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Technological Advancement, Import Penetration, and Labour Markets: Evidence from Thai Manufacturing

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Abstract: *This paper examines the impacts of advanced technology on a possible change in workers' skills, wages, and employment due to such technological advancement. Three proxies of advanced technologies are used in the study: (i) information and communications technology, (ii) intensity of robot use, and (iii) value of e-commerce. Our study compares the effects of technological advancements 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 reallocation of workers between skilled and unskilled positions. The results vary amongst proxies of technology and sectors. It seems that workers in comparatively capital-intensive industries, including automotive, plastics and chemicals, and electronics and machinery, are the most affected by advanced technology. Dampened wage/income is found only in some proxies of technology and sectors. Our results show less concern of negative impacts induced by imports, particularly imports of capital goods and raw materials, on employment status and income than technological advancement.*

Keywords: Technological advancement, import penetration, labour markets

JEL Classification: F16, O30, O53

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1. Introduction

There is a long history of industries being revolutionised by waves of new technology. Clearly, the world is experiencing the Fourth Industrial Revolution that allows innovation invented in the three previous industrial revolutions connect to each other. This fourth revolution has witnessed major advances in technology, which will likely transform the structure and dynamics of many industries. Industry 4.0 is the next wave of digital and online transformation as industries are changed through, for example, further automation, artificial intelligence, robotics, cloud computing, 3D printing, big data analytics, and 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 impacts of advancing technologies on economic development in both developed and developing countries, especially on labour market outcome. With such advancing technologies, a wide range of job tasks in many sectors and in many countries would be fully or partially automated, recently including one considered as non-routine tasks, e.g. diagnosing disease from X-rays, picking orders in a warehouse, or driving cars (Bessen et al., 2019). Frey and Osborne (2017) and Ford (2015) argued that the pace of technological advancements, especially in terms of automation, artificial intelligence, and robotics, would be accelerating both in developed and developing countries, and the range of jobs affected by such technologies would be widening. Autor et al. (2003), Acemoglu and Autor (2011), and Acemoglu and Restrepo (2018b) developed a theoretical model showing that, with a task-based approach where the central unit of production is task whilst labour and capital have comparative advantages in different tasks, automation can create displacement effects resulting in a decline in the demand for labour and wage rate.

Interestingly, so far empirical studies on the impacts of advanced technology on labour market outcomes, which are mostly based on developed countries, are mixed. On the one hand, Cirera and Sabetti (2019), Crespi et al. (2019), Hou et al. (2019), Mairesse and Wu (2019), and Calvino (2019), using outcome measures from technological advancements, showed that, to some extent, technological advancements help create product innovation and improve labour market outcomes, including employment and productivity. Bartel et al. (2007), studying the impacts of new information technologies (IT), revealed that the adoption of new IT supports skilled workers whilst improving efficiency of all stages of production process. On the other hand, Arntz et al. (2016), Gaggl and Wright (2017), Acemoglu and Restrepo (2017), and Bessen et al. (2019) showed threats from technological advancements. Gaggl and Wright (2017) disclosed that non-routine, cognitive tasks are affected by the adoption of information and communications technology (ICT); however, there is only modest impact of ICT replacing routine, cognitive work. Acemoglu and Restrepo (2017) showed the negative effects of robots on employment and wages across commuting zones in the United States (US). Bessen et al. (2019) pointed out that automation decreases the probability of day works but not wage rate.

With unclear impacts of advanced technology on labour market outcomes, this study aims to examine such impacts on the labour market of developing countries, like the Thai labour market during 2012–2017 as a case study. This study contributes to the existing literature in three ways. First, whilst previous studies analysed the impacts of advanced technology on labour market outcomes, either employment levels or wage or both, this study examines a possible change in skills and wages of workers that could be induced by technological advancements, and the possibility of employed workers becoming unemployed due to such technological changes. Our analysis used both whole data set of the manufacturing sector and an individual sector. Autor and Salomons (2018) argued that advanced technology may only reallocate employment but will not depress overall demand for labour. In addition, to confirm the effects of technological advancement on wage and income, the wage equation is applied among workers over time using information of the whole manufacturing sector and individual sector.

Second, this is different from other studies in the sense that technological advancements are proxied by three key aspects 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 technology involvements in supply chains. ICT use and the value of e-commerce in the industry are utilised to capture possible technological involvements in inbound and outbound activities. Robots are used in industries to capture the possible impacts of technological advancements in internal production. Third, since trade, particularly import penetration, is another paramount force shaping the labour market, this study compares the effects of technological advancements on labour market outcomes with import penetration. Only a few studies – such as those of Autor et al. (2015) and Acemoglu and Restrepo (2017) – compared the effects of two forces, but their works still concentrated only on developed countries. In addition, whilst previous studies examined the impacts of penetration in terms of total imports, this study investigates penetration from the perspectives of finished products, capital, and raw materials.

The rest of the paper is structured as follows. Section 2 provides a literature survey on the impacts of technological advancements on the labour market. Section 3 presents policy changes towards Industry 4.0 in Thailand and how technology has progressed so far in the country. Section 4 discusses the empirical model and data sources whilst Section 5 shows the empirical results. The last section concludes with key findings and provides policy inferences.

2. Literature Survey

There is a long history of industries being revolutionised by waves of new technology. With advancing technologies, there are concerns about their impacts on economic development in both developed and developing countries, especially on labour market outcomes. However, studies about such impacts are mixed. On the one hand, some studies showed that technological advancements, to some extent, help improve labour market outcomes. For example, Beaudry et al. (2006) examined the impacts of technology adoption on city-level outcomes, mainly focusing on abundance of skilled labour and wages during 1980–2000. Skilled labour refers to workers who have at least some college education. Technology adoption is measured by personal computer (PC) intensity, PCs per employee of each city. Cities that aggressively adopt PCs have a relative abundance of skilled labour and witness the significant increase in relative wages. Bartel et al. (2007) studied the impacts of new IT on productivity and worker skills of valve manufacturing during 1999–2003. The results showed that adoption of new IT supports skilled workers whilst improving efficiency in all stages of the production process. Meanwhile, the adoption of new IT helps shift from mass production to more customised valve products.

Cirera and Sabetti (2019) studied the impacts of innovation on employment in 53 developing countries in 2013–2015. Innovation in this study is examined in terms of outcome measures, i.e. either product, process, or organisation innovation. The study applied that of Harrison et al. (2014) as a base model where the two types of products – old and new – can generate demand corresponding to those products. Using a cross-sectional analysis of both manufacturing and services, they showed that product innovation increases employment, and the effect is more than job losses due to cannibalisation of old products, particularly in the high-tech manufacturing sector. The impact of process and organisational innovations on employment seems negligible. Graetz and Michaels (2018) examined the implications of the use of robots on labour productivity, total factor productivity, output prices, and employment in 1993–2007 for 17 countries. The results showed that robot use contributes positively to labour and factor productivity growth thereby lowering output prices. Robots have insignificant effects on employment across a panel of countries and industries, but they reduce the employment share of low-skilled workers. Dauth et al. (2018) found the positive impact of robotics on wage and no impact on total employment.

Crespi et al. (2019), Hou et al. (2019), and Mairesse and Wu (2019) also applied the model based on Harrison et al. (2014) in examining the impacts of innovation on employment. Crespi et al. (2019) used the model for Chile, Uruguay, Costa Rica, and Argentina during 1995–2012 whilst Hou et al. (2019) applied that for the countries of the European Union and

China in 1999–2006 and Mairesse and Wu (2019) for China in 1999–2006. Note that Mairesse and Wu (2019) extended Harrison et al. (2014) by splitting output into domestic and exports, both of which are decomposed further into new and old products. The results of these three papers resembled those of Cirera and Sabetti (2019). Calvino (2019) applied different underlying theories of production and competition for Spain during 2004–2012 in examining the impact of innovation on employment. As in the previous studies, product innovation positively affects employment growth of both fast-growing and shrinking firms. However, the effect of process innovation on employment is insignificant, except in new production methods or auxiliary processes such as IT, which could stimulate employment growth at the lower end of its conditional distribution. Barbieri et al. (2019) used different underlying theories of production and competition for Italy during 1998–2010. However, instead of using outcome measures for innovation, they used input measures, i.e. research and development and innovation expenditure, to represent innovation. Innovation tends to have a positive – though the magnitude is rather small – impact on employment.

On the other hand, several empirical studies found negative impacts of technological advancements on labour market outcomes. Arntz et al. (2016), for example, followed an occupation-based approach proposed by Frey and Osborne (2013) but considered the heterogeneity of workers' tasks within occupations to determine the risk of automation for jobs in 21 countries of the Organisation for Economic Co-operation and Development (OECD). On average, the threat from technological advances seemed to exist but the results differed across OECD countries. Gaggl and Wright (2017) studied the effect of ICT adoption on employment and wage distribution. ICT adoption is proxied by the number of workers using a PC and the number of PCs in the workplace. The result showed that the adoption of ICT affects non-routine, cognitive tasks whilst it only modestly impacts the replacement of routine, cognitive work.

Bessen et al. (2019) estimated the impact of automation on individual workers by using Dutch microdata – and all are in private non-financial industries – in 2000–2016. Direct measures of automation at the firm level – i.e. automation costs defined as costs of third-party automation services, including non-activated purchases of custom software and costs of new software releases – are employed in the study. The paper showed that automation decreases the probability of day works, which leads to a 5-year cumulative wage income loss of about 8% of 1 year's earnings, but wage rates are not significantly affected by automation. The impacts of automation are more gradual and displace far fewer workers than mass layoffs. Frey and Osborne (2017) examined the impacts of future computerisation on US labour market outcomes, composed of wages and educational attainment. They applied a Gaussian process to estimate the probability of computerisation for 702 detailed occupations. The author showed that around 47% of total US jobs has a high probability of being computerised, especially those in transportation, logistics, and office and administrative support. Wages and educational attainment exhibit a strong negative relationship with the probability of computerisation.

