analysing the impact of such technological advancements through a short-panel dataset would probably yield some interesting findings. In addition, the survey reveals changes in workers' positions during the two-years panel, e.g. in almost ten percent of observations workers moved from relatively unskilled to skilled positions, with around five percent of such workers receiving higher incomes, and in almost another ten percent of observations, workers changed from relatively skilled to unskilled with around six percent of these workers receiving lower remuneration.

With respect to the technology variables under consideration, ICT usage at the industry level is derived from the Information and Communication Technology (ICT) survey, National Statistical Office (NSO). Employment at the industry level is used to adjust ICT data to be in terms of ICT usage per worker. Data of e-commerce usage at the industry level is sourced from the values of the e-commerce survey, Electronic Transactions Development Agency (ETDA). Gross output at the industry level derived from the Office of the National Economic and Social Development Council is employed to adjusted e-commerce data figures. Data on the operational stock of robots stems from the International Federation of Robotics (IFR) and employment at industry level is applied to adjust robotic data in terms of the intensity of robot usage. The import data is from UNCOMTRADE, the United Nations Commodity Trade Statistics Database. We use import data at 4-digit HS code and convert it into 2-digit ISIC using concordance from the United Nations. Import data is adjusted by gross output at the 2-digit industry level. Note that import data is divided into finished, capital and raw material products using Broad Economic Categories (BEC) rev.4. Age, gender, and education from the labour force survey are used as control variables in equations (1)-(3).

Table 3: Frequency of employment status and income changes ($EmployS_{i,j_t,t}$) among eight categories during 2012-2017

Total				2013&2012				2014&2013			
Employment/income status	Freq.	Percent	Cum.		Freq.	Percent	Cum.		Freq.	Percent	Cum.
1	5,880	27.11	27.11	1	1,154	28.97	28.97	1	1,119	26.74	26.74
2	11,569	53.34	80.45	2	1,772	44.49	73.46	2	2,133	50.98	77.72
3	1,130	5.21	85.66	3	325	8.16	81.62	3	218	5.21	82.93
4	977	4.5	90.17	4	272	6.83	88.45	4	201	4.8	87.74
5	735	3.39	93.56	5	164	4.12	92.57	5	177	4.23	91.97
6	1,277	5.89	99.45	6	272	6.83	99.4	6	316	7.55	99.52
7	69	0.32	99.76	7	13	0.33	99.72	7	11	0.26	99.78
8	51	0.24	100	8	11	0.28	100	8	9	0.22	100
Total	21,688	100		Total	3,983	100		Total	4,184	100	
2015&2014				2016&2015				2017&2016			
Employment/income status	Freq.	Percent	Cum.		Freq.	Percent	Cum.		Freq.	Percent	Cum.
1	1,170	26.22	26.22	1	1,171	26.19	26.19	1	1,266	27.6	27.6
2	2,578	57.76	83.98	2	2,512	56.18	82.38	2	2,574	56.12	83.71
3	203	4.55	88.53	3	189	4.23	86.6	3	195	4.25	87.97
4	153	3.43	91.96	4	182	4.07	90.67	4	169	3.68	91.65
5	124	2.78	94.73	5	127	2.84	93.51	5	143	3.12	94.77
6	210	4.71	99.44	6	263	5.88	99.4	6	216	4.71	99.48
7	20	0.45	99.89	7	15	0.34	99.73	7	10	0.22	99.69
8	5	0.11	100	8	12	0.27	100	8	14	0.31	100
Total	4,463	100		Total	4,471	100		Total	4,587	100	

Note: We use total income, including salary, overtime payments and bonus, to define employment status and income changes. The result is robust when wages is used instead of total income as salary is a key component in total income.
Source: Authors' calculations

Data for analysing the impact of technological advancements, as well as import penetration on changes in employment status and income changes, is summarized in Table 4. As mentioned in section 4.1, due to the process of data collection in the labour force survey, around half of observations from the survey are throwed away when analysing impacts of technological advancement on employment status and income change (*EmployS*i,j,t). To ensure the impacts of technological advancement on labour outcome, especially wage/total income, another equation (equation 2) is conducted to examine impacts of technological advancement on individual income by using the whole observations in manufacturing sector. Data for analysing individual income are shown in Table 5.

Table 4: Data Summary, 2012-2017

Variable	Obs	Mean	Std. Dev.	Min	Max
$EmployS_{i,j,t}$	21,688	2.24	1.36	1	8
$age_{i, jt-1,t-1}$	21,688	39.39	11.92	14	74
$sex_{i,j,t}$	21,688	1.53	0.50	1	2
$education_{i, jt-1,t-1}$	21,688	0.74	0.75	0	3
$ICTUSE_{i, jt-1, t-1}$	21,688	0.13	0.22	0.04	2.27
$ecommerce_{i, jt-1, t-1}$	12,777	0.03	0.12	0	2.12
$robot_{i, jt-1, t-1}$	19,665	2.22	4.58	0	22.91
$IMpen_{i, jt-1, t-1}$	16,275	1.73	2.81	0	180.85
$IMpen\_finish_{i, jt-1, t-1}$	16,257	25.24	53.95	0	829.98
$IMpen\_capital_{i, jt-1, t-1}$	16,257	3.13	14.08	0	366.13
$IMpen\_raw_{i, jt-1, t-1}$	16,257	2.05	14.36	0	502.23
$wage_{i, jt-1, t-1}$	21,688	8150.85	9888.00	0	400000
$totalincome_{i, jt-1, t-1}$	21,688	9110.38	10677.96	0	400000

Note: E-commerce data is available during 2014-2017. Sex, which equals '1' represents males, while '2' represents females. Education composes four ranks, i.e. '0' represents lower or equal to primary education; '1' lower secondary education; '2' upper secondary and post-secondary education; '3' bachelor's degree and higher.
Source: Authors' calculations

Table 5: Data Summary for wage/income analysis, 2012-2017

Variable	Obs	Mean	Std. Dev.	Min	Max
$robot_{i, j, t}$	88,059	1.66	4.39	0	25.93
$robot_{i, jt-1, t-1}$	72,936	2.10	4.43	0	22.91
$ICTUSE_{i, j, t}$	96,654	0.14	0.22	0.04	2.27
$ICTUSE_{i, jt-1, t-1}$	79,863	0.14	0.24	0.04	2.27
$ecommerce_{i, j, t}$	59,891	0.03	0.12	0	2.12
$ecommerce_{i, jt-1, t-1}$	44,556	0.03	0.14	0	2.12
$IMpen_{i, j, t}$	72,959	1.82	3.02	0	226.76
$IMpen\_raw_{i, j, t}$	72,872	29.69	60.02	0	1038.03
$IMpen\_capital_{i, j, t}$	72,872	3.01	13.76	0	366.13
$IMpen\_finish_{i, j, t}$	72,872	2.09	14.07	0	502.23
$IMpen_{i, jt-1, t-1}$	60,745	1.82	3.06	0	226.76
$IMpen\_raw_{i, jt-1, t-1}$	60,668	28.85	56.86	0	829.98
$IMpen\_capital_{i, jt-1, t-1}$	60,668	2.92	14.17	0	366.13
$IMpen\_finish_{i, jt-1, t-1}$	60,668	2.02	12.89	0	502.23
$age_{i, j,t}$	96,654	39.40	12.57	15	75
$sex_{i,j,t}$	96,654	1.53	0.50	1	2
$education_{i, j,t}$	96,654	0.27	0.64	0	3
$wage_{i, j, t}$	68,426	10790.30	9338.26	0	400000
$totalincome_{i, j, t}$	68,426	12951.52	16101.70	0	450000

Source: Authors' calculation

Multinomial (polytomous) logistic and probit regression models are employed to analyse the impact of technological advancement on employment status and income change (equation 1). The multinomial logit model is chosen since outcomes of the model have no natural ordering. The multinomial probit is employed as an alternative model to check the robustness of our results. Results are interpreted in terms of elasticity using margin estimates for both multinomial logistic and probit models. Since in the model the lag values of all independent variables are used, any endogeneity problem becomes of diminished concern in the model. However, to redress any possible self-selection problem in which technology may self-select into industries where workers have a high tendency to move up the ladder, a control function approach is followed in which an endogenous predictor is instrumented as a first step using OLS, and then the residuals are included in the second step in a multinomial response model (Petrin and Train, 2010).[10]

5. Results

Table Appendix I-III presents the results of equation (1) using a multinomial logistic regression model where a possible endogeneity problem is redressed employing a control function approach.[11] Tables 6 and 7 illustrate the findings of equations (1) and (2), respectively in terms of elasticity using margin estimates. With Table 6, columns A-C, proxies of technology variables, namely ICT, robots and e-commerce, are estimated separately, while in column D these three proxies of technology are estimated together. The results of both methods are similar, but based on indicators of explanatory power, such as LR-chi 2 and Log likelihood, our analysis below follows the former method wherein proxies of technology variables are separately estimated.

[10] Regarding the instrument, we use a lag of its own variable as an instrument for the technology variable. In fact, it may be better to use other variables, such as progress in technology, in other Asian countries as an instrument variable. However, with our data limitations, especially the value of e-commerce at the industry level, a lag of its own technology variable is used instead.

[11] Note that independence of irrelevant alternatives (IIA) where the choice between a collection of alternatives is not affected by non-chosen alternatives, are tested in all regressions based on Hausman and McFadden (1984) test principles. It was found that in all outcomes (1-8), we accept the null hypothesis where IIA assumption is satisfied. In some cases, the chi-2 turns to be negative, but as mentioned in Hausman and McFadden (1984: p. 1226), a negative result is evidence that IIA has not been violated. In addition, the multinomial probit regression model yields the similar results to the multinomial logit model so that we analyse our findings through the multinomial logistic model.

Where the whole manufacturing sector is concerned, there is no evidence that advancements in technology so far have pushed workers out of the job market in Thailand. The coefficients associated with our three proxies of technology, i.e. ICT usage, robots and e-commerce in outcome No. 7 (*EmployS*i,j,t = 7) are all statistically insignificant (Table 6: columns A-C).[12] This implies that statistically no workers have been rendered unemployed as a result of the introduction of more advanced technology in supply chains. However, when each sector is investigated separately, it seems that advancement in ICT usage increases the probability that workers will move from employed to unemployed in the food and beverage sector. The elasticity associated with *ICTUSE* in the food and beverage sector for outcome No.7 (*EmployS*i,j,t = 7) is positive and statistically significant, implying that an increase in ICT use per worker by a value of one percent raises a probability of workers becoming unemployed by 0.1 percent (Table 7: column A). The distribution of occupations in the food and beverage sector could explain such a finding (See table 8). Table 8 shows a high proportion of workers in the 'basic job' category, such as drivers who deliver products, sellers of products in small shops and cleaners in the food and beverage sector. Workers in this category can be easily replaced by technology. In other sectors, the proportion of workers in 'basic jobs' was far lower, e.g. in the electronics and automotive sectors the proportions were only 4.5 and 6.1 percent, respectively. Interestingly, the results show that only in ICT usage, not robots or e-commerce, were workers forced out of the job market. The relatively lower penetration of robots and e-commerce than ICT usage may limit the impact of these technologies on redundancies in Thailand. In other words, to some certain extent the *displacement effect* induced by advanced technology mentioned in Acemoglus and Restrepo (2018a, b, 2019) is still limited in Thai manufacturing.

Although the impact of advanced technology in pushing workers out of the job market in Thailand is limited, such technology tends to affect the reallocation of workers between skilled and unskilled positions.[13] This finding is similar to that of Dauth et.al (2018) who used Germany as a case study and showed that the *displacement effect* was minimal as workers tended to either stay in their original occupation or switch to another at their original workplace.