Acemoglu and Restrepo (2017) examined the impacts of industrial robots on employment and wages in the US during 1990–2007 on the US local labour market. They used a model in which robots compete against human labour in producing different tasks. The results showed that robots negatively affect jobs and wages across commuting zones. However, the negative impact arising from robots is relatively smaller due to the relatively few robots in the US economy at that time. Acemoglu and Restrepo (2017) argued that if robots were used widely in the future, the aggregate implications could be much more sizeable. Autor et al. (2017) assessed the fall in labour share based on the rise of superstar firms. They applied US Economic Census data for 3 decades during 1982–2012. The results showed that industries where concentration rises most tend to have the largest decline in labour share. If technological changes advantage the most productive firms in each industry, product market concentration increases from the dominance of superstar firms thereby reducing aggregate labour share. Autor et al. (2017) showed that the fall in the labour share is driven mainly by firm reallocation rather than a fall in labour share within firms; this occurs greatly in sectors with increased market concentration.

However, some studies arguing the impacts of technological advancements on labour market were unclear, depending on conditions in labour markets and production structure. Acemoglu and Restrepo (2018a, 2018b, 2019) developed a conceptual framework to understand how machines replace human labour and how jobs and wages are affected. In such task-based framework, automation is modelled as the expansion of the set of tasks that can be performed by capital and can replace labour. In addition to automation, the model introduces another type of technological change that leads to more complex tasks than existing ones. It is assumed that labour tends to have more comparative advantage in these new tasks than automation. In the short run, a displacement effect in which automation can replace labour could occur 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 can remain stable even in the face of rapid automation. Acemoglu and Restrepo (2018b) clearly argued that the presence of a displacement effect may eventually not reduce demand for labour due to three channels, namely, productivity channel, capital accumulation, and expansion of automation. Yet, Acemoglu and Restrepo (2019) illustrated productivity improvement in non-automated tasks induced by automation technology, and in which technology creates new tasks reinstating labour into a broader range of tasks that could counterbalance the 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 argued that technological innovations replace workers with machines. But 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 and between-industry compositional changes – and increase final demand. The harmonised cross-country and cross-industry data covering 19 countries of the Organisation for Economic Co-operation and Development (OECD) during 1970–2007 were used. They showed that automation directly displaces employment and reduces labour's share of value added in the industries. However, there is another effect from inter-industry demand linkages and final demand countering employment displacement. There is no evidence of indirect effect in countering the negative impact of the aggregate fall in the labour share. Dauth et al. (2018), using data from Germany's labour market in 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 impacts of robots on individual workers and showed that 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, few studies – such as Autor et al. (2015) and Acemoglu and Restrepo (2017) – compared the impacts of technological advancements with those of imports. In fact, recently both technology and trade were set as two important sources shaping labour markets, especially in developed countries. For trade, Autor et al. (2015) argued that trade with lower-wage countries tends to depress wages and employment in industries, occupations, and regions, exposing import penetration They examined the impacts of technological change and trade on the US labour market within 722 commuting zones. The results showed that trade competition, especially from Chinese imports, leads to noticeable declines in manufacturing jobs in all major occupation groups, including managerial, professional, and technical jobs. Particularly, 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 occupations. Acemoglu and Restrepo (2017), as mentioned, also supported the findings of Autor et al.

(2015), i.e. the impacts of imports from lower-wage countries, China and Mexico, on employment and wages are relatively larger than those of technological advancements.

3. Technological Advancements in Thailand

Many countries, including Thailand, have formulated and implemented Industry 4.0 policies. The Thai government has been formulating Industry 4.0 policies since 2016 to transform the economy into a value-based one. To do so, a policy package is introduced, which is the combination between picking-up the winner types of industrial policy and economic corridor framework where economic agents are well connected along a defined geography. The government selected the 10 newly targeted industries to hopefully serve as new and more sustainable growth engines. These 10 industries are equally divided into two segments, five S-curved and five new S-curved industries. The five S-curved industries include new-generation automotive, smart electronics, affluent medical and wellness tourism, agriculture and biotechnology, and food for the future. The five new S-curved industries include manufacturing robotics, medical hub, aviation and logistics, biofuels and biochemicals, and digital industries. In the latter, the Eastern Economic Corridor (EEC) – the newest special economic zone – was established in 2017 to achieve industrial transformation under Thailand 4.0. The EEC straddles the three eastern provinces of Thailand – Chonburi, Rayong, and Chachoengsao –located off the coast of the Gulf of Thailand. It covers a total area of 13,285 square kilometres. The government hopes to complete the EEC by 2021, turning these provinces into a hub for technological manufacturing and services with strong connectivity to its ASEAN neighbours by land, sea, and air.[1]

Incentives through the Board of Investment (BOI) have been granted to support Thailand moving towards Industry 4.0. The BOI Investment Promotion Plan (2015–2021) was amended in 2014. Incentives provided by the BOI for the newly targeted industries are a combination of two sub-incentive schemes: activity-based incentives and merit-based incentives. For activity-based incentives, the 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,

[1] To enhance connectivity within and to the Eastern Economic Corridor (EEC), the Thai government has invested heavily on infrastructure to improve connectivity of these three provinces with the rest of the world. Total infrastructure investment amounting to US$43 billion will be channeled into the EEC by 2021. These investments will come from state funds, foreign direct investment, and through infrastructure development under a public–private partnership framework, such as expanding the Laem Chabang seaport (Laem Chabang Phase 3) aimed at transforming it into a marine hub of Southeast Asia. This could establish sea routes from the eastern provinces of Thailand to Myanmar's ongoing Dawei deep-sea port project, Cambodia's Sihanoukville port, and Viet Nam's Vung Tau port (US$2.5 billion).

biotech, advanced material, and digital. A1 refers to knowledge-based activities focusing on research and development (R&D) and design, and A2 represents incentives for infrastructure activities using advanced technology to create value added. For merit-based incentives, additional incentives are stipulated when activities add additional value to the economy in three areas: (i) competitiveness enhancements, (ii) decentralisation, and (iii) industrial area developments. Incentives for investors are in the form of corporate income tax exemption (the maximum is up to 13 years)[2], exemption of 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. Seemingly, incentives provided by the BOI in Thailand tend to be the most generous in Southeast Asia.[3]

ICT adoption is a key factor in harnessing the benefits of Industry 4.0. The first plan introduced the Thailand National IT Policy (1996–2000) in the mid-1990s to promote the use of ICT nationwide. Since then, several national plans have been launched, including the Thailand Information and Communication Technology (ICT) Policy Framework (2001–2010), the National Broadband Policy (2009), the Information and Communication Technology Policy Framework (2011–2020), the Universal Service Obligation Master Plan for Provision of Basic Telecommunication Services (2012–2014), and, more recently, the Digital Thailand Plan (2016). The plan in 2016 has five main elements, including (i) investing in both hard ICT-related infrastructure; (ii) e-government services; (iii) soft infrastructure (e.g. cybersecurity, 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 acquisition, instead of greenfield investment (Jongwanich and Kohpaiboon, 2020).

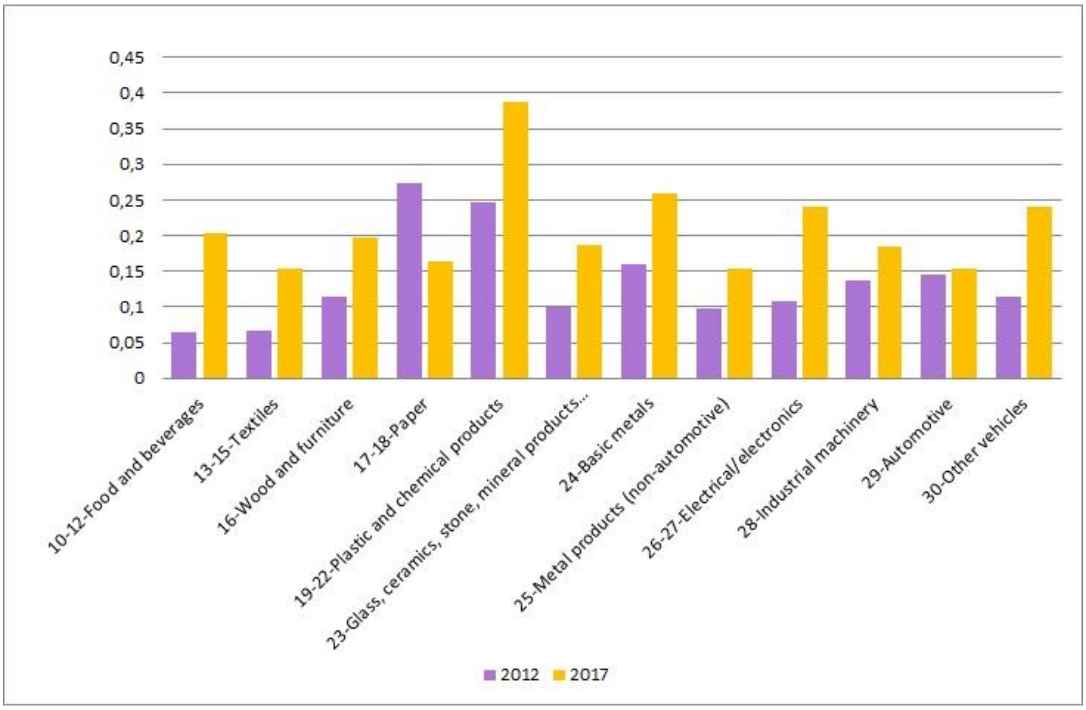
So far, Thailand has shown progress in technological advancements along with manufacturing supply chains, which could be divided into three key areas: (i) inbound (automated e-sourcing), (ii) outbound (e-commerce), and (iii) internal production (e.g. industrial robot uses) (UNCTAD, 2017). However, the progress tends to be concentrated in some industries. To delineate the relative important effects of technology involvements in supply chains, the uses of ICT and e-commerce in industries are applied to proxy possible

[2] Note that under section 24 of the Competitiveness Enhancement Act, corporate income tax exemption for targeted industries could be extended to 15 years, basing on judgement of the Board of Investment (BOI).