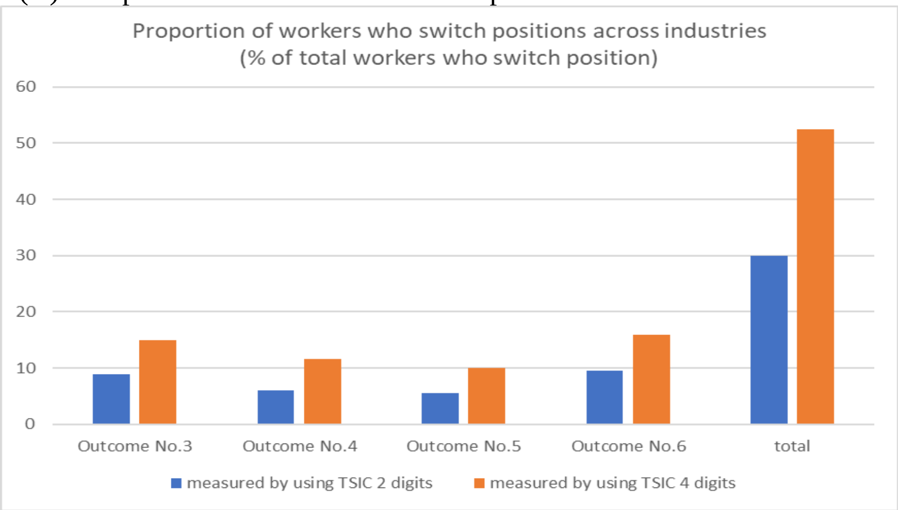
[12] Results when all three proxies of technology are included together in equation (1) are similar to those when all proxies are included in the equation separately.

[13] Note that due to the model setting, evidence of reallocation of workers would not effectively provide evidence of any *reinstatement effect* where new tasks would be created from introducing new technology, as shown in Acemoglus and Restrepo (2019). Jobs, within which workers are reallocated, could represent either new or existing tasks in industries.

Evidence from the Thai labour force survey shows that around 70 percent of total workers who stay in the same position (outcomes 1 and 2) remain in the same industry. However, in contrast to Dauth et.al (2018), our evidence reveals that only 50 percent of total workers who change their positions (outcomes 3-6) switched within the same industry (Figure 6A). With the other 50 percent changes in position occur across industries and such a reallocation was observed in five industries, the food and beverage; electronics; plastics and chemicals; textiles; and automotive sectors (Figure 6B). In food and beverages, however, the survey revealed that the reallocation of workers within the industry was almost two times higher than that of across industries (Figure 6C). This may imply either a relatively high demand for workers in this sector or less flexibility of workers in adjusting to shocks, especially when a high proportion of workers in this sector were willing to switch positions from relatively skilled to unskilled positions (Figure 6C).

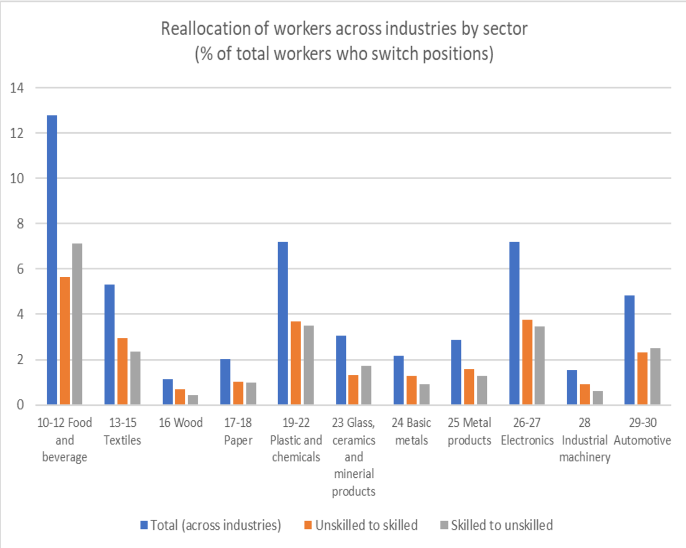
Figure 6: Proportion of workers who switch job positions

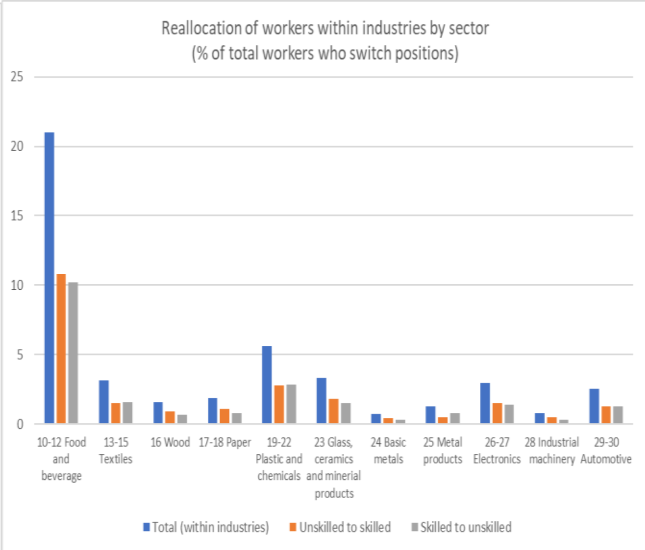
(A). Proportion of workers who switch positions across industries



(B). Reallocation of workers across industries by sector

(C). Reallocation of workers within industries by sector





Source: Authors' compilation from labour force survey

The results vary in terms of proxies of technology and sectors. In ICT usage, where the entire manufacturing sector is concerned, technology tends to lower the probability of shifting workers from unskilled to skilled positions. This is shown by the negative and statistical significance of the coefficient associated with *ICTUSE* for outcome No. 4 (*EmployS*i,j,t = 4) (Table 6: Column A). The negative sign reflects that an increase in ICT usage per worker of one percent results in a lower probability of moving workers from unskilled to skilled job of 0.07 percent. Regarding sector-wise factors, such negative impacts are found in relatively high capital-intensive industries, including automotive, plastic and chemicals and electronics and machinery. The coefficients associated with the interaction term between *ICTUSE* and industrial dummy variables in these sectors for outcome No. 4 (*EmployS*i,j,t = 4) are statistically insignificant (Table 7: column A).

The impact of ICT usage on employment status tends to be more noticeable in the automotive sector compared to the other two sectors (plastic and chemicals and electronics and machinery). In the automotive sector, the probability of moving workers from skilled to unskilled increases when ICT is employed more. Evidence for this occurs in the group of workers whose income does not change in line with skill level adjustments reflecting the positive and statistically significant coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables of automotive sector observed for outcome No. 6 (*EmployS*i,j,t = 6). In contrast, in the electronics and machinery sector introducing more ICT generates benefits some groups of workers. This is reflected by the higher probability that workers were able to transfer from unskilled to skilled positions and receive higher income, i.e. the coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables of electronics and machinery for outcome No.3 (*EmployS*i,j,t = 3) is positive and statistically significant (Table 7: column A). Meanwhile, introducing ICT helped some groups of workers in this sector stay in relatively skilled positions, as the coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables of electronics and machinery for outcome No.5 (*EmployS*i,j,t = 5) is negative and statistically significant (Table 7: column A). This implies that an increase in ICT usage by one percent results in a decline in the probability of moving workers from skilled to unskilled positions of 0.13 percent.

Table 6: Impact of advanced technology on employment status and income changes (elasticity estimation)

	Column A		Column B		Column C		Column D						
	ICTUSE $_{i, jt-1, t-1}$		*robot* $_{i, jt-1, t-1}$		*ecommerce* $_{i, jt-1, t-1}$			*ICTUSE* $_{i, jt-1, t-1}$		robot $_{i, jt-1, t-1}$		ecommerce $_{i, jt-1, t-1}$	
_predict	Coefficient	Z	Coefficient	Z	Coefficient	Z	_predict	Coefficient	Z	Coefficient	Z	Coefficient	Z
1	0.002	0.18	0.013	1.11	0.001	0.14	1	-0.012	-0.79	-0.005	-0.27	-0.005	-0.79
2	0.005	0.94	-0.012	-1.17	0.000	-0.01	2	0.015	2.38	0.012	0.83	0.004	1.65*
3	0.024	1.07	-0.026	-0.78	-0.019	-1.04	3	-0.022	-0.66	-0.037	-0.65	-0.031	-1.38
4	-0.073	-2.13**	0.009	0.23	0.016	1.68***	4	-0.085	-1.91**	-0.006	-0.09	0.011	1.08
5	0.026	0.8	0.031	0.76	-0.020	-0.85	5	0.023	0.48	0.014	0.21	-0.029	-0.92
6	-0.029	-1.11	-0.023	-0.71	0.007	0.67	6	-0.039	-1.15	-0.026	-0.48	0.000	-0.02
7	-0.074	-0.6	0.025	0.20	-0.115	-0.88	7	-0.196	-1.05	-0.142	-0.83	-0.101	-0.75
8	-0.180	-0.98	0.064	0.59	-0.066	-0.8	8	-0.161	-0.65	-0.092	-0.39	-0.060	-0.63
	IMpen $_{i, jt-1, t-1}$		*IMpen* $_{i, jt-1, t-1}$		*IMpen* $_{i, jt-1, t-1}$					*IMpen* $_{i, jt-1, t-1}$			
_predict	Coefficient	Z	Coefficient	Z	Coefficient	Z			_predict	Coefficient	Z		
1	-0.036	-3.33***	-0.040	-3.35***	-0.054	-3.27***			1	-0.063	-3.61***		
2	0.012	2.01**	0.014	2.13**	0.016	1.98**			2	0.019	2.27**		
3	-0.030	-1.06	-0.035	-1.14	-0.024	-0.55			3	-0.029	-0.64		
4	0.085	3.92***	0.089	3.93***	0.124	3.26***			4	0.127	3.26***		
5	-0.086	-2.27**	-0.101	-2.45**	-0.082	-1.53			5	-0.095	-1.69*		
6	0.051	2.37**	0.058	2.56***	0.043	1.19			6	0.050	1.35		
7	-0.184	-1.21	-0.189	-1.16	-0.156	-0.75			7	-0.100	-0.48		
8	-0.208	-1.33	-0.267	-1.52	0.050	0.29			8	0.083	0.46		
Industry dummy	Yes		Yes		Yes		Industry dummy			Yes			
Year dummy	Yes		Yes		Yes		Year dummy			Yes			
Number of obs	16,275		14,169		9,344		Number of obs			8,820			
LR chi2	2371.90		2043.47		963.35		LR chi2			950.56			
Prob > chi2	0.00		0.00		0.00		Prob > chi2			0.00			
Pseudo R2	0.0553		0.0534		0.0408		Pseudo R2			0.0425			
Log likelihood	-20255.424		-18107.519		-11310.391		Log likelihood			-10708.156			

Note: Numbers 1 to 8 is corresponding to change in employment status and income changes as identified in equation (1),

***, ** and * represent 1, 5 and 10 percent significant level, respectively.

In columns A-C, proxies of technology variables, namely ICT, robot and e-commerce, are estimated separately while in column D, these three proxies of technology are estimated together.

Elasticities estimated in this table are from results reported in Appendix I.

Source: Authors' estimation

Table 7: Impact of advanced technology on employment status and income changes, by sector (elasticity estimation)

	Column A		Column B		Column C	
	$ICTUSE_{i, jt-1, t-1}$		$robot_{i, jt-1, t-1}$		$ecommerce_{i, jt-1, t-1}$	
_predict	Coefficient	Z	Coefficient	Z	Coefficient	Z
1	-0.001	-0.07	-5.660	-1.86**	-0.001	-0.13
2	0.007	1.24	5.316	2.23**	0.001	0.62
3	0.015	0.62	-11.360	-1.53	-0.013	-0.72
4	-0.089	-2.2	10.200	1.09	0.015	1.66*
5	0.056	1.69*	-30.237	-2.78***	-0.027	-0.96
6	-0.027	-0.97	17.140	2.00**	-0.003	-0.27
7	-0.135	-0.74	-21.088	-0.59	-0.238	-0.92
8	-0.256	-1.03	22.001	0.34	0.001	0.02
	$ICTUSE_{i, jt-1, t-1}$*dumfood		$robot_{i, jt-1, t-1}$*dumfood		$ecommerce_{i, jt-1, t-1}$*dumfood	
_predict						
1	0.016	1.68*	1.603	2.10**	-0.038	-0.02
2	-0.009	-1.89*	-0.613	-1.94**	-0.013	-0.01
3	0.025	1.35	2.728	1.78*	-0.051	-0.03
4	0.030	1.62*	-1.595	-0.84	0.009	0.01
5	-0.012	-0.44	6.568	2.97***	-0.065	-0.04
6	-0.017	-0.73	-3.005	-1.73*	-0.079	-0.04
7	0.111	2.04**	4.262	0.59	12.7	0.01
8	0.123	1.17	-4.256	-0.33	0.092	0.05
	$ICTUSE_{i, jt-1, t-1}$*dumcloth				$ecommerce_{i, jt-1, t-1}$*dumcloth	
_predict						
1	-0.017	-2.07**			0.004	2.26**
2	0.011	2.60***			-0.002	-1.5
3	-0.018	-0.65			-0.004	-0.51
4	0.043	1.91**			-0.006	-0.63
5	-0.106	-2.06**			0.001	0.06
6	-0.052	-1.52			-0.004	-0.45
7	0.041	0.94			0.021	1.28
8	0.158	1.86*			-1.329	-0.01
	$ICTUSE_{i, jt-1, t-1}$*dumplas		$robot_{i, jt-1, t-1}$*dumplas		$ecommerce_{i, jt-1, t-1}$*dumplas	
_predict						
1	0.003	0.46	0.067	1.73*	-0.010	-2.58***
2	0.002	0.46	-0.068	-2.28***	0.001	0.37
3	0.009	0.61	0.164	1.90**	0.001	0.2
4	-0.011	-0.53	-0.115	-1.03	0.006	1.09
5	-0.032	-1.37	0.368	2.84***	0.007	1.13
6	-0.011	-0.68	-0.189	-1.89**	0.008	2.15**
7	-0.061	-0.35	0.182	0.42	0.036	1.24
8	0.173	1.06	-0.218	-0.28	-1.973	-0.69
	$ICTUSE_{i, jt-1, t-1}$*dumelec		$robot_{i, jt-1, t-1}$*dumelec		$ecommerce_{i, jt-1, t-1}$*dumelec	
_predict						
1	-0.004	-0.28	1.897	1.72*	-0.004	-0.77
2	-0.007	-0.48	-2.381	-2.32**	0.011	2.38**
3	0.081	2.17**	4.136	1.44	-0.005	-0.27
4	0.025	0.52	-4.265	-1.16	-0.009	-0.35
5	-0.131	-2.35**	11.555	2.73***	-0.049	-1.81*
6	0.045	1.11	-6.949	-2.07**	-0.021	-0.99
7	-0.030	-0.19	8.042	0.58	-0.049	-0.49
8	-0.005	-0.03	-8.428	-0.34	-0.125	-1.21
	$ICTUSE_{i, jt-1, t-1}$*dumauto		$robot_{i, jt-1, t-1}$*dumauto		$ecommerce_{i, jt-1, t-1}$*dumauto	
_predict						
1	0.003	0.71	2.063	1.79*	0.004	1.54
2	-0.006	-1.37	-2.262	-2.19**	-0.003	-0.8
3	-0.009	-0.71	4.275	1.46	0.003	0.3
4	0.008	0.59	-4.177	-1.13	-0.009	-0.59
5	-0.005	-0.36	11.703	2.75***	0.017	2.19**
6	0.020	2.12**	-6.923	-2.06**	-0.029	-1.92**
7	-0.008	-0.18	8.096	0.58	-0.062	-0.71
8	-0.024	-0.41	-8.710	-0.34	-0.045	-0.87
Industry dummy	Yes		Yes		Yes	
Year dummy	Yes		Yes		Yes	
Number of obs	16,275		14,169		9,344	
LR chi2	2426.36		2094		1023	
Prob > chi2	0.00		0.00		0.00	
Pseudo R2	0.0566		0.0547		0.0434	
Log likelihood	-20228.191		-18082.257		-11280.568	

Note: ***, ** and * represent 1, 5 and 10 percent significant level, respectively,

There is no information in textile and clothing sectors since data on operational stocks of robot use in this sector reports as zero during 2002-16. The small positive number of operational stocks of robot use in clothing and textile was shown in 2017,

To be consistent with results in Table 6, proxies of technology variables, namely ICT, robot and e-commerce, are estimated separately in this table,

Elasticities estimated in this table are from results reported in Appendix II.

Source: Authors' estimation

Table 8: Proportion of workers by occupation code and sector during 2012-17

Occupation code		10-12: Food and Beverage	13-15: Textile and Clothing	19-23: Plastics and Chemicals	26-28: Electronics and machinery	29-30: Automotive
1	Executive manager	0.10	0.08	0.38	0.16	0.08
2	Manager	3.19	1.62	5.17	3.35	4.42
3	Professional	1.31	0.62	5.07	3.59	3.44
4	Associate professional	4.14	1.82	8.90	8.87	9.66
5	Technician	61.59	64.52	62.06	74.72	69.53
6	Service and Sale Workers	4.64	0.30	1.50	0.56	0.66
7	Clerical support work	4.26	28.87	6.60	4.27	6.06
8	Basic job	20.78	2.16	10.31	4.48	6.14

Source: Authors' calculations from Thai Labour Force Survey data

In the food and beverages and clothing and textiles sectors, an increase in ICT usage raises the probability of workers shifting their positions from unskilled to skilled labour, as reflected by the positive and significant coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables in these two sectors for outcome No. 4 (*EmployS*i,j,t = 4) (Table 7: column A). In the food and beverage sector, the usage of ICT also helps increase the probability of workers remaining in the same position and receiving higher income (the coefficient associated with *ICTUSE* for outcome No. 1 is positive and higher than that with *ICTUSE* for outcome No. 2).

In textiles and clothing, introducing more ICT helped workers remain in the same position, but the group of workers who receive such a benefit are those who receive relatively lower pay. This is reflected by the positive and significant coefficient associated with the interaction term between *ICTUSE* and the industrial dummy variables in this sector for outcome No. 2 (*EmployS*i,j,t = 2) (Table 7: column A). In addition, in this sector the probability of workers moving from skilled to unskilled work declines when ICT is introduced more. The coefficient associated with the interaction term between *ICTUSE* and the industrial dummy variables in this sector for outcome No. 5 (*EmployS*i,j,t = 5) is negative and significant.

In terms of the intensity of robot usage, its impact on employment status/income changes emerges only when it is analysed by sector. Workers in the automotive, electronics, and plastics and chemical sectors tend to experience a net negative impact from the introduction of more robots. First, in these sectors the probability of workers moving from unskilled to skilled jobs declines. This is reflected by the positive coefficients associated with the interaction term between the *robot* and dummy variables in these sectors for outcome No. 3 (*EmployS*i,j,t = 3), but the value is less than the negative value observed in the base case (Table 7: column B). Second, the probability of workers staying in the same position and receiving higher payments declines (*EmployS*i,j,t = 1) (Table 7: column B). Although the introduction of robots benefits workers at lower pay levels, i.e. the increased probability of workers staying in the same position, butincome does not change (*EmployS*i,j,t = 2), the magnitude of gains from this group of workers cannot cover the possible loss that arises from the group of workers whose income is adjusted upwards for staying in the same position. Third, the probability wherein workers change from skilled to unskilled declines (see the net value of coefficients associated with the interaction term between robots and the industrial dummy variables for outcomes 5 and 6 (*EmployS*i,j,t = 5 and *EmployS*i,j,t = 6) and the value of the base case. However, when comparing the net value of the elasticity between cases 5 and 6 with that of case 3, the magnitude of the latter (which is negative) is higher than that of the former. This implies that the net impact was that workers were likely to move from skilled to unskilled jobs. Note that in the third case, less evidence was found in the plastic and chemical sectors (Table 7: column B).

Regarding the food and beverages sector, introducing robots helps workers stay in the same position, but income does not adjust upwards, i.e. the coefficient associated with *EmployS*i,j,t = 2 is positive and statistically significant. The magnitude of gain from this group of workers is higher than the possible loss arising from the group of workers whose income is adjusted upwards when staying in the same position (*EmployS*i,j,t = 1) (Table 7: Column B). In addition, the net impact is that there is a lower probability of workers moving from skilled to unskilled employment. The net value of elasticity between cases 5 and 6 (in absolute terms) is higher than that observed in Case 3. All in all, the intensity of robot usage has less severe effects within the food and beverages sector. Part of the reason for this could lie in the nature of the industry itself, which still relies more on labour, and another could be in the developments in the technology itself, which may still not match the particular needs of this sector. The usage of robots in this field is minimal in Thailand, though increasing, compared to the above three sectors.

Introducing e-commerce tends to benefit labour market outcomes. When the whole manufacturing sector is concerned, the probability of workers shifting to skilled position from unskilled increases by 0.02 percent when the value of e-commerce as a percentage of GDP increases by one percent. However, workers moving to higher skilled positions do not receive commensurately higher payment along with the skill changes. This is reflected by the positive and significant coefficient of *ecommerce* for outcome 4, but not outcome 3 (Table 6: column C). When analyzing by sector, the impact of e-commerce on employment status in the food and beverages sector resembles that of manufacturing as a whole, while workers in the clothing and textiles as well as electronic sectors seem to receive additional benefits from using e-commerce. In the clothing and textiles sector, using e-commerce helps workers stay in the same position and receive higher income (see the positive coefficient associated with the interaction terms between *ecommerce* and the industrial dummy for outcome 1) (Table 7: column C). With the electronics and machinery sector e-commerce supports workers staying in the same position as is the case observed in the clothing and textiles sector, but the effect occurs with workers who receiving relatively low payment (see the positive coefficient associated with the interaction terms between *ecommerce* and the industrial dummy for outcome 2). In addition, the probability of workers moving from skilled to unskilled jobs declines (the negative coefficient associated with the interaction terms between *ecommerce* and the industrial dummy for outcome 5).

The automotive sector receives benefits from using e-commerce, but the impact tends to be smaller than the above two sectors. The likelihood of workers transferring from skilled to unskilled employment declines for staff receiving lower pay. However, this positive effect is countered by another group of workers who receive higher pay (see the net elasticity of the interaction terms between *ecommerce* and the industrial dummy for outcomes 5 and 6) (Table 7: column C). Evidence from the labour force survey shows that in the automotive sector workers who move from skilled to unskilled position are mostly emanating from other industries, i.e. this represents reallocation across industries (Figure 6B).

In contrast to other sectors, e-commerce seems to have a negative impact on employment status in the plastics and chemicals sector. The probability wherein workers remain in the same position and receive higher payments declines (there is a negative coefficient associated with the interaction terms between *ecommerce* and the industrial dummy in outcome 1) (Table 7: column C). Meanwhile, there is a higher probability of employees transferring from skilled to unskilled jobs in response to the higher value of e-commerce employed in this sector (reflected by the positive coefficient associated with the interaction terms between *ecommerce* and the industrial dummy for outcome 6). The negative impact found in the plastics and chemicals sector is probably due to the significant increase in the value of e-commerce per output in this sphere, compared to the other sectors under our consideration (see Figure 2B). In addition, the proportion of workers who are in 'basic jobs' is also high at around ten percent of total employment in this sector (Table 8).

Comparing the effects of technological advancement and import penetration, our results reflect a diminished influence concerning the negative impact induced by imports on employment status. Three pieces of evidence support this finding.[14] First, there is no significant evidence that higher import penetration forces workers out of the job market. The coefficient associated with *IMpen* for outcome 7 is statistically insignificant for all three proxies of technology (Table 6: columns A-C). Second, the probability of moving from unskilled to skilled work becomes higher, though this occurs in the group of workers whose income does not increase commensurate with skill improvements. This is reflected by the positive and significant coefficient associated with *IMpen* for outcome 4. Thirdly, the probability of employees moving from skilled to unskilled work declines, reflected in the coefficients associated with *IMpen* for outcomes 5 and 6 in which the negative coefficient associated with *IMpen* for outcome 5 is higher than that associated with the *IMpen* for outcome 6. However, imports reduce the probability that workers stay in the same job (see the net value of coefficients associated with *IMpen* for outcomes 1 and 2, Table 6: columns A-C).

[14] It is crucial to note that when we analyse the impact of import penetration sector-wise, the results of the five key sectors of our interest, namely the food and beverages; clothing and textiles; plastics and chemicals; electronics and machinery; and automotive sectors, are similar to that for manufacturing as a whole. In some sectors, especially automotive, plastics and chemicals, and electronics, however, there is evidence that the probability of shifting workers from skilled to unskilled jobs increases, especially those who receive higher pay. Nevertheless, an increase in such probability is lower than the higher probability of moving workers from unskilled to skilled roles. Thus, the net positive impact of imports on employment status in these sectors occurs.