[3] In addition to the BOI incentives, the government committed 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 US$43 billion between 2019 and 2025. See Jongwanich and Kohpaiboon (2019) for a detailed discussion.

technological involvements in inbound and outbound activities whilst industrial robot uses in industries capture the advancements in internal production. Figure 1 shows the picture of ICT use per worker by industry in Thailand in 2012 and 2017. The figure shows significant use of ICT in all industries over the past 5 years, except in the automotive sector where ICT use was relatively stable during this period. However, the use of ICT in which the ratio exceeded 0.25 was revealed in four industries: plastics and chemicals, papers, basic metals, and electronics. For the automotive sector, it could be due to the nature of the industry where the development of technology use is more concentrated in internal production so that ICT uses were relatively stable during 2012–2017.

Figure 1: The Use of ICT, by Industry



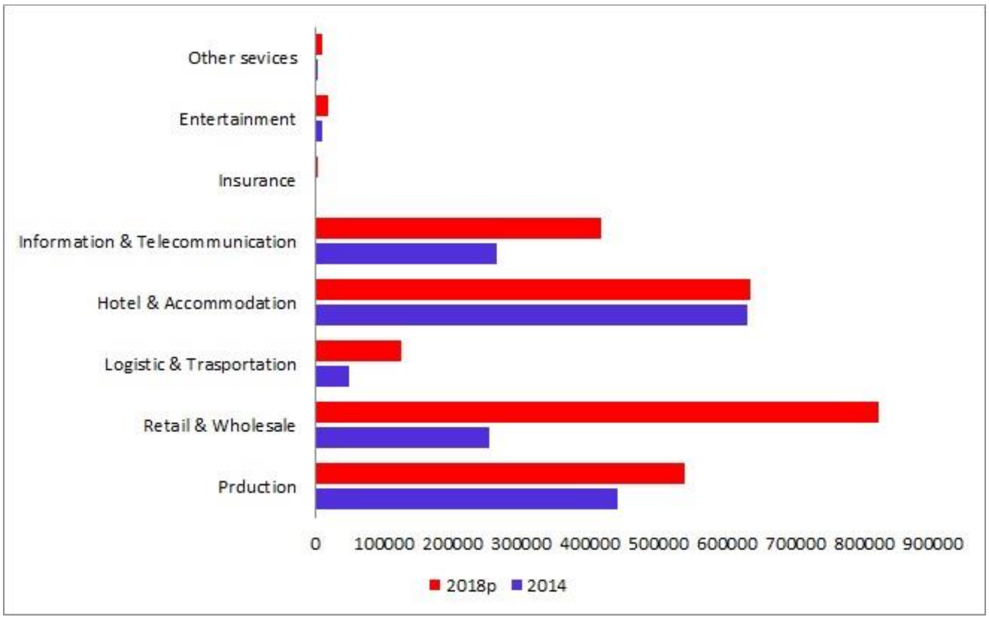
Note: The use of ICT is measured by the value of ICT used per worker.
Source: National Statistical Office (NSO) (2012-2017).

The use of e-commerce in the manufacturing sector expanded in 2014–2017, but its value was far lower than that in the service sector, especially retail and wholesale and hotel and accommodation (Figure 2A). In the manufacturing sector, paper, wood and furniture, plastics, and apparel and textile tended to increasingly use e-commerce over the period 2014–2017. By contrast, due to the nature of the industry where direct buying is still crucial, the use of e-commerce in automotive, electronics, and electrical appliances and machines were relatively low and stable. E-commerce utilised in the manufacturing sector is mostly around 91% in the form of a business-to-business (B2B) model whilst another 9% is in the form of business-to-consumer (B2C) model. Enterprises mostly used the benefits emerging from e-commerce, i.e. around 95% of total e-commerce users, and only 5% are small and medium-sized enterprises (SMEs). This contrasts with the service sector where most of the users are SMEs and belong to the B2C model.

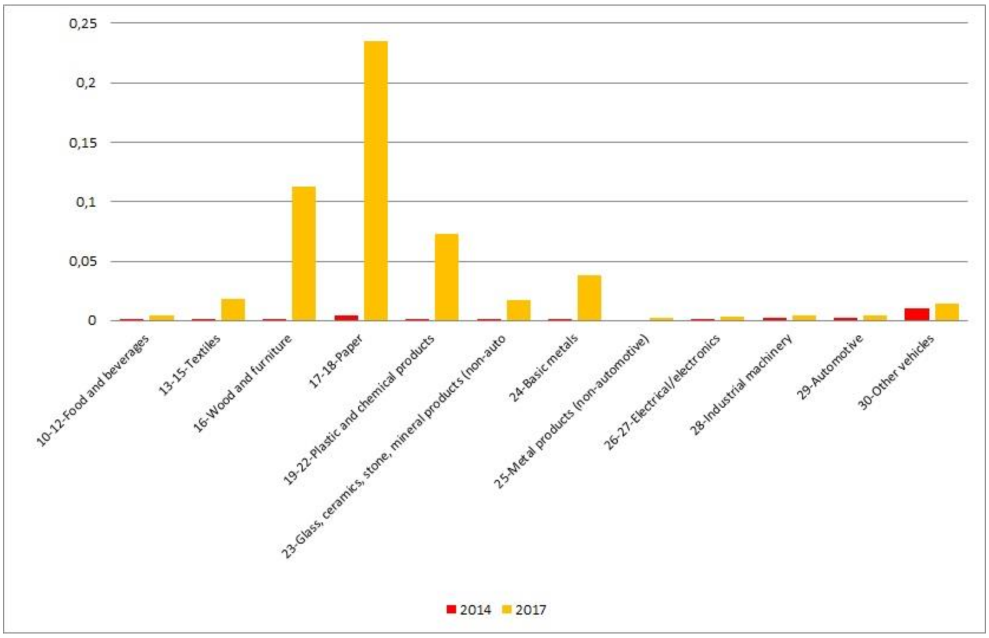
In industries, the intensity of robot use, measured by operational stock of robots per worker, increased in Thailand in 2012–2017. However, such increase was concentrated only in three industries: the automotive sector, electronics and electrical appliances, and plastics and chemical products. For metals and food, the use of robots was increasing in 2017 but the absolute value of operational stock of robots was relatively low, compared to the automotive and electronic sectors. A surge in robot use in Thai industries mentioned earlier was in line with a trend in the global economy (IFR, 2019). However, compared to the Republic of Korea and Singapore, the intensity of robot use in Thailand was far lower, especially in the automotive and electronic sectors.

Figure 2: The Use of E-commerce in Thailand

2A. The value of e-commerce, by industry



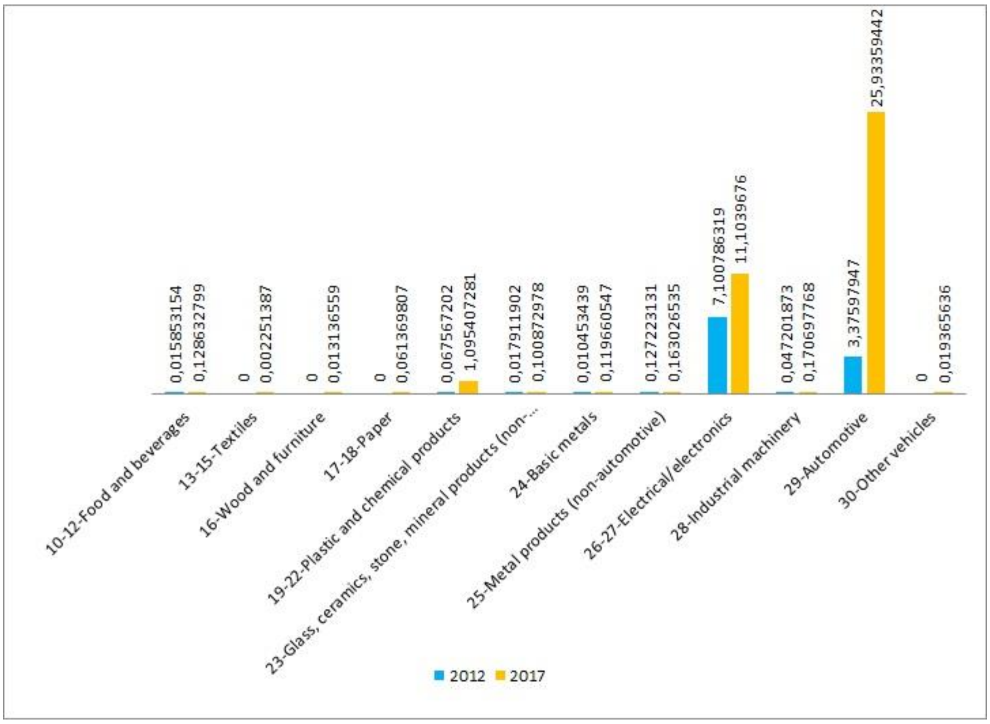
2B. The use of e-commerce adjusted, by gross output



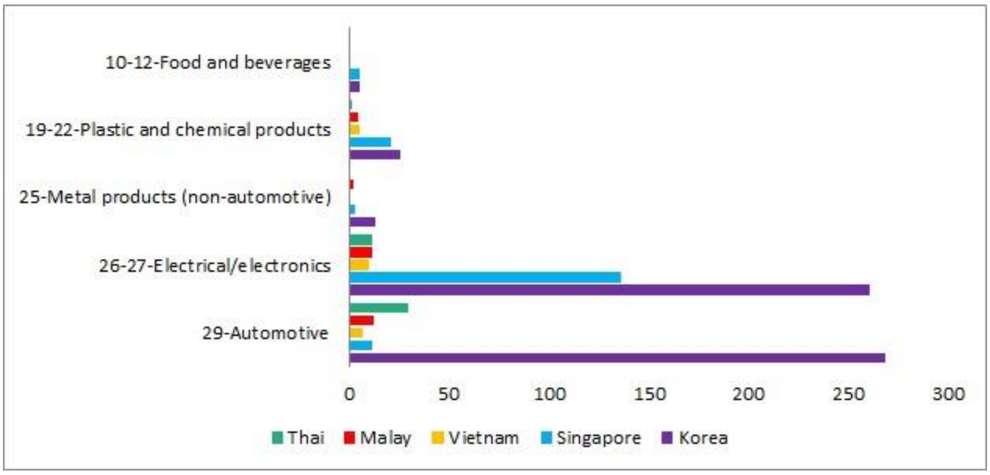
Source: Electronic Transactions Development Agency (ETDA) (2014 and 2018) and Office of the National Economic and Social Development Council (2014 and 2017).