Table 9: Impact of import penetration by products on employment status and income changes (elasticity estimation)

_predict	Column A		Column B		Column C	
	$IMpen\_raw_{jt-1, t-1}$		$IMpen\_capital_{jt-1, t-1}$		$IMpen\_finish_{jt-1, t-1}$	
	Coefficient	Z	Coefficient	Z	Coefficient	Z
1	-0.070	-6.33***	0.001	0.39	-0.057	-4.52***
2	0.013	3.43***	-0.003	-1.29	0.029	5.91***
3	0.002	0.09	0.003	0.45	-0.036	-1.19
4	0.069	3.66	0.013	1.97**	-0.050	-1.5
5	-0.054	-1.90*	0.007	0.7	-0.030	-0.79
6	0.033	1.91*	0.004	0.57	0.015	0.91
7	-0.008	-0.07	-0.083	-1.02	0.052	0.96
8	-0.272	-1.82*	-0.033	-0.41	0.093	1.64*
Industry dummy	Yes					
Year dummy	Yes					
Number of obs	14,151					
LR chi2(126)	2128.26					
Prob > chi2	0.00					
Pseudo R2	0.0557					
Log likelihood	-18037.456					

Note: ***, ** and * represent 1, 5 and 10 percent significant level, respectively.
Elasticities estimated in this table are from results reported in Appendix III.
Source: Authors' estimation

When imports are disaggregated into finished products (*IMpen_finish*$_{jt-1, t-1}$), capital (*IMpen_capital*$_{jt-1, t-1}$) and raw materials (*IMpen_raw*$_{jt-1, t-1}$), our results show that the impact of import penetration in terms of raw materials on employment status/income changes resemble that of total imports (Table 9: column A). With regard to capital-goods imports, the only impact found is that it helps workers move to roles in higher skilled positions, though this occurs in the group of workers whose income does not adjust according to skill improvements. There is no significant impact found for outcomes 1, 2 and 5 as shown in the cases of total imports and imports of raw materials (Table 9: column B). All in all, there is less evidence of any negative impact induced by the import of capital goods and raw materials on employment status.

In contrast, concerns regarding employment status are uncovered in the case of final-product imports. An increase in the import penetration ratio in finished products tends to shift workers into unskilled jobs, especially with workers whose income does not match well with skill changes (see the negative coefficient associated with *IMpen_finish*$_{jt-1, t-1}$ for outcome 4) (Table 9: column C). In addition, imports in finished products reduce the probability of workers staying in the same position and receiving a higher income. The magnitude of such probability reductions is higher than that of workers receiving relatively lower pay staying in the same position, as can be seen in the coefficients associated with $IMpen\_finish_{jt-1,\ t-1}$ for outcomes 1 and 2 (Table 9: column C). The greater negative impact found in finished products compared to raw materials and capital-goods imports on labour markets is, to some extent, in line with the recent literature (e.g. Amiti and Konings, 2007 and Sala-i-Martin et.al., 2004) which recorded that liberalization in upstream sectors (intermediate inputs) generates higher firm productivity improvement than that in downstream (final products). The productivity improvement supports the labour market, including shifting workers to work in higher skilled positions. Interestingly, higher imports in finished products could potentially bring workers from unemployed status back into the job market. The coefficient associated with $IMpen\_finish_{jt-1,\ t-1}$ for outcome 8 is positive, though only weakly significant (Table 9: column C). Some firms, e.g. in the garment industry, import final products for imitation purposes and expand their new production lines so more workers are hired to feed such growth. (Kohpaiboon and Jongwanich, 2019)

Regarding income equation[15] where all observations in the labour force survey are utilized, the results show that impacts of technological advancements on wage/income differ among ICT, robots and ecommerce. When the whole manufacturing sector is concerned, introducing more ICT leads to a decline in total income of workers while there is a negative but statistically insignificant impact of introducing more robots on income (Table 10: columns A-B and D-E). The results are consistent with the analysis of probability changes in employment status/income induced by advanced technologies, i.e for the ICT use, an increase in ICT uses reduces the probability which workers, receiving relatively lower pay, move from unskilled to skilled positions, while introducing more robots does not significantly affect employment status when the whole manufacturing sector is concerned. When sector-wise is analysed, there is no difference in wage/income found in each sector in cases of ICT use and robots (Table 10: column C).

By contrast, it seems that an increase in value of e-commerce in output increases wage/income of workers (Table 10: columns G-H). The result seems to be consistent with the previous analysis on employment status in which workers move from unskilled to skilled positions, though benefits are in a group of workers who income does not adjust according to

[15] Note that results of wage equation are similar to those of income equation so that we report only income equation here.

skill changes. For a sector-wise analysis, wage increases tend to occur only in clothing and textile and food and beverage sectors while decline in wage/income found in plastics and chemicals, automotive and electronic sector (Table 10: column I). This could be because in plastics and chemicals and automotive, workers tend to move from skilled to unskilled positions as shown in the previous analysis, which would have a negative impact on wage/income. For electronic sector, although e-commerce support workers to stay at the same position, it occurs only in a group of workers whose receive low payments.

Regarding impacts of import penetration on income, our results show that imports of final products dampen income of workers significantly, regardless proxies of technology employed in the analysis (Table 10: columns B, E, H). As mentioned in the previous analysis, imports of final products tend to generate negative impacts on employment status, including shifting workers from skilled to unskilled jobs, thereby generating an adverse impact on workers' wage/income. Imports of raw materials also have a negative impact on wage/income, but the results are found only when ICT use and robots are proxies of technology. In a case of e-commerce, there is no significant effects of such imports on wage/income changes. The impact of raw material imports on wage/income are far lower than that of final products. One percent increase in imports of final products results in around 0.07-0.08 percent reduction in workers' income while for raw material imports, the reduction is less than 0.01 percent (Table 10: columns B, E, H). For capital goods, its imports could lead to higher wage/income of workers, regardless of proxies used in our analysis. One percent increase in imports of capital goods results in higher workers' income by around 0.01-0.03 percent (Table 10: columns B, E, H). As mentioned in the previous section, imports of capital goods and raw materials could increase probability of workers to move from unskilled to skilled positions. In a case of raw materials, the slight reduction on wage is revealed, partly due to the evidence revealed earlier, i.e. imports of raw materials reduce the probability, which workers would stay at the same position and receive higher income. Comparing effects of advanced technology and import penetration on wage/income, our results reveal that impacts of the former (in absolute term) tend to be greater than that of the latter.

Table 10: Impacts of advanced technology and import penetration on income

Column A				Column B				Column C			
Variables	Coefficient	Std. Err.	Z	Variables	Coefficient	Std. Err.	Z	Variables	Coefficient	Std. Err.	Z
ICTUSE $_{i,j,t}$	-0.591	0.339	-1.74*	*ICTUSE* $_{i,j,t}$	-0.590	0.336	-1.76*	*ICTUSE* $_{i,j,t}$	-0.611	0.418	-1.46
								ICTUSE $_{i,j,t}$**dumfood*	-0.289	1.019	-0.28
								ICTUSE $_{i,j,t}$**dumcloth*	12.202	17.709	0.69
								ICTUSE $_{i,j,t}$**dumplas*	0.081	0.778	0.10
								ICTUSE $_{i,j,t}$**dumelec*	0.802	1.081	0.74
								ICTUSE $_{i,j,t}$**dumauto*	0.940	1.237	0.76
IMpen $_{i,j,t}$	-0.005	0.008	-0.68					*IMpen* $_{i,j,t}$	-0.001	0.013	-0.05
				IMpen_raw $_{i,j,t}$	-0.015	0.003	-4.41***				
				IMpen_capital $_{i,j,t}$	0.029	0.006	5.12***				
				IMpen_finish $_{i,j,t}$	-0.083	0.008	-10.23***				
age $_{i,j,t}$	0.002	0.000	5.12***	age $_{i,j,t}$	0.002	0.000	5.31***	age $_{i,j,t}$	0.002	0.000	4.90***
2. sexi,j,t	-0.185	0.007	-25.91***	2. sexi,j,t	-0.178	0.007	-24.85***	2. sexi,j,t	-0.186	0.007	-25.21***
education $_{i,j,t}$				*education* $_{i,j,t}$				*education* $_{i,j,t}$			
1	0.341	0.011	30.89***	1	0.338	0.011	30.63***	1	0.346	0.013	26.87***
2	0.666	0.015	43.42***	2	0.661	0.015	42.84***	2	0.668	0.016	42.28***
3	1.184	0.072	16.53***	3	1.182	0.072	16.40***	3	1.188	0.072	16.50***
_cons	9.070	0.055	166.39***	_cons	9.155	0.055	167.77***	_cons	9.027	0.059	153.2***
Industry dummy	Yes			Industry dummy	Yes			Industry dummy	Yes		
Year dummy	Yes			Year dummy	Yes			Year dummy	Yes		
Number of obs	42,806			Number of obs	42,746			Number of obs	42,806		
Wald chi2(33)	7140.17			Wald chi2(33)	7592.87			Wald chi2(33)	6949.41		
Prob > chi2	0.00			Prob > chi2	0.00			Prob > chi2	0.00		
R-squared	0.182			R-squared	0.186			R-squared	0.1354		
Root MSE	0.694			Root MSE	0.693			Root MSE	0.71396		

Column D				Column E				Column F			
Variables	Coefficient	Std. Err.	Z	Variables	Coefficient	Std. Err.	Z	Variables	Coefficient	Std. Err.	Z
robot $_{i,j,t}$	-0.121	0.256	-0.47	*robot* $_{i,j,t}$	-0.187	0.257	-0.73	*robot* $_{i,j,t}$	3.691	2.738	1.35
								*roboti, j, t *dumfood*	-1.745	1.204	-1.45
								*roboti, j, t *dumcloth*			
								*roboti, j, t *dumplas*	-3.380	2.494	-1.36
								*roboti, j, t *dumelec*	-3.317	2.409	-1.38
								*roboti, j, t *dumauto*	-3.467	2.550	-1.36
IMpen $_{i,j,t}$	-0.013	0.009	-1.45					*IMpen* $_{i,j,t}$	-0.013	0.008	-1.59
				IMpen_raw $_{i,j,t}$	-0.006	0.003	-1.82*				
				IMpen_capital $_{i,j,t}$	0.027	0.006	4.42***				
				IMpen_finish $_{i,j,t}$	-0.070	0.009	-8.11***				
age $_{i,j,t}$	0.003	0.000	8.30***	age $_{i,j,t}$	0.003	0.000	8.3***	age $_{i,j,t}$	0.003	0.000	8.18***
2. sexi,j,t	-0.180	0.008	-24.02***	2. sexi,j,t	-0.176	0.007	-23.41***	2. sexi,j,t	-0.180	0.008	-24.00***
education $_{i,j,t}$				*education* $_{i,j,t}$				*education* $_{i,j,t}$			
1	0.342	0.011	30.26***	1	0.340	0.011	30.08***	1	0.342	0.011	30.10***
2	0.655	0.016	41.36***	2	0.651	0.016	40.86***	2	0.656	0.016	41.45***
3	1.166	0.074	15.70***	3	1.166	0.075	15.57***	3	1.167	0.074	15.74***
_cons	9.280	0.050	185.56***	_cons	9.305	0.050	184.74***	_cons	9.139	0.114	80.05***
Industry dummy	Yes			Industry dummy	Yes			Industry dummy	Yes		
Year dummy	Yes			Year dummy	Yes			Year dummy	Yes		
Number of obs	38,386			Number of obs	38,326			Number of obs	38,386		
Wald chi2(33)	6303.37			Wald chi2(33)	6594.14			Wald chi2(33)	6660.64		
Prob > chi2	0.00			Prob > chi2	0.00			Prob > chi2	0.00		
R-squared	0.1842			R-squared	0.186			R-squared	0.180		
Root MSE	0.691			Root MSE	0.690			Root MSE	0.692		

Column G				Column H				Column I			
Variables	Coefficient	Std. Err.	Z	Variables	Coefficient	Std. Err.	Z	Variables	Coefficient	Std. Err.	Z
ecommerce i, j, t	0.889	0.376	2.37**	*ecommerce* i, j, t	0.903	0.376	2.40**	*ecommerce* i, j, t	0.357	0.356	1.00
								*ecommercei, j, t*dumfood*	-6.384	10.073	-0.63
								*ecommercei, j, t*dumcloth*	-3.018	2.220	-1.36
								*ecommercei, j, t*dumplas*	-57.800	15.946	-3.62***
								*ecommercei, j, t*dumelec*	-5.663	2.562	-2.21**
								*ecommercei, j, t*dumauto*	-3.109	1.575	-1.97**
IMpen i, j, t	-0.008	0.008	-0.98					*IMpen* i, j, t	-0.014	0.008	-1.66*
				IMpen_raw i, j, t	0.001	0.003	0.17				
				IMpen_capital i, j, t	0.011	0.005	2.10**				
				IMpen_finish i, j, t	-0.073	0.008	-8.67***				
agei, j,t	0.003	0.000	9.06***	agei, j,t	0.003	0.000	9.13***	agei, j,t	0.003	0.000	9.00***
2. sexi,j,t	-0.165	0.007	-22.67***	2. sexi,j,t	-0.160	0.007	-22.04***	2. sexi,j,t	-0.167	0.007	-22.53***
education i, j,t				*education* i, j,t				*education* i, j,t			
1	0.354	0.010	36.68***	1	0.352	0.010	36.44***	1	0.353	0.010	35.39***
2	0.685	0.015	45.33***	2	0.682	0.015	44.92***	2	0.684	0.015	44.53***
3	1.226	0.067	18.36***	3	1.223	0.067	18.31***	3	1.240	0.067	18.39***
_cons	9.052	0.024	380.63***	_cons	9.103	0.025	366.21***	_cons	9.010	0.027	337.67***
Industry dummy	Yes			Industry dummy	Yes			Industry dummy	Yes		
Year dummy	Yes			Year dummy	Yes			Year dummy	Yes		
Number of obs	23,571			Number of obs	23,540			Number of obs	23,571		
Wald chi2(33)	6985.33			Wald chi2(33)	7085.81			Wald chi2(33)	6956.02		
Prob > chi2	0.00			Prob > chi2	0.00			Prob > chi2	0.00		
R-squared	0.278			R-squared	0.280			R-squared	0.260		
Root MSE	0.524			Root MSE	0.523			Root MSE	0.531		

Note: (1) Sex, which equals to '1' represents male while '2' represents female. (2) Education composes of four ranks, i.e. '0' represents lower or equal to primary education; '1' lower secondary education; '2' upper secondary and post-secondary education; '3' bachelor's degree and higher. (3) All proxies of technology and import penetration are in logarithm. (4) ***, ** and * represent 1, 5 and 10 percent significant level, respectively.