Figure 3: Intensity of Robot Use in Thailand

3A. Intensity of robot use in Thailand



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



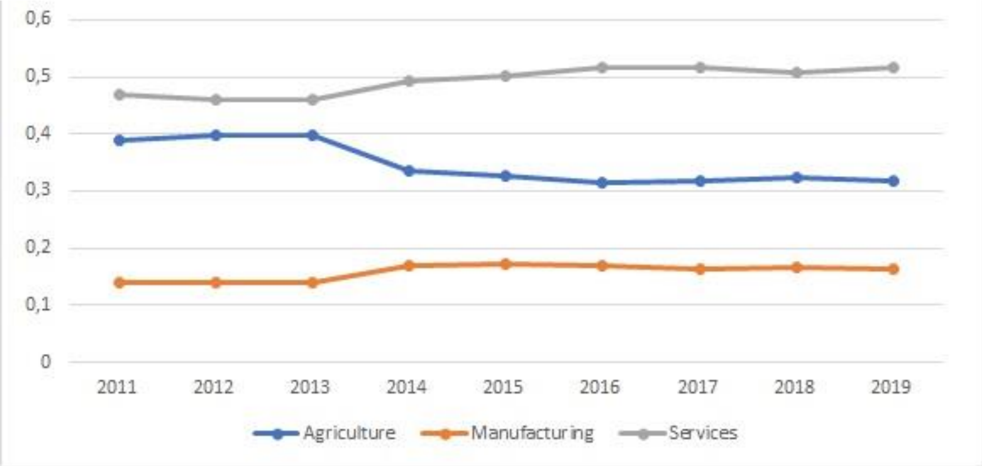
Note: Figure 3A shows the intensity of robot use in Thailand, measured by operational stock of robots per worker whilst Figure 3b presents the intensity of robot use in Thailand and other Asian countries in 2017.
Source: International Federation of Robotics (IFR) and National Statistical Office (NSO) (2012 and 2017).

When employment and wage in Thailand are considered, Figure 4 shows that the share of employment to total employment in the manufacturing sector was relatively stable at around 17% in 2014–2019 whilst that in the service sector had increased to around 52% since 2014, from around 47% in 2011. For the agriculture sector, the share of employment declined significantly from 40% in 2013 to around 32% in 2019. The labour force survey, in which 50% of samples at time t-1 are matched exactly with those at time t so that we can construct a 2-year panel data, shows that most workers moving to the service sector are from the agriculture sector.[4] Average wage, measured by baht per month, in the manufacturing and service sectors increased sharply in 2011–2014 and improved gradually in 2015–2019. Wage in agriculture by contrast had showed a relatively low and stable rate since 2011. The service and manufacturing sectors had a wage rate higher than the agriculture sector by around two times. Agriculture is the only sector in which wage rate in some years, e.g. in 2015 and 2018, was adjusted lower than headline inflation.

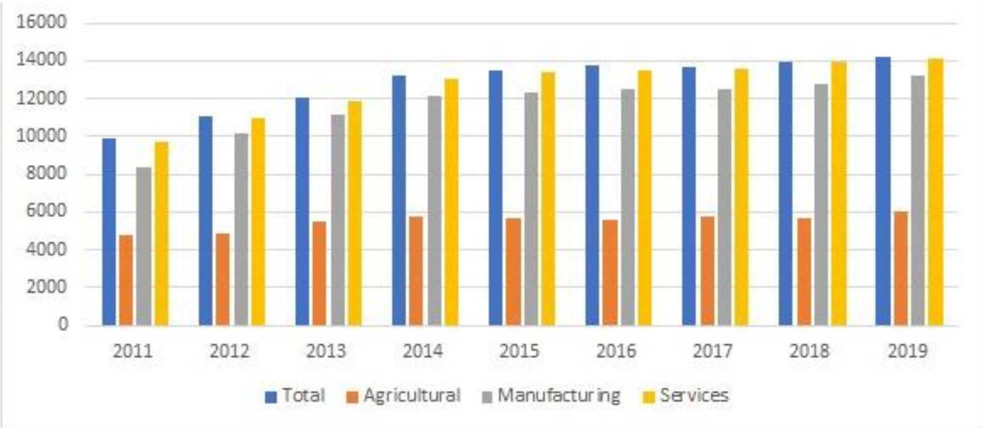
[4] Note that, in this study, we consider only workers in the manufacturing sector due to limited data in technological advancement.

Figure 4: Employment and Wage in Thailand, by Industry

4A. Share of employment by sector



4B. Wage (baht per month) by sector



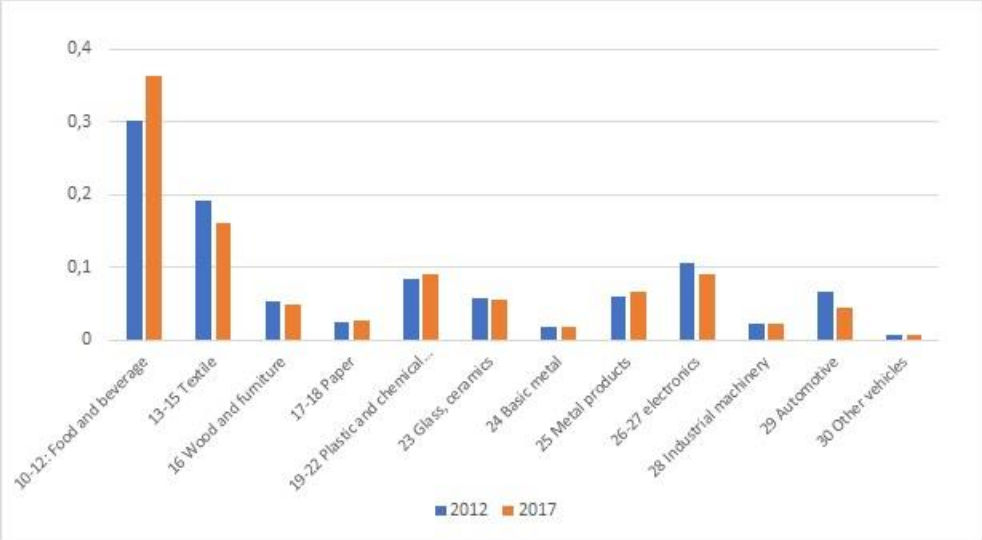
Source: National Statistical Office (2011-2019).

In the manufacturing sector, more than 30% of workers are in food and beverage, followed by clothing and textile, electronics, and plastics and chemicals. Comparing between 2012 and 2017, employment increased noticeably in the food sector whilst it showed a declining trend in some sectors, including clothing and textile, automotive, and electronics. For the other sectors, employment during these two periods was relatively stable. The picture of wage is different. Sectors, which have a relatively lower share of labour, such as in automotive, plastics and chemicals, and paper and electronics, tended to offer higher wages. In the clothing and textile and food sectors, workers receive lower wage (as well as net income)[5] whilst workers in automotive, plastic and chemicals, and paper receive the highest wage rate. Due to different patterns of wage and employment, this study examines the reallocation of workers along with wage changes.

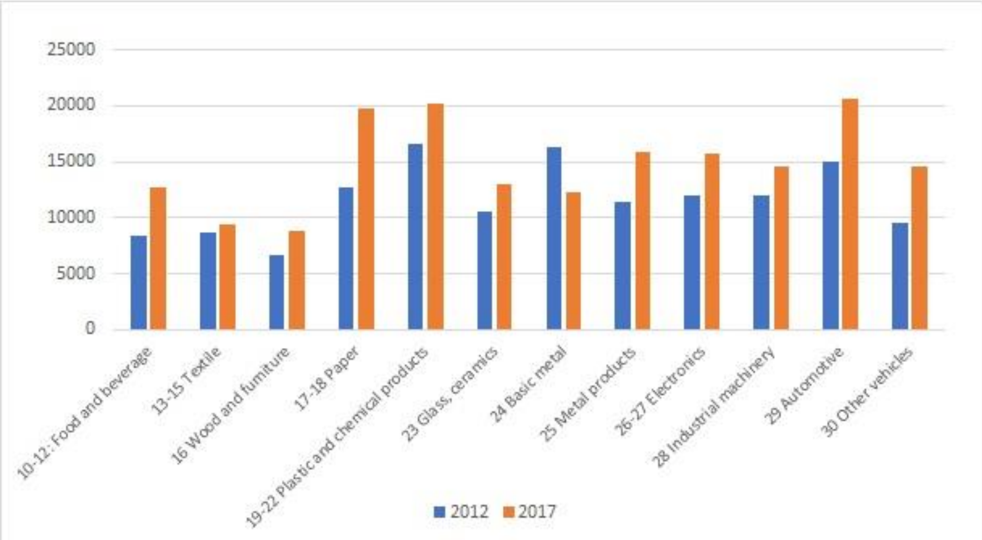
[5] Note that net income refers to wage and other benefits for workers, including overtime payments and bonus.

Figure 5: Employment and Wage in Thai Manufacturing Sector

5A. Share of employment by sector



5B. Wage (baht per month) by sector



Source: Labour force survey, National Statistical Office (2012 and 2017)

4. Empirical Model and Data Sources

4.1 Empirical Model

Empirical models applied in this study are based on a framework developed by Acemoglu and Restrepo (2018b) where the central unit of production is a task, and labour and capital have comparative advantages in different tasks. An example of a task-based approach is textile production. It requires many tasks, including production of fibre, production of yarn, production of fabric, pre-treatment, dyeing and printing, as well as design, marketing, and retail (see Acemoglu and Restrepo, 2018b). In each task, labour has different comparative advantages. For example, (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 factor-augmenting technology framework where, in general, labour demand is expanded along with productivity improvement, except in a case where elasticity of substitution between capital and labour is small. However, as Acemoglu and Restrepo (2018b) argued, the demand for labour may eventually not be reduced from the displacement effect when productivity improvement in a subset of tasks induces more demand for labour in non-automated tasks, if technology advancements increase capital intensity of production, and if the deepening of automation leads to intensifying the productive use of machines and stimulating more demand for labour.

To examine the impacts 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 used. 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 maintain the status quo. On changing tasks/jobs, workers can change skills in both directions, i.e. from skilled to unskilled and vice versa. Whilst there is no guarantee that changing jobs/tasks results in higher wage/income, this study brings examines the impacts of technological advancements on wage and income along with skill changes. Eight possible scenarios could occur from technological advancement when both employment status and wage/income are considered together, as follows: (1) workers who are employed at the same task/job and wage/income becomes higher; (2) workers employed at the same task/job, but wage/income is lower (or unchanged); (3) workers changing skills, from unskilled to skilled task/job, and wage/income is higher; (4) workers changing skills, from unskilled to skilled task/job, but wage/income becomes lower (or unchanged); (5) workers changing skills, from skilled to unskilled, but wage/income is higher; (6) workers changing skills, from skilled to unskilled, and wage/income is lower (unchanged); (7) workers who lose jobs; 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), 2012–2017), 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 the manufacturing supply chains – (i) inbound (automated e-sourcing), (ii) outbound (e-commerce), and (iii) internal production (e.g. factory automation) (UNCTAD, 2017) – to delineate the relative important effects of technology involvements in supply chains in the labour market. As mentioned in the analytical framework, trade is 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 variables included in examining the probability of being employed, unemployed, or changing jobs/skills as follows.

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

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

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

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

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

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

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

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

$EmployS_{i,j_t,t}$ = 7 for workers who lose jobs, and

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

$Technology_{j_{t-1},t-1}$ represents 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 uses per worker in sector j_{t-1} at time *t-1*

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

(3) $robot_{j_{t-1},t-1}$ = intensity of industrial robot uses (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 from 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 import at industry *j* to GDP.[6] 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 control variables for individual workers *i* in industry j_{t-1} at time t. This includes age, gender, and education.

[6] 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).

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

The impacts of advanced technology and import penetration are examined sector-wise. Five key sectors in Thailand are examined: (i) food and beverage, (ii) clothing and textile, (iii) plastics and chemicals, (iv) electronics and machinery, and (v) automotive. To investigate such impacts, interaction terms between proxies of technology/import penetration and industry-dummy variables are introduced in the model as in equation (2).

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

(2)

where $DumINDUS_{j_{t-1},t-1}$ is industry-dummy variables, composed of five key sectors, as mentioned earlier: (i) food and beverage (*dumfood*), (ii) clothing and textile (*dumcloth*), (iii) plastics and chemicals (*dumplas*), (iv) electronics and machinery (*dumelec*), and (v) automotive (*dumauto*).

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 identify $EmployS_{i,j_t,t}$. To ensure the impact of technological advancement on labour outcome, especially on wage/total income, another equation is introduced to examine the impacts of technological advancement on individual wage/income by using the whole observations in the manufacturing sector.[7] Equation (3) is a 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

[7] We also analysed the impacts of technological advancement on employment also by specifying a dummy variable equal to 1 if workers are employed, and 0, if not. The results are similar to those in equation (1) when half of the observations are used. We did not examine the effects of employment at the industry level due to limited data, especially when we tried to control for industry-specific effects (by including industrial dummy variables) and using two-stage least squares to redress the endogeneity problem.

wage plus overtime payments and bonus. As discussed in section 4.2, we also use lag values of technology and import penetration to examine such impacts on wage. The results are like those when current value (time *t*) of technology and import penetration are employed.

4.2 Data and Methodology

The Thai Labour Force Survey of the NSO, in 2012–2017, was used to construct employment status ($EmployS_{i,j_t,t}$). Although the NSO conducts a labour force survey every quarter, we conduct our analysis annually due to data collection of our technology variables.[8] To avoid overestimation of employment, which arises from temporary workers, in either the manufacturing or the service sectors, we use information from the third quarter of the labour force survey, i.e. during a harvest season. 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 were included in the Thai Labour Force Survey.

Table 1: Observations Included in the Thai Labour Force Survey

		Sampling	Sampling (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, adopted from the Thai Labour Force Survey.

From Table 1, the NSO divided samples in the labour force survey into two groups: 1C and 2C in 2012Q3 and 2C and 3C in 2013Q3. For every year, around 50% of samples in the labour force survey at time *t-1* were matched precisely with those at time *t*. In 2012Q3, a group of persons in 2C were the same persons in 2013Q3, and a group of persons in 3C in 2013Q3 were the persons in 2014Q3. Thus, from the survey, we can have a 2-year panel, which can be used to determine whether a worker changes jobs from skilled to unskilled or vice versa, or becomes employed to unemployed or vice versa, or maintains the status quo. Along with

[8] Note that a sampling method of each quarter is similar to that on an annual basis, i.e. only half of observations in the current quarter (e.g. second quarter) are matched with the previous quarter (first quarter).

changing employment status, we looked at how wage/income is adjusted over the 2-year panel. Note that in the construction of employment status and wage/income changes, we excluded workers who are not in the labour force, such as persons who are studying, disabled, older than 75 years, and those who do not specify their wage and other incomes. Due to limited data on technology variables, our analysis focused only on the manufacturing sector, as classified by the Thailand Standard of Industrial Classification, (TSIC 10-32), excluding the agriculture and the service sectors.

To determine workers' changing position from skilled to unskilled, or vice versa, we used job position as provided in the labour force survey. Eight principal positions in each industry were classified in the survey: (1) executive manager, (2) manager, (3) professional, (4) associate professional, (5) technicians, (6) services and sale workers, (7) clerical support work, (8) basic job (Table 2). A worker who moves up a position, e.g. from services and sale worker to technician or to associate professional, is classified as changing from an unskilled to skilled job. By contrast, a worker changing jobs, say, from associate professional to technician or to services and sale worker is classified as changing from a skilled to an unskilled job. As mentioned in the previous section, we used only job position and wage/total income as 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 position status are classified as employed workers and status quo, i.e. $EmployS_{i,j_t,t}$ = 1 or 2 depending on wage/income of those workers. By contrast, if employed workers at time *t-1* become unemployed at time *t*, they are classified as $EmployS_{i,j_t,t}$ = 7; vice versa, they are classified 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 sale worker	5111-5419		
7	Clerical support work	4110-4419		
8	Basic job	9111-9629		

Source: Thai Labour Force Survey (2012–2017).

Table 3 shows the frequency of employment status and distribution of workers amongst eight categories (*EmploySi,j,t*) during 2012–2017. It seems that *EmploySi,j,t* = 2 has the highest frequency, followed by *EmploySi,j,t* = 1. This shows that in the manufacturing sector, most workers in the survey were employed at the same occupation position and income level during the 2-year panel, on average around 50% of total observations. This is not surprising as our panel is short. In fact, it would be better if we could construct *EmploySi,j,t* from a long period of panel data as normally changing occupation positions takes time. However, the technology involved in moving the country towards Industry 4.0, such as robots/automation, could create a possible disruption on labour market outcome. Thus, analysing the impacts of such technological advancements through a short-panel data would probably yield some interesting findings. In addition, the survey revealed changes in workers' occupation positions during the 2-year panel. For example, in almost 10% of observations, workers moved from unskilled to skilled positions, with around 5% of workers receiving higher incomes. In almost another 10% of observations, workers changed positions from skilled to unskilled, with around 6% of workers receiving lower payments.

For technology variables, ICT use in industries was from the ICT survey of the NSO. Employment in industries was used to adjust the ICT data to be in terms of ICT use per worker. Data on e-commerce use in industries were from the value of e-commerce survey, Electronic Transactions Development Agency. Gross output at the industry level, from the Office of the National Economic and Social Development Council, was employed to adjusted e-commerce data. Data on operational stock of robots were from the International Federation of Robotics, and employment at the industry level was applied to adjust robotic data in terms of intensity of robot use. Import data were from UNCOMTRADE, United Nations Commodity Trade Statistics Database. We used import data at the 4-digit Harmonized System code and converted them into 2-digit International Standard Industry Classification using product concordance from the United Nations. Import data were adjusted by gross output at the 2-digit industry level. Note that import data were divided into finished, capital, and raw material products using Broad Economic Categories rev. 4. Age, gender, and education from the labour force survey were used as control variables in equations (1) to (3).

Table 3: Frequency of Employment Status and Income Changes ($EmployS_{i,j_t,t}$) amongst Eight Categories in 2012–2017

Total				2013 and 2012				2014 and 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 and 2014				2016 and 2015				2017 and 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 used total income, including salary, overtime payment, and bonus, to define employment status and income changes. The result is robust when wage is used instead of total income as salary is a key component in total income.
Source: Authors' calculation.

The data for analysing impacts of technological advancements and import penetration on change in employment status as well as income changes are summarised in Table 4. Per section 4.1, due to the data collection process in the labour force survey, around half of observations from the survey are thrown away when impacts of technological advancement on employment status and income change ($EmploySi,j,t$) are analysed. To ensure the impacts of technological advancement on labour outcome, especially wage/total income, another equation (equation 2) is employed to examine the impacts of technological advancement on individual income by using the whole observations in the 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

Notes: Data for e-commerce are from 2014 to 2017 while for other variables, data start from 2012 to 2017. Sex, which is equal to '1', represents male whilst '2' represents female. Education comprises four ranks, i.e. '0' represents lower or equal to primary education; '1' represents lower secondary education; '2', upper secondary and post-secondary education; '3', bachelor's degree and higher.
Source: Authors' calculation.