Source: Authors' calculation

6. Conclusions and Policy Implications

This paper examines the impact of advanced technology on possible changes in workers' skills and wages and the possibility that employees become unemployed due to such technological progress. In contrast to other studies, technological advancements are proxied by three key aspects according to their involvement in supply chains, i.e. ICT usage, e-commerce (both inbound and outbound), and internal production (e.g. factory automation/robots). Our study compares the effects of technological advancement on labour market outcomes with import penetration, delineated into raw materials, capital goods and final products.

Our results reveal that in Thailand, the impact of advanced technology in pushing workers out of the job market is limited. Instead, it tends to affect the reallocation of workers between skilled and unskilled positions. The results vary among the proxies of technology and sectors. Among the three proxies of advanced technology, e-commerce tends to have a positive impact on employment status, especially the higher probability of shifting workers from unskilled to skilled positions. Workers in the clothing and textiles, food and beverages and electronics and machinery sectors tend to derive greater benefits from using e-commerce in their supply chains than the automotive and plastics and chemicals industries. Where the impact of wages/income induced by e-commerce are concerned, our results reveal wages/income increases tend to occur only in the clothing and textiles and food and beverages sectors, while a decline in wages/income is found in the plastics and chemicals, automotive and electronic sectors.

In contrast to e-commerce, a negative impact on employment status was uncovered in the case of ICT usage, especially in terms of the diminished probability of shifting workers from skilled to unskilled positions. Existence of a negative impact is found in relatively high capital-intensive industries, including the automotive, plastics and chemicals and electronics and machinery sectors. When assessing the intensity of robot usage, workers in the automotive, electronics, and plastics and chemical sectors tend to suffer from introducing a greater number of robots into production assembly lines. The intensity of robot usage has a less severe effect within the food and beverages sector. Wages/income tends to adjust downward in response to an increase in ICT usage, while there is a negative but statistically insignificant impact of introducing more robots on income levels

Comparing the effects of technological advancement and import penetration, our results show less evidence of the negative impact induced by imports on employment status, particularly in the case of imports of capital and raw materials. In contrast, a significant impact on employment status is uncovered in the case of final-product imports. In particular, such imports tend to cause a shift of workers from skilled to unskilled positions and reduce the probability of workers remaining in the same job and receiving a higher income. However, higher imports in finished products could potentially bring workers from unemployed status back into the job market. The negative effect of wages/income induced by import penetration is far lower than that of technological advancement.

Three policy inferences are drawn from our study. First, the reallocation of workers is unavoidable in response to technological advancement. In addition to supporting the skill improvement of workers, governments should act as facilitators to vigorously reduce friction in the labour market and smoothen the transition of workers from one place to another. Cooperation with private firms is necessary to effectively manage information, especially that relating to job creation and redundancies across firms and industries, and minimise friction in the labour market. Attention should be paid more to capital-intensive industries where a greater negative impact of advanced technology are apparent. Secondly, wages/income should be properly readjusted commensurate to skills improvements. From our study, in some cases advanced technology helps shift workers from relatively unskilled to skilled positions, but such benefits fall in a group of workers whose wages/income fails to be adjust to reflect their greater skills. Proper payment schemes, beyond relying on merely providing the minimum wage, should be developed to treat workers fairly, along with encouraging them to improve skills and be flexible. Thirdly, trade liberalization needs to continue in Thailand with less concern on the labour market outcomes that have preoccupied some developed countries, especially in terms of capital goods and raw materials. Although liberalization of final products could reduce the probability of shifting workers from unskilled to skilled positions, they create a higher probability of allowing some unemployed workers to re-enter the job market.

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Appendix I: Multinomial logistic regression for employment status

ICTUSE			
Outcomes / variables	Coef.	z	P>z
1			
age i, jt-1,t-1	0.077	4.53	0
2.sex i,j,t	-0.001	0	0.997
education i, jt-1,t-1			
1	-0.026	-0.08	0.938
2	0.130	0.27	0.783
3	-1.186	-0.98	0.327
ICTUSE i, jt-1, t-1	0.517	0.61	0.54
IMpen i, jt-1, t-1	0.086	0.97	0.332
totalincome i, jt-1, t-1	0.000	-0.47	0.635
ICTUSE_Residual i, jt-1, t-1	2.475	1.24	0.213
_cons	2.240	2.77	0.006
2			
age i, jt-1,t-1	0.108	6.38	0
2.sex i,j,t	0.105	0.37	0.713
education i, jt-1,t-1			
1	-0.006	-0.02	0.986
2	0.370	0.78	0.434
3	-0.594	-0.49	0.622
ICTUSE i, jt-1, t-1	0.538	0.64	0.522
IMpen i, jt-1, t-1	0.113	1.29	0.198
totalincome i, jt-1, t-1	0.000	-0.88	0.379
ICTUSE_Residual i, jt-1, t-1	2.490	1.25	0.21
_cons	1.792	2.22	0.026
3			
age i, jt-1,t-1	0.083	4.78	0
2.sex i,j,t	0.049	0.17	0.867
education i, jt-1,t-1			
1	0.171	0.49	0.623
2	0.843	1.75	0.081
3	-1.063	-0.84	0.4
ICTUSE i, jt-1, t-1	0.665	0.78	0.436
IMpen i, jt-1, t-1	0.089	1	0.318
totalincome i, jt-1, t-1	0.000	-0.09	0.926
ICTUSE_Residual i, jt-1, t-1	2.586	1.3	0.194
_cons	-1.061	-1.27	0.205
4			
age i, jt-1,t-1	0.095	5.46	0
2.sex i,j,t	0.228	0.78	0.437
education i, jt-1,t-1			
1	0.247	0.71	0.48
2	1.137	2.35	0.019
3	-0.191	-0.15	0.878
ICTUSE i, jt-1, t-1	0.011	0.01	0.99
IMpen i, jt-1, t-1	0.156	1.75	0.08
totalincome i, jt-1, t-1	0.000	0.24	0.807
ICTUSE_Residual i, jt-1, t-1	2.408	1.21	0.227
_cons	-1.130	-1.35	0.176
5			
age i, jt-1,t-1	0.079	4.49	0
2.sex i,j,t	0.313	1.05	0.293
education i, jt-1,t-1			
1	0.241	0.68	0.496
2	0.973	1.99	0.047
3	-2.232	-1.42	0.155
ICTUSE i, jt-1, t-1	0.683	0.79	0.432
IMpen i, jt-1, t-1	0.057	0.63	0.53
totalincome i, jt-1, t-1	0.000	-0.7	0.482
ICTUSE_Residual i, jt-1, t-1	2.679	1.34	0.18
_cons	-1.412	-1.64	0.101
6			
age i, jt-1,t-1	0.095	5.48	0
2.sex i,j,t	0.330	1.13	0.258
education i, jt-1,t-1			
1	-0.001	0	0.998
2	0.928	1.93	0.053
3	-1.102	-0.89	0.375
ICTUSE i, jt-1, t-1	0.308	0.36	0.719
IMpen i, jt-1, t-1	0.136	1.53	0.126
totalincome i, jt-1, t-1	0.000	0.85	0.397
ICTUSE_Residual i, jt-1, t-1	2.130	1.07	0.286
_cons	-1.254	-1.51	0.132
7			
8			
age i, jt-1,t-1	-0.021	-0.8	0.421
2.sex i,j,t	0.247	0.55	0.585
education i, jt-1,t-1			
1	1.410	2.28	0.022
2	1.288	1.66	0.097
3	-11.784	-0.02	0.985
ICTUSE i, jt-1, t-1	-0.721	-0.48	0.633
IMpen i, jt-1, t-1	-0.013	-0.11	0.915
totalincome i, jt-1, t-1	-0.001	-5.88	0
ICTUSE_Residual i, jt-1, t-1	2.284	1.08	0.281
_cons	0.763	0.56	0.577
Industry dummy for all out	Yes		
Year dummy for all outcon	Yes		
Number of obs	16,275		
LR chi2	2,372		
Prob > chi2	0.00		
Pseudo R2	0.0553		
Log likelihood	-20255.424		

robot			
Outcomes / variables	Coef.	z	P>z
1			
age i, jt-1,t-1	0.074	4.08	0
2.sex i,j,t	0.000	0	0.999
education i, jt-1,t-1			
1	0.001	0	0.997
2	0.277	0.55	0.584
3	-1.025	-0.84	0.403
robot i, jt-1, t-1	-0.005	-0.09	0.924
IMpen i, jt-1, t-1	0.080	0.91	0.362
totalincome i, jt-1, t-1	0.000	-0.53	0.597
robot_Residual i, jt-1, t-1	-0.039	-0.42	0.677
_cons	2.500	2.17	0.03
2			
age i, jt-1,t-1	0.104	5.79	0
2.sex i,j,t	0.162	0.53	0.595
education i, jt-1,t-1			
1	-0.006	-0.02	0.986
2	0.470	0.93	0.352
3	-0.520	-0.43	0.67
robot i, jt-1, t-1	-0.014	-0.29	0.775
IMpen i, jt-1, t-1	0.109	1.24	0.215
totalincome i, jt-1, t-1	0.000	-0.76	0.445
robot_Residual i, jt-1, t-1	-0.046	-0.49	0.627
_cons	1.665	1.44	0.149
3			
age i, jt-1,t-1	0.081	4.41	0
2.sex i,j,t	0.068	0.22	0.828
education i, jt-1,t-1			
1	0.169	0.45	0.649
2	0.962	1.87	0.062
3	-0.912	-0.71	0.475
robot i, jt-1, t-1	-0.020	-0.39	0.7
IMpen i, jt-1, t-1	0.083	0.93	0.353
totalincome i, jt-1, t-1	0.000	-0.15	0.878
robot_Residual i, jt-1, t-1	-0.036	-0.38	0.706
_cons	0.042	0.04	0.972
4			
age i, jt-1,t-1	0.092	5.01	0
2.sex i,j,t	0.300	0.95	0.34
education i, jt-1,t-1			
1	0.294	0.78	0.433
2	1.274	2.47	0.014
3	-0.099	-0.08	0.937
robot i, jt-1, t-1	-0.006	-0.12	0.904
IMpen i, jt-1, t-1	0.150	1.69	0.091
totalincome i, jt-1, t-1	0.000	0.26	0.798
robot_Residual i, jt-1, t-1	-0.032	-0.33	0.738
_cons	-1.082	-0.9	0.366
5			
age i, jt-1,t-1	0.076	4.11	0
2.sex i,j,t	0.319	1.01	0.315
education i, jt-1,t-1			
1	0.229	0.6	0.546
2	1.087	2.09	0.037
3	-2.074	-1.31	0.189
robot i, jt-1, t-1	0.002	0.04	0.966
IMpen i, jt-1, t-1	0.047	0.52	0.601
totalincome i, jt-1, t-1	0.000	-0.82	0.412
robot_Residual i, jt-1, t-1	-0.038	-0.39	0.698
_cons	-0.163	-0.14	0.892
6			
age i, jt-1,t-1	0.091	4.96	0
2.sex i,j,t	0.332	1.07	0.287
education i, jt-1,t-1			
1	0.048	0.13	0.897
2	1.030	2.01	0.044
3	-1.087	-0.86	0.388
robot i, jt-1, t-1	-0.018	-0.36	0.717
IMpen i, jt-1, t-1	0.133	1.5	0.134
totalincome i, jt-1, t-1	0.000	0.84	0.404
robot_Residual i, jt-1, t-1	-0.052	-0.55	0.585
_cons	-0.453	-0.38	0.701
7	(base outcome		
8			
age i, jt-1,t-1	-0.025	-0.91	0.361
2.sex i,j,t	0.395	0.83	0.407
education i, jt-1,t-1			
1	1.207	1.9	0.057
2	1.284	1.6	0.109
3	-11.621	-0.02	0.983
robot i, jt-1, t-1	0.120	1.58	0.114
IMpen i, jt-1, t-1	-0.042	-0.32	0.745
totalincome i, jt-1, t-1	-0.001	-5.95	0
robot_Residual i, jt-1, t-1	0.094	0.62	0.536
_cons	2.524	1.41	0.157
Industry dummy for all ou	Yes		
Year dummy for all outco	Yes		
Number of obs	14,252		
LR chi2	2,043		
Prob > chi2	0.00		
Pseudo R2	0.0534		
Log likelihood	-18107.519		

ecommerce			
Outcomes / variables	Coef.	z	P>z
1			
age i, jt-1,t-1	0.070	3.36	0.001
2.sex i,j,t	0.061	0.17	0.866
education i, jt-1,t-1			
1	-0.141	-0.34	0.733
2	0.674	0.99	0.321
3	13.865	0.01	0.995
ecommerce i, jt-1, t-1	3.538	0.88	0.377
IMpen i, jt-1, t-1	0.056	0.49	0.624
ecommerce_Residual i, jt-1, t-1	-0.252	-0.16	0.871
_cons	1.512	1.49	0.137
2			
age i, jt-1,t-1	0.101	4.9	0
2.sex i,j,t	0.174	0.48	0.631
education i, jt-1,t-1			
1	-0.105	-0.26	0.799
2	0.881	1.3	0.194
3	14.303	0.01	0.995
ecommerce i, jt-1, t-1	3.514	0.88	0.38
IMpen i, jt-1, t-1	0.093	0.83	0.408
ecommerce_Residual i, jt-1, t-1	-0.401	-0.26	0.795
_cons	1.001	0.99	0.324
3			
age i, jt-1,t-1	0.079	3.75	0
2.sex i,j,t	0.092	0.25	0.805
education i, jt-1,t-1			
1	0.284	0.66	0.509
2	1.500	2.17	0.03
3	14.684	0.01	0.995
ecommerce i, jt-1, t-1	2.947	0.73	0.466
IMpen i, jt-1, t-1	0.072	0.62	0.534
ecommerce_Residual i, jt-1, t-1	-0.246	-0.16	0.876
_cons	-1.449	-1.35	0.179
4			
age i, jt-1,t-1	0.095	4.47	0
2.sex i,j,t	0.289	0.77	0.444
education i, jt-1,t-1			
1	0.307	0.71	0.479
2	1.771	2.56	0.011
3	15.038	0.01	0.995
ecommerce i, jt-1, t-1	3.988	0.99	0.32
IMpen i, jt-1, t-1	0.152	1.33	0.185
ecommerce_Residual i, jt-1, t-1	-0.462	-0.29	0.77
_cons	-1.867	-1.74	0.081
5			
age i, jt-1,t-1	0.074	3.43	0.001
2.sex i,j,t	0.230	0.6	0.547
education i, jt-1,t-1			
1	0.042	0.1	0.923
2	1.333	1.91	0.056
3	-0.271	0	1
ecommerce i, jt-1, t-1	2.897	0.71	0.476
IMpen i, jt-1, t-1	0.040	0.35	0.728
ecommerce_Residual i, jt-1, t-1	-0.863	-0.51	0.61
_cons	-1.590	-1.43	0.154
6			
age i, jt-1,t-1	0.095	4.49	0
2.sex i,j,t	0.378	1.01	0.311
education i, jt-1,t-1			
1	0.115	0.27	0.789
2	1.718	2.5	0.013
3	14.900	0.01	0.995
ecommerce i, jt-1, t-1	3.723	0.93	0.354
IMpen i, jt-1, t-1	0.108	0.94	0.345
ecommerce_Residual i, jt-1, t-1	-0.405	-0.26	0.797
_cons	-1.474	-1.4	0.162
7	(base outcome		
8			
age i, jt-1,t-1	-0.008	-0.23	0.815
2.sex i,j,t	0.293	0.54	0.589
education i, jt-1,t-1			
1	0.135	0.2	0.842
2	0.871	0.93	0.353
3	0.283	0	1
ecommerce i, jt-1, t-1	1.495	0.32	0.752
IMpen i, jt-1, t-1	0.112	0.76	0.447
ecommerce_Residual i, jt-1, t-1	-8.184	-1.15	0.249
_cons	-15.141	-0.02	0.988
Industry dummy for all outcom	Yes		
Year dummy for all outcomes	Yes		
Number of obs	9,344		
LR chi2	963.35		
Prob > chi2	0.00		
Pseudo R2	0.0408		
Log likelihood	-11310.391		

total proxies of technology			
Outcomes / variables	Coef.	z	P>z
1			
age i, jt-1,t-1	0.066	3.03	0.002
2.sex i,j,t	0.203	0.53	0.598
education i, jt-1,t-1			
1	-0.042	-0.1	0.922
2	0.721	1.05	0.294
3	12.798	0.01	0.993
ICTUSE i, jt-1, t-1	1.057	0.99	0.325
robot i, jt-1, t-1	0.041	0.8	0.425
ecommerce i, jt-1, t-1	2.928	0.71	0.475
IMpen i, jt-1, t-1	0.020	0.18	0.86
ICTUSE_Residual i, jt-1, t-1	3.139	1.15	0.252
robot_Residual i, jt-1, t-1	-0.08397	-0.54	0.591
ecommerce_Residual i, jt-1, t-1	0.154	0.08	0.939
_cons	1.363	1.02	0.306
2			
age i, jt-1,t-1	0.095	4.39	0
2.sex i,j,t	0.340	0.89	0.376
education i, jt-1,t-1			
1	-0.056	-0.13	0.897
2	0.899	1.31	0.19
3	13.210	0.01	0.993
ICTUSE i, jt-1, t-1	1.212	1.13	0.258
robot i, jt-1, t-1	0.046	0.9	0.37
ecommerce i, jt-1, t-1	3.218	0.78	0.432
IMpen i, jt-1, t-1	0.063	0.56	0.573
ICTUSE_Residual i, jt-1, t-1	2.560	0.94	0.349
robot_Residual i, jt-1, t-1	-0.073	-0.47	0.638
ecommerce_Residual i, jt-1, t-1	0.069	0.03	0.973
_cons	0.147	0.11	0.912
3			
age i, jt-1,t-1	0.075	3.36	0.001
2.sex i,j,t	0.239	0.6	0.547
education i, jt-1,t-1			
1	0.298	0.66	0.509
2	1.480	2.11	0.035
3	13.441	0.01	0.993
ICTUSE i, jt-1, t-1	0.998	0.92	0.358
robot i, jt-1, t-1	0.032	0.58	0.559
ecommerce i, jt-1, t-1	2.123	0.51	0.609
IMpen i, jt-1, t-1	0.038	0.33	0.743
ICTUSE_Residual i, jt-1, t-1	4.747	1.69	0.091
robot_Residual i, jt-1, t-1	-0.084	-0.53	0.598
ecommerce_Residual i, jt-1, t-1	0.165	0.08	0.936
_cons	-1.142	-0.82	0.411
4			
age i, jt-1,t-1	0.092	4.13	0
2.sex i,j,t	0.477	1.2	0.231
education i, jt-1,t-1			
1	0.366	0.81	0.42
2	1.789	2.55	0.011
3	14.009	0.01	0.992
ICTUSE i, jt-1, t-1	0.639	0.58	0.561
robot i, jt-1, t-1	0.041	0.73	0.466
ecommerce i, jt-1, t-1	3.429	0.83	0.404
IMpen i, jt-1, t-1	0.121	1.06	0.289
ICTUSE_Residual i, jt-1, t-1	2.754	0.98	0.328
robot_Residual i, jt-1, t-1	-0.059	-0.37	0.709
ecommerce_Residual i, jt-1, t-1	-0.059	-0.03	0.977
_cons	-2.572	-1.81	0.071
5			
age i, jt-1,t-1	0.071	3.15	0.002
2.sex i,j,t	0.362	0.9	0.369
education i, jt-1,t-1			
1	0.130	0.28	0.777
2	1.390	1.97	0.049
3	-0.641	0	1
ICTUSE i, jt-1, t-1	1.258	1.14	0.255
robot i, jt-1, t-1	0.047	0.85	0.396
ecommerce i, jt-1, t-1	2.209	0.53	0.599
IMpen i, jt-1, t-1	0.003	0.02	0.981
ICTUSE_Residual i, jt-1, t-1	3.476	1.22	0.223
robot_Residual i, jt-1, t-1	-0.093	-0.58	0.559
ecommerce_Residual i, jt-1, t-1	-0.382	-0.18	0.858
_cons	-1.343	-0.95	0.345
6			
age i, jt-1,t-1	0.092	4.14	0
2.sex i,j,t	0.493	1.25	0.212
education i, jt-1,t-1			
1	0.235	0.52	0.601
2	1.783	2.56	0.011
3	13.820	0.01	0.993
ICTUSE i, jt-1, t-1	0.903	0.83	0.406
robot i, jt-1, t-1	0.035	0.65	0.516
ecommerce i, jt-1, t-1	3.079	0.75	0.454
IMpen i, jt-1, t-1	0.080	0.7	0.483
ICTUSE_Residual i, jt-1, t-1	3.870	1.39	0.165
robot_Residual i, jt-1, t-1	-0.087	-0.55	0.584
ecommerce_Residual i, jt-1, t-1	-0.047	-0.02	0.982
_cons	-1.758	-1.27	0.204
7	(base outcome		
8			
age i, jt-1,t-1	-0.012	-0.36	0.719
2.sex i,j,t	0.436	0.78	0.434
education i, jt-1,t-1			
1	0.174	0.25	0.8
2	0.842	0.89	0.372
3	-0.013	0	1
ICTUSE i, jt-1, t-1	0.203	0.11	0.909
robot i, jt-1, t-1	0.015	0.17	0.865
ecommerce i, jt-1, t-1	1.233	0.24	0.807
IMpen i, jt-1, t-1	0.097	0.66	0.507
ICTUSE_Residual i, jt-1, t-1	3.639	0.69	0.487
robot_Residual i, jt-1, t-1	0.637	1.45	0.146
ecommerce_Residual i, jt-1, t-1	-6.309	-0.76	0.448
_cons	-0.898	-0.42	0.676
Industry dummy for all outcome	Yes		
Year dummy for all outcomes	Yes		
Number of obs	8,820		
LR chi2	950.56		
Prob > chi2	0.00		
Pseudo R2	0.0425		
Log likelihood	-10708.156		