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.

The multinomial (polytomous) logistic and probit regression models are employed to analyse the impacts of technological advancement on employment status and income changes (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 the lag values of all independent variables are used in the model, the endogeneity problem is less of a concern in the model. However, to redress a 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 in which an endogenous predictor is instrumented in a first step using ordinary least squares (OLS) and then including the residuals in the second step in multinomial response model (Petrin and Train, 2010).[9]

[9] Regarding an instrument, we use a lag of its variable as an instrument for technology variable. In fact, it may be better to use other variables such as progress in technologies in other Asian countries as an instrument variable.

For the individual income/wage equation, two-stage least squares is employed to redress a problem of endogeneity, and lag values of independent variables are used as instruments.

5. Results

Table Appendix 1 presents the results of equation (1) by using multinomial logistic regression model where a possible endogeneity problem is redressed by using a control function approach.[10] Tables 6 and 7 show the results of equations (1) and (2), respectively, in terms of elasticity by using margin estimates. For Table 6, columns A–C, proxies of technology variables – namely, ICT, robot, and e-commerce – are estimated separately whilst in column D, these three proxies of technology are estimated together. The results of both methods are similar. However, based on indicators of explanatory power, such as LR-chi 2 and log likelihood, our analysis below is based on the former method where proxies of technology variables are separately estimated.

When the whole manufacturing sector is concerned, there is no evidence that advancement in technology had so far pushed workers out of the job market in Thailand. Coefficients associated with three proxies of technology – ICT use, robots, and e-commerce – in outcome no. 7 ($EmployS_{i,j,t} = 7$) are all statistically insignificant (Table 6, columns A–C).[11] This implies that statistically no worker becomes unemployed when more advanced technology is introduced in supply chains. However, when each sector is investigated separately, advancement in ICT use seems to increase the probability of workers in the food and beverage sector moving from employed to unemployed. 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. This implies that an increase in ICT use per worker by 1% raises the probability of workers becoming unemployed by 0.1% (Table 7, column A). The distribution of occupations in the food and beverage sector could explain such finding. Table 8 shows a high proportion of workers who were in a 'basic job' category, such as drivers who deliver products, sellers of products in a small shop, and cleaners, in the food and beverage sector.

However, with limited data, especially the value of e-commerce at the industry level, a lag of its technology variable is used instead.

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

[11] When all three proxies of technology are included together in equation (1), the results are similar to those when all proxies are included in the equation separately.

Workers in this category can be easily replaced by technology. In other sectors, a proportion of workers who were in a 'basic job' were far lower. For example, in the electronics and the automotive sectors, a proportion of workers who were in a basic job was only 4.5% and 6.1% of the total workforce, respectively. Interestingly, the results show that only ICT use, not robots or e-commerce, could push workers out of the job market. A relatively lower penetration of robots and e-commerce than ICT use may limit the impacts of these technologies on job destruction in Thailand. In other words, to some certain extent, the displacement effect induced by advanced technologies mentioned in Acemoglu and Restrepo (2018a, 2018b, 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, it tends to affect the reallocation of workers between skilled and unskilled positions.[12] This finding is similar to 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 with their original employer or switch occupations at their original workplace. Evidence from the Thai Labour Force Survey showed that around 70% of total workers who stayed at the same positions (outcomes no. 1 and 2) remained in the same industries. However, in contrast to Dauth et al. (2018), our evidence reveals that only 50% of total workers who changed their positions (outcomes no. 3 to 6) switched within the same industries (Figure 6A). For another 50%, changes in positions occurred across industries, and such reallocation was shown obviously in five industries: (i) food and beverage, (ii) electronics, (iii) plastics and chemicals, (iv) textiles, and (v) automotive (Figure 6B). In the food and beverage sector, however, the survey showed that reallocation of workers within the industry was almost two times higher than 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 a skilled to an unskilled position (Figure 6C).

[12] Note that due to the model setting, evidence of the reallocation of workers would not well provide evidence of the reinstatement effect where new tasks would be created from introducing new technology as shown in Acemoglu and Restrepo (2019). Jobs, which workers reallocate, could be either new or existing tasks in industries.

Figure 6: Proportion of Workers Who Switch Job Positions

Figure 6a: Proportion of workers who switch positions across industries

(% of total workers who switch position)

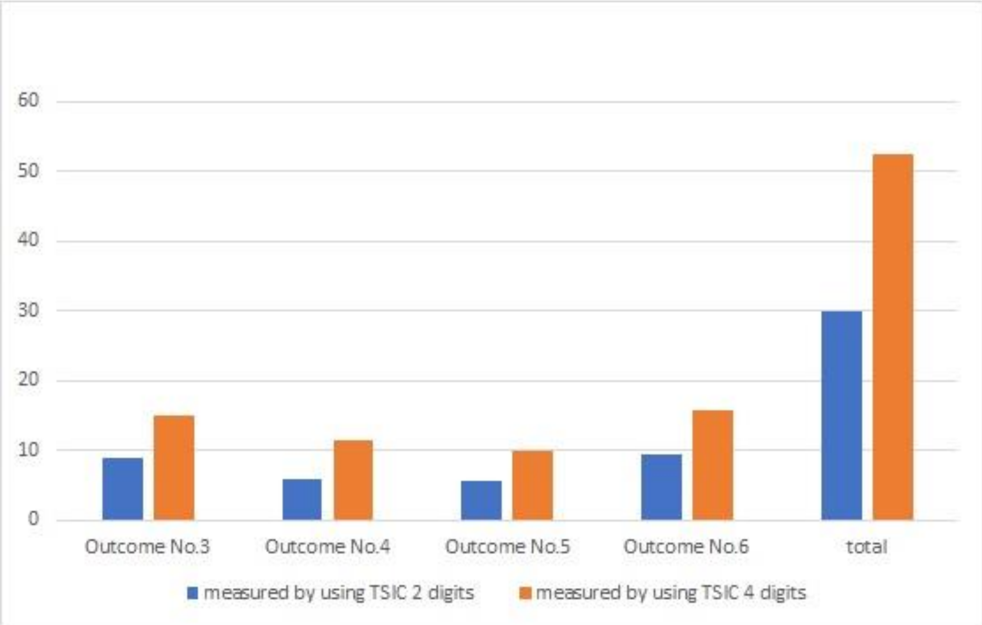


Figure 6b: Reallocation of workers across industries by sector

(% of total workers who switch positions)

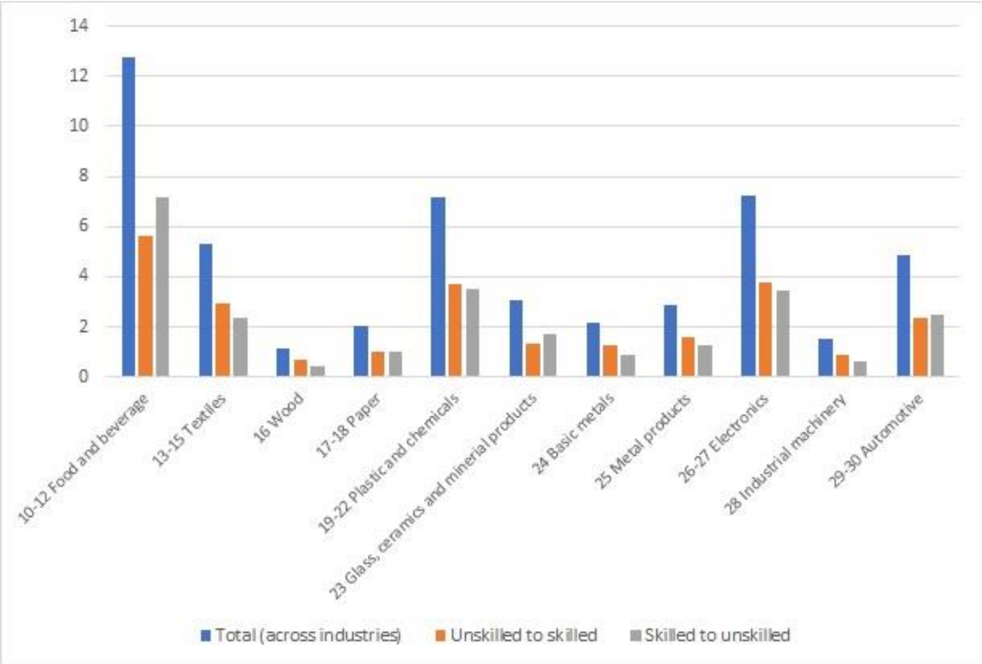
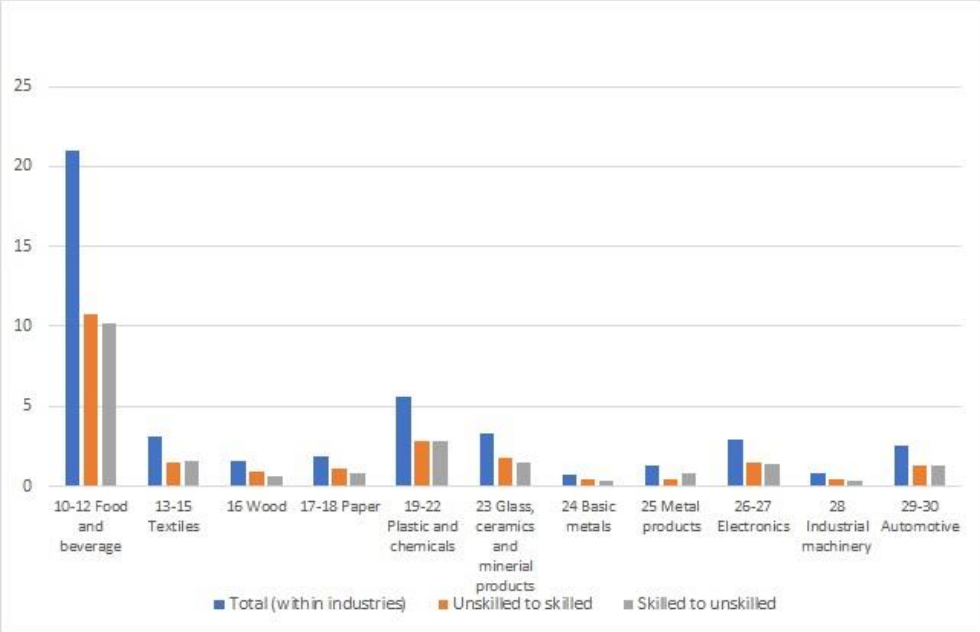


Figure 6c: Reallocation of workers within industries by sector

(% of total workers who switch positions)



Source: Authors' compilation from the Thai Labour Force Survey.