Source: Authors' estimation

Appendix II: Multinomial logistic regression for employment status, by sector

ICTUSE			
Outcomes / variables	Coef.	z	P>z
1			
age i, jt-1,t-1	0.077	4.48	0
2.sex i,j,t	0.007	0.02	0.982
education i, jt-1,t-1			
1	-0.017	-0.05	0.96
2	0.137	0.29	0.772
3	-1.069	-0.87	0.386
ICTUSE i, jt-1, t-1	0.914	0.73	0.465
ICTUSE i, j, t*dumfood	-4.873	-1.73	0.084
ICTUSE i, j, t*dumcloth	-5.602	-1.29	0.198
ICTUSE i, j, t*dumplas	2.863	0.37	0.71
ICTUSE i, j, t*dumelec	1.381	0.17	0.868
ICTUSE i, j, t*dumauto	1.084	0.24	0.813
IMpen i, j, t	0.076	0.86	0.389
totalincome i, jt-1, t-1	0.000	-0.55	0.583
ICTUSE_Residual i, jt-1, t-1	3.013	1.21	0.228
_cons	2.182	2.68	0.007
2			
age i, jt-1,t-1	0.108	6.33	0
2.sex i,j,t	0.111	0.39	0.696
education i, jt-1,t-1			
1	0.006	0.02	0.987
2	0.381	0.81	0.42
3	-0.471	-0.38	0.702
ICTUSE i, jt-1, t-1	0.968	0.77	0.439
ICTUSE i, j, t*dumfood	-6.162	-2.19	0.029
ICTUSE i, j, t*dumcloth	-2.948	-0.69	0.493
ICTUSE i, j, t*dumplas	2.831	0.37	0.713
ICTUSE i, j, t*dumelec	1.224	0.15	0.883
ICTUSE i, j, t*dumauto	0.227	0.05	0.961
IMpen i, j, t	0.102	1.16	0.245
totalincome i, jt-1, t-1	0.000	-0.95	0.342
ICTUSE_Residual i, jt-1, t-1	3.056	1.22	0.221
_cons	1.733	2.13	0.033
3			
age i, jt-1,t-1	0.082	4.73	0
2.sex i,j,t	0.059	0.2	0.841
education i, jt-1,t-1			
1	0.177	0.51	0.609
2	0.847	1.75	0.079
3	-0.965	-0.75	0.453
ICTUSE i, jt-1, t-1	1.022	0.81	0.418
ICTUSE i, j, t*dumfood	-4.433	-1.52	0.129
ICTUSE i, j, t*dumcloth	-5.679	-1.13	0.257
ICTUSE i, j, t*dumplas	3.133	0.41	0.685
ICTUSE i, j, t*dumelec	5.862	0.69	0.492
ICTUSE i, j, t*dumauto	-0.138	-0.03	0.977
IMpen i, j, t	0.083	0.92	0.355
totalincome i, jt-1, t-1	0.000	-0.18	0.857
ICTUSE_Residual i, jt-1, t-1	3.163	1.26	0.206
_cons	-1.131	-1.34	0.181
4			
age i, jt-1,t-1	0.095	5.43	0
2.sex i,j,t	0.238	0.81	0.418
education i, jt-1,t-1			
1	0.254	0.73	0.467
2	1.146	2.37	0.018
3	-0.066	-0.05	0.958
ICTUSE i, jt-1, t-1	0.318	0.25	0.804
ICTUSE i, j, t*dumfood	-4.129	-1.41	0.159
ICTUSE i, j, t*dumcloth	0.221	0.05	0.963
ICTUSE i, j, t*dumplas	2.218	0.29	0.775
ICTUSE i, j, t*dumelec	2.909	0.33	0.738
ICTUSE i, j, t*dumauto	1.650	0.34	0.731
IMpen i, j, t	0.148	1.67	0.095
totalincome i, jt-1, t-1	0.000	0.2	0.84
ICTUSE_Residual i, jt-1, t-1	2.970	1.19	0.236
_cons	-1.198	-1.42	0.155
5			
age i, jt-1,t-1	0.078	4.43	0
2.sex i,j,t	0.316	1.06	0.29
education i, jt-1,t-1			
1	0.252	0.71	0.477
2	0.985	2.01	0.044
3	-2.061	-1.3	0.194
ICTUSE i, jt-1, t-1	1.303	1.03	0.305
ICTUSE i, j, t*dumfood	-6.285	-2.02	0.043
ICTUSE i, j, t*dumcloth	-14.273	-2.16	0.031
ICTUSE i, j, t*dumplas	1.281	0.17	0.869
ICTUSE i, j, t*dumelec	-5.330	-0.6	0.546
ICTUSE i, j, t*dumauto	0.259	0.05	0.957
IMpen i, j, t	0.042	0.47	0.641
totalincome i, jt-1, t-1	0.000	-0.72	0.474
ICTUSE_Residual i, jt-1, t-1	3.235	1.29	0.197
_cons	-1.444	-1.67	0.096
6			
age i, jt-1,t-1	0.094	5.42	0
2.sex i,j,t	0.339	1.16	0.246
education i, jt-1,t-1			
1	0.013	0.04	0.97
2	0.948	1.97	0.049
3	-0.950	-0.75	0.452
ICTUSE i, jt-1, t-1	0.734	0.58	0.562
ICTUSE i, j, t*dumfood	-6.543	-2.15	0.032
ICTUSE i, j, t*dumcloth	-8.986	-1.66	0.098
ICTUSE i, j, t*dumplas	2.231	0.29	0.773
ICTUSE i, j, t*dumelec	3.943	0.46	0.646
ICTUSE i, j, t*dumauto	2.801	0.6	0.549
IMpen i, j, t	0.126	1.42	0.157
totalincome i, jt-1, t-1	0.000	0.8	0.421
ICTUSE_Residual i, jt-1, t-1	2.717	1.08	0.278
_cons	-1.302	-1.55	0.12
7	(base outcome)		
8			
age i, jt-1,t-1	-0.021	-0.83	0.408
2.sex i,j,t	0.258	0.57	0.57
education i, jt-1,t-1			
1	1.438	2.32	0.02
2	1.277	1.63	0.102
3	-10.925	-0.03	0.978
ICTUSE i, jt-1, t-1	-0.820	-0.39	0.696
ICTUSE i, j, t*dumfood	0.606	0.1	0.92
ICTUSE i, j, t*dumcloth	11.307	1.22	0.221
ICTUSE i, j, t*dumplas	10.495	0.99	0.323
ICTUSE i, j, t*dumelec	1.293	0.09	0.927
ICTUSE i, j, t*dumauto	-1.664	-0.22	0.825
IMpen i, j, t	-0.006	-0.05	0.961
totalincome i, jt-1, t-1	-0.001	-5.88	0
ICTUSE_Residual i, jt-1, t-1	2.738	1.05	0.295
_cons	0.712	0.52	0.605
Industry dummy for all out	Yes		
Year dummy for all outcom	Yes		
Number of obs	16,275		
LR chi2	2,426.36		
Prob > chi2	0.00		
Pseudo R2	0.0566		
Log likelihood	-20228.191		

robot			
Outcomes / variables	Coef.	z	P>z
1			
age i, jt-1,t-1	0.074	4.09	0
2.sex i,j,t	0.024	0.08	0.938
education i, jt-1,t-1			
1	-0.013	-0.04	0.97
2	0.257	0.51	0.611
3	-0.999	-0.81	0.418
robot i, j, t	5.835	0.43	0.667
roboti, j, t*dumfood	-5.000	-0.36	0.716
roboti, j, t*dumcloth			
roboti, j, t*dumplas	-3.627	-0.26	0.794
roboti, j, t*dumelec	-5.962	-0.44	0.66
roboti, j, t*dumauto	-5.808	-0.43	0.668
IMpen i, j, t	0.090	0.99	0.32
totalincome i, jt-1, t-1	0.000	-0.62	0.533
robot_Residual i, jt-1, t-1	0.138	0.94	0.345
_cons	1.830	1.71	0.088
2			
age i, jt-1,t-1	0.105	5.81	0
2.sex i,j,t	0.184	0.6	0.548
education i, jt-1,t-1			
1	-0.023	-0.06	0.95
2	0.449	0.89	0.374
3	-0.502	-0.41	0.683
robot i, j, t	9.986	0.74	0.461
roboti, j, t*dumfood	-9.166	-0.67	0.504
roboti, j, t*dumcloth			
roboti, j, t*dumplas	-7.899	-0.57	0.568
roboti, j, t*dumelec	-10.111	-0.75	0.455
roboti, j, t*dumauto	-9.972	-0.74	0.461
IMpen i, j, t	0.122	1.34	0.179
totalincome i, jt-1, t-1	0.000	-0.84	0.402
robot_Residual i, jt-1, t-1	0.127	0.86	0.388
_cons	1.033	0.96	0.335
3			
age i, jt-1,t-1	0.081	4.44	0
2.sex i,j,t	0.084	0.27	0.789
education i, jt-1,t-1			
1	0.154	0.41	0.679
2	0.939	1.83	0.068
3	-0.878	-0.68	0.494
robot i, j, t	3.679	0.27	0.789
roboti, j, t*dumfood	-2.885	-0.21	0.836
roboti, j, t*dumcloth			
roboti, j, t*dumplas	-0.574	-0.04	0.967
roboti, j, t*dumelec	-3.789	-0.28	0.783
roboti, j, t*dumauto	-3.679	-0.27	0.789
IMpen i, j, t	0.087	0.94	0.346
totalincome i, jt-1, t-1	0.000	-0.27	0.788
robot_Residual i, jt-1, t-1	0.122	0.82	0.412
_cons	-0.506	-0.46	0.647
4			
age i, jt-1,t-1	0.093	5.03	0
2.sex i,j,t	0.319	1.01	0.311
education i, jt-1,t-1			
1	0.276	0.74	0.461
2	1.253	2.43	0.015
3	-0.077	-0.06	0.952
robot i, j, t	11.833	0.85	0.397
roboti, j, t*dumfood	-11.012	-0.78	0.436
roboti, j, t*dumcloth			
roboti, j, t*dumplas	-9.381	-0.66	0.511
roboti, j, t*dumelec	-11.940	-0.86	0.393
roboti, j, t*dumauto	-11.815	-0.85	0.398
IMpen i, j, t	0.163	1.78	0.075
totalincome i, jt-1, t-1	0.000	0.19	0.846
robot_Residual i, jt-1, t-1	0.135	0.89	0.374
_cons	-1.678	-1.49	0.136
5			
age i, jt-1,t-1	0.077	4.15	0
2.sex i,j,t	0.332	1.04	0.297
education i, jt-1,t-1			
1	0.222	0.58	0.559
2	1.073	2.06	0.039
3	-2.024	-1.28	0.202
robot i, j, t	-3.460	-0.25	0.806
roboti, j, t*dumfood	4.336	0.3	0.761
roboti, j, t*dumcloth			
roboti, j, t*dumplas	5.847	0.41	0.685
roboti, j, t*dumelec	3.408	0.24	0.809
roboti, j, t*dumauto	3.472	0.25	0.806
IMpen i, j, t	0.043	0.46	0.645
totalincome i, jt-1, t-1	0.000	-0.95	0.342
robot_Residual i, jt-1, t-1	0.158	1.05	0.295
_cons	-0.612	-0.54	0.589
6			
age i, jt-1,t-1	0.091	4.99	0
2.sex i,j,t	0.346	1.1	0.269
education i, jt-1,t-1			
1	0.031	0.08	0.934
2	1.010	1.97	0.049
3	-1.063	-0.84	0.401
robot i, j, t	14.457	1.04	0.298
roboti, j, t*dumfood	-13.664	-0.97	0.331
roboti, j, t*dumcloth			
roboti, j, t*dumplas	-11.731	-0.83	0.408
roboti, j, t*dumelec	-14.543	-1.05	0.295
roboti, j, t*dumauto	-14.459	-1.04	0.298
IMpen i, j, t	0.146	1.6	0.11
totalincome i, jt-1, t-1	0.000	0.78	0.433
robot_Residual i, jt-1, t-1	0.103	0.69	0.49
_cons	-0.979	-0.89	0.374
7	(base outcome)		
8			
age i, jt-1,t-1	-0.026	-0.95	0.341
2.sex i,j,t	0.441	0.92	0.357
education i, jt-1,t-1			
1	1.165	1.84	0.066
2	1.221	1.52	0.129
3	-10.922	-0.03	0.979
robot i, j, t	16.296	0.58	0.56
roboti, j, t*dumfood	-16.015	-0.57	0.568
roboti, j, t*dumcloth	0 (omitte		
roboti, j, t*dumplas	-12.637	-0.45	0.653
roboti, j, t*dumelec	-15.978	-0.57	0.568
roboti, j, t*dumauto	-16.179	-0.58	0.563
IMpen i, j, t	-0.071	-0.5	0.618
totalincome i, jt-1, t-1	-0.001	-6	0
robot_Residual i, jt-1, t-1	0.068	0.3	0.762
_cons	2.635	1.61	0.107
Industry dummy for all ou	Yes		
Year dummy for all outcor	Yes		
Number of obs	14,169		
LR chi2	2094		
Prob > chi2	0.00		
Pseudo R2	0.0547		
Log likelihood	-18082.257		