The results vary amongst proxies of technology and sectors. For ICT use in the entire manufacturing sector, the technology tends to lower the probability of shifting workers from unskilled to skilled positions. This is shown by a negative and statistical significance of coefficients associated with *ICTUSE* for outcome no. 4 ($EmploySi,j,t = 4$) (Table 6, column A). The negative sign reflects that a 1% increase in ICT use per worker results in a lower probability (0.07%) of workers moving from unskilled to skilled jobs. Sector-wise, such negative impacts are found in relatively high capital-intensive industries, including automotive, plastics and chemicals, and electronics and machinery. Coefficients associated with the interaction term between *ICTUSE* and industrial dummy variables in these sectors for outcome no. 4 ($EmploySi,j,t = 4$) are statistically insignificant (Table 7, column A).

Table 6: Impacts of Advanced Technology on Employment Status and Income Changes (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	0,002	0,18	0,013	1,11	0,001	0,14
2	0,005	0,94	-0,012	-1,17	0,000	-0,01
3	0,024	1,07	-0,026	-0,78	-0,019	-1,04
4	-0,073	-2.13**	0,009	0,23	0,016	1.68***
5	0,026	0,8	0,031	0,76	-0,020	-0,85
6	-0,029	-1,11	-0,023	-0,71	0,007	0,67
7	-0,074	-0,6	0,025	0,20	-0,115	-0,88
8	-0,180	-0,98	0,064	0,59	-0,066	-0,8
	*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
1	-0,036	-3.33***	-0,040	- 3.35***	-0,054	- 3.27***
2	0,012	2.01**	0,014	2.13**	0,016	1.98**
3	-0,030	-1,06	-0,035	-1,14	-0,024	-0,55
4	0,085	3.92***	0,089	3.93***	0,124	3.26***
5	-0,086	-2.27**	-0,101	-2.45**	-0,082	-1,53
6	0,051	2.37**	0,058	2.56***	0,043	1,19
7	-0,184	-1,21	-0,189	-1,16	-0,156	-0,75
8	-0,208	-1,33	-0,267	-1,52	0,050	0,29
Industry dummy	Yes		Yes		Yes	
Year dummy	Yes		Yes		Yes	
Number of obs	16.275		14.169		9.344	
LR chi2	2371,90		2043,47		963,35	
Prob > chi2	0,00		0,00		0,00	
Pseudo R2	0,0553		0,0534		0,0408	
Log likelihood	-20255.424		-18107.519		-11310,391	

Column D						
	***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	-0,012	-0,79	-0,005	-0,27	-0,005	-0,79
2	0,015	2,38	0,012	0,83	0,004	1.65*
3	-0,022	-0,66	-0,037	-0,65	-0,031	-1,38
4	-0,085	-1.91**	-0,006	-0,09	0,011	1,08
5	0,023	0,48	0,014	0,21	-0,029	-0,92
6	-0,039	-1,15	-0,026	-0,48	0,000	-0,02
7	-0,196	-1,05	-0,142	-0,83	-0,101	-0,75
8	-0,161	-0,65	-0,092	-0,39	-0,060	-0,63

	*IMpen*i, jt-1, t-1	
_predict	Coefficient	Z
1	-0,063	- 3.61***
2	0,019	2.27**
3	-0,029	-0,64
4	0,127	3.26***
5	-0,095	-1.69*
6	0,050	1,35
7	-0,100	-0,48
8	0,083	0,46

Industry dummy	Yes
Year dummy	Yes
Number of obs	8.820
LR chi2	950,56
Prob > chi2	0,00
Pseudo R2	0,0425
Log likelihood	-10708,156

Notes: Numbers 1 to 8 correspond to a change in employment status and income changes as identified in equation (1).
***, **, and * represent 1%, 5%, and 10% significant level, respectively.
In columns A to C, proxies of technology variables – namely, ICT, robot, and e-commerce – are estimated separately whilst 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.

The impacts of ICT use on employment status tend to be more noticeable in the automotive sector than in the other two sectors (plastics and chemicals, and electronics and machinery). In the automotive sector, the probability of workers moving from skilled to unskilled jobs increases when ICT is used more. This evidence occurs in a group of workers whose income does not adjust according to skill changes reflected by a positive and statistically significant coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables of the automotive sector for outcome no. 6 ($EmploySi,j,t$ = 6). By contrast, in the electronics and machinery sector, introducing more ICT benefits some groups of workers in the sector. This is reflected by the higher probability that workers could move from unskilled to skilled positions and receive higher income payments, i.e. the coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables of electronics and machinery for outcome no. 3 ($EmploySi,j,t$ = 3) is positive and statistically significant (Table 7, column A). Meanwhile, introducing ICT helps some groups of workers in this sector to stay in skilled positions, as the coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables of electronics and machinery for outcome no. 5 ($EmploySi,j,t$ = 5) is negative and statistically significant (Table 7, column A). This implies that an increase in ICT use by 1% results in a 0.13% decline in the probability of workers moving from skilled to unskilled positions.

Table 7: Impacts 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**		***roboti,* 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
_predict	*ICTUSEi, jt-1, t-1*dumfood*		*roboti, jt-1, t-1*dumfood*		*ecommercei, jt-1, t-1*dumfood*	
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
_predict	*ICTUSEi, jt-1, t-1*dumcloth*				*ecommercei, jt-1, t-1*dumcloth*	
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
_predict	ICTUSEi, jt-1, t-1*dumplas		roboti, jt-1, t-1*dumplas		ecommercei, jt-1, t-1*dumplas	
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
_predict	*ICTUSEi, jt-1, t-1*dumelec*		*roboti, jt-1, t-1*dumelec*		*ecommercei, jt-1, t-1*dumelec*	
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
_predict	*ICTUSEi, jt-1, t-1*dumauto*		*roboti, jt-1, t-1*dumauto*		*ecommercei, jt-1, t-1*dumauto*	
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	

Notes: ***, **, and * represent 1%, 5%, and 10% significant level, respectively,
There is no information in textile and clothing sector since data on operational stocks of robot use in this sector is reported as zero during 2002–2016. The small positive number of operational stocks of robot use in clothing and textile was shown in 2017,
To be consistent with the 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 (2012–2017)

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' calculation from the Thai Labour Force Survey.

In the food and beverage and the clothing and textile sectors, an increase in ICT use raises the probability of workers to shift their positions from unskilled to skilled as reflected by a positive and significant coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables in these two sectors for outcome no. 4 (*EmploySi,j,t* = 4)

(Table 7, column A). In the food and beverage sector, the use of ICT also helps increase the probability of workers to stay at the same position and receive higher income payments (the coefficient associated with *ICTUSE* for outcome no. 1 is positive and higher than that with *ICTUSE* for outcome no. 2).

In the clothing and textile sector, introducing more ICT could maintain workers at the same job position, but workers who receive such benefit receive relatively lower pay. This is reflected by a positive and significant coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables in this sectors for outcome no. 2 ($EmploySi,j,t = 2$) (Table 7, column A). In addition, in this sector, the probability of workers moving from skilled to unskilled jobs declines when more ICT use is introduced. The coefficient associated with the interaction term between *ICTUSE* and industrial dummy variables in this sector for outcome no. 5 ($EmploySi,j,t = 5$) is negative and significant.

For the intensity of robot use, its impacts on employment status/income changes emerge only when the individual sectors are analysed. Workers in the automotive, electronics, and plastics and chemical sectors tend to get net negative impacts 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 robot and dummy variables in these sectors for outcome no. 3 ($EmploySi,j,t = 3$). However, the value is less than the negative value at the base case (Table 7, column B). Second, the probability of workers staying at the same position and receiving higher payments declines ($EmploySi,j,t = 1$) (Table 7, column B). Although the introduction of robots benefits workers with lower pay – i.e. the probability of workers staying at the same position but whose income does not adjust ($EmploySi,j,t = 2$) increases – the magnitude of gains from this group of workers cannot cover the possible loss that arises from a group of workers whose income is adjusted upward for staying at the same position. Third, the probability that workers would change from skilled to unskilled jobs declines (see the net value of coefficients associated with the interaction term between robot and industrial dummy variables for outcomes no. 5 and 6 ($EmploySi,j,t = 5$ and $EmploySi,j,t = 6$) and value of the base case. But when comparing the net value of elasticity between cases 5 and 6 with that of case 3, the magnitude of case 3 (which is negative) is higher than cases 5 and 6. This implies that at the net impacts, workers will likely move from skilled to unskilled jobs. Note that for the third point, less concern is found for the plastics and chemical sectors (Table 7, column B).

For the food and beverage sector, introducing robots helps workers stay at the same positions but income does not adjust upward, i.e. the coefficient associated with $EmploySi,j,t$ = 2 is positive and statistically significant. The magnitude of gains from this group of workers is higher than the possible loss that arises from a group of workers whose income increases when staying at the same position ($EmploySi,j,t$ = 1) (Table 7, column B). In addition, at the net impact, there is a lower probability of workers to move from skilled to unskilled jobs. The net value of elasticity between cases 5 and 6 (in absolute terms) is higher than that of case 3. All in all, the intensity of robot use has a less severe effect on the food and beverage sector. Part of the reasons could be the nature of the industry itself, which still needs to rely more on labour, and the development in technology, which may still not match well with a need in the food sector. The use of robots in this sector is minimal in Thailand, though increasing, compared to the above three sectors. The same trend is found globally.