ecommerce			
Outcomes / variables	Coef.	z	P>z
1			
age i, jt-1,t-1	0.068	3.25	0.001
2.sex i,j,t	0.102	0.28	0.779
education i, jt-1,t-1			
1	-0.140	-0.34	0.734
2	0.706	1.04	0.299
3	19.366	0	1
ecommerce i, j, t	7.216	0.92	0.358
ecommercei, j, t*dumfood	-6150.1	-0.01	0.99
ecommercei, j, t*dumcloth	-20.571	-1.03	0.303
ecommercei, j, t*dumplas	-13.482	-1.55	0.12
ecommercei, j, t*dumelec	33.967	0.44	0.657
ecommercei, j, t*dumauto	56.161	0.76	0.448
IMpen i, jt-1, t-1	0.003	0.03	0.978
ecommerce_Residual i, jt-1, t-1	-0.982	-0.5	0.617
_cons	1.490	1.41	0.158
2			
age i, jt-1,t-1	0.100	4.79	0
2.sex i,j,t	0.220	0.6	0.546
education i, jt-1,t-1			
1	-0.099	-0.24	0.81
2	0.918	1.35	0.176
3	19.807	0	1
ecommerce i, j, t	7.281	0.93	0.354
ecommercei, j, t*dumfood	-6138.4	-0.01	0.99
ecommercei, j, t*dumcloth	-27.718	-1.39	0.164
ecommercei, j, t*dumplas	-10.396	-1.21	0.227
ecommercei, j, t*dumelec	45.304	0.59	0.553
ecommercei, j, t*dumauto	50.175	0.68	0.498
IMpen i, jt-1, t-1	0.042	0.35	0.723
ecommerce_Residual i, jt-1, t-1	-1.071	-0.55	0.585
_cons	1.055	1	0.316
3			
age i, jt-1,t-1	0.078	3.66	0
2.sex i,j,t	0.142	0.38	0.705
education i, jt-1,t-1			
1	0.290	0.67	0.501
2	1.547	2.23	0.025
3	20.190	0	1
ecommerce i, j, t	6.855	0.87	0.384
ecommercei, j, t*dumfood	-6156.4	-0.01	0.99
ecommercei, j, t*dumcloth	-30.464	-1.35	0.175
ecommercei, j, t*dumplas	-10.214	-1.16	0.245
ecommercei, j, t*dumelec	33.248	0.43	0.668
ecommercei, j, t*dumauto	55.038	0.74	0.46
IMpen i, jt-1, t-1	0.022	0.18	0.857
ecommerce_Residual i, jt-1, t-1	-0.751	-0.38	0.705
_cons	-0.996	-0.91	0.362
4			
age i, jt-1,t-1	0.094	4.37	0
2.sex i,j,t	0.332	0.88	0.379
education i, jt-1,t-1			
1	0.311	0.72	0.472
2	1.806	2.6	0.009
3	20.528	0	1
ecommerce i, j, t	7.688	0.98	0.328
ecommercei, j, t*dumfood	-6127.5	-0.01	0.99
ecommercei, j, t*dumcloth	-31.967	-1.41	0.158
ecommercei, j, t*dumplas	-8.922	-1.02	0.307
ecommercei, j, t*dumelec	30.698	0.39	0.695
ecommercei, j, t*dumauto	44.676	0.59	0.552
IMpen i, jt-1, t-1	0.099	0.83	0.406
ecommerce_Residual i, jt-1, t-1	-1.182	-0.59	0.552
_cons	-1.866	-1.7	0.089
5			
age i, jt-1,t-1	0.072	3.34	0.001
2.sex i,j,t	0.280	0.73	0.465
education i, jt-1,t-1			
1	0.050	0.11	0.909
2	1.387	1.99	0.047
3	-0.382	0	1
ecommerce i, j, t	6.421	0.81	0.416
ecommercei, j, t*dumfood	-6163.4	-0.01	0.99
ecommercei, j, t*dumcloth	-24.444	-1.08	0.279
ecommercei, j, t*dumplas	-8.516	-0.97	0.333
ecommercei, j, t*dumelec	0.229	0	0.998
ecommercei, j, t*dumauto	66.718	0.9	0.369
IMpen i, jt-1, t-1	-0.010	-0.08	0.937
ecommerce_Residual i, jt-1, t-1	-1.299	-0.63	0.528
_cons	-1.118	-1	0.317
6			
age i, jt-1,t-1	0.093	4.38	0
2.sex i,j,t	0.423	1.13	0.258
education i, jt-1,t-1			
1	0.126	0.29	0.769
2	1.761	2.56	0.011
3	20.38	0	1
ecommerce i, j, t	7.144	0.91	0.363
ecommercei, j, t*dumfood	-6170.2	-0.01	0.99
ecommercei, j, t*dumcloth	-29.895	-1.33	0.184
ecommercei, j, t*dumplas	-8.267	-0.95	0.34
ecommercei, j, t*dumelec	21.292	0.27	0.785
ecommercei, j, t*dumauto	27.607	0.37	0.713
IMpen i, jt-1, t-1	0.056	0.47	0.637
ecommerce_Residual i, jt-1, t-1	-1.128	-0.57	0.57
_cons	-1.355	-1.25	0.212
7	(base outcome)		
8			
age i, jt-1,t-1	-0.009	-0.27	0.788
2.sex i,j,t	0.339	0.62	0.533
education i, jt-1,t-1			
1	0.097	0.14	0.886
2	0.871	0.93	0.354
3	0.276	0	1
ecommerce i, j, t	7.267	0.91	0.363
ecommercei, j, t*dumfood	-6088	-0.01	0.99
ecommercei, j, t*dumcloth	-10830	-0.01	0.991
ecommercei, j, t*dumplas	-592.443	-0.7	0.484
ecommercei, j, t*dumelec	-56.367	-0.52	0.603
ecommercei, j, t*dumauto	14.797	0.17	0.863
IMpen i, jt-1, t-1	0.044	0.29	0.772
ecommerce_Residual i, jt-1, t-1	-3.019	-0.56	0.578
_cons	-0.716	-0.43	0.664
Industry dummy for all outcome	Yes		
Year dummy for all outcomes	Yes		
Number of obs	9,344		
LR chi2	1,023		
Prob > chi2	0.00		
Pseudo R2	0.0434		
Log likelihood	-11280.568		

Source: Authors' estimation

Appendix III: Multinomial logistic regression for employment status, by different imported products

Outcomes / variables	Coef.	z	P>z		Outcomes / variables	Coef.	z	P>z
1					**5**			
age $_{i, jt-1,t-1}$	0.075	4.15	0		*age* $_{i, jt-1,t-1}$	0.077	4.14	0
2.*sex* $_{i,j,t}$	0.050	0.16	0.871		2.*sex* $_{i,j,t}$	0.356	1.12	0.264
education $_{i, jt-1,t-1}$					*education* $_{i, jt-1,t-1}$			
1	-0.003	-0.01	0.994		1	0.222	0.59	0.558
2	0.267	0.53	0.598		2	1.067	2.05	0.04
3	-1.010	-0.82	0.413		3	-2.069	-1.3	0.192
robot $_{i, jt-1, t-1}$	0.014	0.29	0.774		*robot* $_{i, jt-1, t-1}$	0.019	0.38	0.706
IMpen_raw $_{jt-1, t-1}$	-0.002	-0.57	0.569		*IMpen_raw* $_{jt-1, t-1}$	-0.002	-0.41	0.682
IMpen_capital $_{jt-1, t-1}$	0.026	1.04	0.301		*IMpen_capital* $_{jt-1, t-1}$	0.027	1.1	0.273
IMpen_finish $_{jt-1, t-1}$	-0.073	-1.94	0.053		*IMpen_finish* $_{jt-1, t-1}$	-0.056	-1.23	0.218
totalincome $_{i, jt-1, t-1}$	0.000	-0.64	0.524		***totalincome*** $_{i, jt-1, t-1}$	0.000	-0.89	0.372
robot_Residual $_{i, jt-1, t-1}$	-0.025	-0.27	0.789		*robot_Residual* $_{i, jt-1, t-1}$	-0.023	-0.25	0.805
_cons	2.286	2.03	0.042		_cons	-0.383	-0.33	0.745
2					**6**			
age $_{i, jt-1,t-1}$	0.104	5.79	0		*age* $_{i, jt-1,t-1}$	0.091	4.97	0
2.*sex* $_{i,j,t}$	0.188	0.61	0.54		2.*sex* $_{i,j,t}$	0.369	1.18	0.238
education $_{i, jt-1,t-1}$					*education* $_{i, jt-1,t-1}$			
1	-0.010	-0.03	0.977		1	0.047	0.13	0.899
2	0.460	0.91	0.362		2	1.026	2	0.045
3	-0.524	-0.43	0.669		3	-1.079	-0.85	0.395
robot $_{i, jt-1, t-1}$	-0.001	-0.03	0.978		*robot* $_{i, jt-1, t-1}$	-0.002	-0.05	0.961
IMpen_raw $_{jt-1, t-1}$	0.001	0.19	0.849		*IMpen_raw* $_{jt-1, t-1}$	0.002	0.37	0.714
IMpen_capital $_{jt-1, t-1}$	0.024	0.98	0.327		*IMpen_capital* $_{jt-1, t-1}$	0.027	1.07	0.285
IMpen_finish $_{jt-1, t-1}$	-0.016	-0.43	0.666		*IMpen_finish* $_{jt-1, t-1}$	-0.025	-0.66	0.509
totalincome $_{i, jt-1, t-1}$	0.000	-0.79	0.431		***totalincome*** $_{i, jt-1, t-1}$	0.000	0.83	0.408
robot_Residual $_{i, jt-1, t-1}$	-0.036	-0.39	0.698		*robot_Residual* $_{i, jt-1, t-1}$	-0.040	-0.43	0.669
_cons	1.529	1.36	0.173		_cons	-0.612	-0.53	0.595
3					**7**	**ase outcome)**		
age $_{i, jt-1,t-1}$	0.081	4.43	0					
2.*sex* $_{i,j,t}$	0.102	0.32	0.746					
education $_{i, jt-1,t-1}$								
1	0.161	0.43	0.664					
2	0.952	1.85	0.064					
3	-0.892	-0.69	0.488					
robot $_{i, jt-1, t-1}$	-0.002	-0.04	0.965					
IMpen_raw $_{jt-1, t-1}$	0.000	0.09	0.931					
IMpen_capital $_{jt-1, t-1}$	0.026	1.06	0.29					
IMpen_finish $_{jt-1, t-1}$	-0.059	-1.41	0.159					
totalincome $_{i, jt-1, t-1}$	0.000	-0.21	0.837					
robot_Residual $_{i, jt-1, t-1}$	-0.021	-0.23	0.819					
_cons	-0.154	-0.13	0.894					
4					**8**			
age $_{i, jt-1,t-1}$	0.092	5.02	0		*age* $_{i, jt-1,t-1}$	-0.023	-0.84	0.403
2.*sex* $_{i,j,t}$	0.354	1.12	0.262		2.*sex* $_{i,j,t}$	0.380	0.8	0.427
education $_{i, jt-1,t-1}$					*education* $_{i, jt-1,t-1}$			
1	0.299	0.8	0.424		1	1.235	1.95	0.052
2	1.268	2.46	0.014		2	1.243	1.55	0.121
3	-0.073	-0.06	0.954		3	-10.892	-0.03	0.979
robot $_{i, jt-1, t-1}$	0.017	0.33	0.744		*robot* $_{i, jt-1, t-1}$	0.120	1.64	0.102
IMpen_raw $_{jt-1, t-1}$	0.003	0.69	0.49		*IMpen_raw* $_{jt-1, t-1}$	-0.010	-1.43	0.153
IMpen_capital $_{jt-1, t-1}$	0.029	1.18	0.239		*IMpen_capital* $_{jt-1, t-1}$	0.015	0.44	0.663
IMpen_finish $_{jt-1, t-1}$	-0.068	-1.59	0.113		*IMpen_finish* $_{jt-1, t-1}$	0.028	0.53	0.597
totalincome $_{i, jt-1, t-1}$	0.000	0.22	0.828		***totalincome*** $_{i, jt-1, t-1}$	-0.001	-5.92	0
robot_Residual $_{i, jt-1, t-1}$	-0.014	-0.15	0.88		*robot_Residual* $_{i, jt-1, t-1}$	0.095	0.64	0.523
_cons	-1.291	-1.1	0.27		_cons	2.384	1.38	0.169
Industry dummy for all outcomes	Yes							
Year dummy for all outcomes	Yes							
Number of obs	14,151							
LR chi2	2128.26							
Prob > chi2	0							
Pseudo R2	0.0557							
Log likelihood	-18037.456							

Note: Results of import penetration when ICTUSE or e-commerce is used are the same as in the case of robots

Source: Authors' estimation.