The introduction of e-commerce tends to benefit labour market outcomes. As far as the whole manufacturing is concerned, the probability of workers shifting to skilled positions from unskilled ones increases by 0.02% when the value of e-commerce as percent of GDP increases by 1%. However, a group of workers who moved to better-skilled positions do not receive higher payments along with skill changes. This is reflected by the positive and significant coefficient of *ecommerce* for outcome no. 4, not outcome no. 3 (Table 6, column C). Sector-wise, the impact of e-commerce on employment status in the food and beverage sector resembles that of the whole manufacturing sector whilst workers in the clothing and textile as well as the electronic sectors seem to receive additional benefits from using e-commerce. In the clothing and textile sector, the use of e-commerce helps workers stay at the same position and receive higher income (see a positive coefficient associated with the interaction terms between *ecommerce* and industrial dummy for outcome no. 1) (Table 7, column C). In the electronics and machinery sector, e-commerce supports workers to stay at the same position as in the clothing and textile sector. However, the effect occurs on a group of workers who receive low payment (see a positive coefficient associated with the interaction terms between *ecommerce* and industrial dummy for outcome no. 2). In addition, the probability of workers moving from skilled to unskilled jobs declines (a negative coefficient associated with the interaction terms between *ecommerce* and industrial dummy for outcome no. 5).

The automotive sector receives benefits from using e-commerce, but impacts tend to be smaller than the above two sectors. The probability of workers moving from skilled to unskilled jobs goes down for a group of workers who receive lower pay. But this positive effect is countered by another group of workers who receive higher pay but will likely move from skilled to unskilled positions (see net elasticity of the interaction terms between *ecommerce* and industrial dummy for outcomes no. 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 positions are mostly from other industries, i.e. reallocation across industries (Figure 6B).

In contrast to other sectors, e-commerce seems to negatively impact employment status in the plastics and chemical sector. The probability of workers staying at the same position and receiving higher payments go down (a negative coefficient associated with the interaction terms between *ecommerce* and industrial dummy for outcome no. 1) (Table 7, column C). Meanwhile, there is a higher probability of workers shifting from skilled to unskilled jobs in response to a higher value of e-commerce employed in this sector (a positive coefficient associated with the interaction terms between *ecommerce* and industrial dummy for outcome no. 6). The negative impact found in the plastics and chemical sector is probably due to a significant increase in the value of e-commerce per output in this sector, compared to other sectors (see Figure 2B). In addition, the proportion of workers in 'basic jobs' is also high, around 10% of total employment in this sector (Table 8).

Comparing the effects of technological advancement and import penetration, our results show less concern for negative impacts induced by imports on employment status. Three evidence support our findings.[13] First, there is no significant evidence that higher import penetration forces workers out of the job market. The coefficient associated with *IMpen* for outcome no. 7 is statistically insignificant for all three proxies of technology (Table 6, columns A–C). Second, the probability of moving from unskilled to skilled jobs becomes higher, though this occurs amongst workers whose income does not increase by skill improvement. This is reflected by the positive and significant coefficient associated with *IMpen* for outcome no. 4. Third, the probability of workers moving from skilled to unskilled jobs declines. See the coefficients associated with *IMpen* for outcomes no. 5 and 6 where the negative coefficient associated with *IMpen* for outcome no. 5 is higher than that associated with *IMpen* for outcome no. 6. However, imports reduce the probability of workers staying at the same job (see the net value of coefficients associated with *IMpen* for outcomes no. 1 and 2 (Table 6, columns A to C).

[13] It is crucial to note that when we analyse the impacts of import penetration across sectors, the results of five key sectors of our interest – food and beverage, clothing and textile, plastics and chemicals, electronics and machinery, and automotive – are similar to those of the whole manufacturing. In some sectors, especially automotive, plastics and chemicals, and electronics, however, there is evidence that the probability of workers shifting from skilled to unskilled jobs increases, especially amongst those who receive a higher pay. However, an increase in such probability is lower than the higher probability of workers moving from unskilled to skilled jobs. Thus, the net positive impacts of imports on employment status in these sectors occur.

Table 9: Impacts of Import Penetration on Employment Status and Income Changes, by Product (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					

Notes: ***, **, and * represent 1%, 5%, and 10% 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 ($IMpen\_raw_{jt-1,\ t-1}$), the impact of import penetration in terms of raw materials on employment status/income changes resembles that of total imports (Table 9, column A). For imports of capital goods, the only impact found is that it could help workers move to a higher-skilled position, though this occurs amongst a group of workers whose income does not adjust according to skill improvement. No significant impact is found for outcomes no. 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 concern for negative impacts induced by imports of capital goods and raw materials on employment status.

By contrast, concerns on employment status is uncovered in a case of imports of final products. An increase in import penetration ratio in finished products tends to shift workers to unskilled jobs, especially amongst workers whose income does not adjust/match well with skill changes (see the negative coefficient associated with $IMpen\_finish_{jt-1,\ t-1}$ for outcome no. 4) (Table 9, column C). In addition, imports in finished products reduce the probability of workers staying at the same job and receiving a higher income. The magnitude of such probability reductions is higher than that of workers who relatively receive lower pay to stay at the same position. See the coefficients associated with $IMpen\_finish_{jt-1, t-1}$ for outcomes no. 1 and 2 (Table 9, column C). The greater negative impact found in finished products than raw materials and imports of capital goods on labour markets is, to some certain extent, in line with the recent literature (e.g. Amiti and Konings, 2007; Sala-i-Martin et al., 2004) who found that liberalisation in upstream sectors (intermediate inputs) generates higher productivity improvement than that in downstream ones (final products). The productivity improvement would support the labour market, including encouraging workers to shift to a higher skill position. Interestingly, higher imports in finished products could bring back unemployed workers into the job market. The coefficient associated with $IMpen\_finish_{jt-1, t-1}$ for outcome no. 8 is positive, though it is weakly significant (Table 9, column C). Some firms, such as those in the garment industry, import final products to imitate and expand their new production lines so that more workers could be hired in response to such expansion (Kohpaiboon and Jongwanich, 2019).

Regarding the income equation[14] where all observations in the labour force survey are utilised, the results show that impacts of technological advancements on wage/income differ amongst ICT, robots, and e-commerce. When the whole manufacturing sector is concerned, introducing more ICT leads to a decline in total income of workers whilst 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 ICT use, an increase in ICT use reduces the probability of workers with relatively lower pay moving from unskilled to skilled positions. Introducing more robots does not significantly affect employment status when the whole manufacturing sector is concerned. Sector-wise, no difference in wage/income is found in each sector in cases of ICT use and robots (Table 10, column C).

By contrast, it seems that an increase in the value of e-commerce in output increases the 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 whose income does not adjust according to skill changes. For a sector-wise analysis, wage increases tend to occur only in the clothing and textile and food and beverage sectors whilst wage/income declines in the plastics and chemicals and automotive and electronics sectors (Table 10, column I). This could be because workers in plastics and chemicals and automotive tend to move from skilled to unskilled positions as shown in the previous analysis, which negatively impacts wage/income. For the

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

electronics sector, although e-commerce supports workers to stay at the same position, it occurs only in a group of workers who receive low payments.

On the impacts of import penetration on income, our results show that imports of final products dampen income of workers significantly, regardless of 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 negatively impact wage/income, but the results are found only when ICT use and robots are proxies of technology. On e-commerce, such imports do not have a significant effect on wage/income changes. The impact of raw material imports on wage/income is far lower than that of final products. A 1% increase in imports of final products results in around 0.07%–0.08% reduction in workers' income whilst for raw material imports, the reduction is less than 0.01% (Table 10, columns B, E, H). Imports of capital goods could lead to higher wages/incomes of workers, regardless of proxies used in our analysis. A 1% increase in imports of capital goods results in a higher income for workers by around 0.01%–0.03% (Table 10, columns B, E, H). As mentioned in the previous section, imports of capital goods and raw materials could increase the probability of workers moving from unskilled to skilled positions. In the case of raw materials, a slight reduction on wage is revealed, partly due to the evidence revealed earlier – i.e. imports of raw materials reduce the probability workers would stay at the same position. All in all, the impact of advanced technology on wage/income tends to be greater (in absolute terms) than that of import penetration.

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***				
agei, j,t	0,002	0,000	5.12***	agei, j,t	0,002	0,000	5.31***	agei, 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***				
agei, j,t	0,003	0,000	8.30***	agei, j,t	0,003	0,000	8.3***	agei, 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		

Notes: (1) For sex = ‘1’ represents male whilst ‘2’ represents female. (2) Education is composed of four ranks: ‘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% significant level, respectively.
Source: Authors’ calculation.

6. Conclusions and Policy Implications

This paper examines the impacts of advanced technology on a possible change in workers' skills and wages and on the possibility of workers becoming unemployed due to such technological advancement. In addition, to confirm the effects of technological advancement on wage/income, a wage equation at the individual level is performed over time using information of the whole manufacturing sector and an individual sector. This study is different from others in that technological advancements are proxied by three key aspects according to their involvements in supply chains, i.e. ICT use, e-commerce (for both inbound and outbound), and internal production (e.g. factory automation/robots). It compares the effects of technological advancements on labour market outcomes with import penetration, delineated 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 amongst proxies of technology and sectors. Amongst the three proxies of advanced technology, e-commerce tends to positively impact employment status, especially with the higher probability of workers shifting from unskilled to skilled positions. Workers in the clothing and textile, food and beverage, and electronics and machinery sectors tend to receive greater benefits from using e-commerce in the supply chains than those in automotive and plastics and chemicals. On the impacts of wage/income induced by e-commerce, our results reveal that wage/income tends to increase only in the clothing and textile and food and beverage sectors whilst it tends to decline in the plastics and chemicals and automotive and electronics sectors.

In contrast to e-commerce, ICT use negatively impacts employment status, especially in lowering the probability of workers shifting from skilled to unskilled positions. The negative impacts are found in relatively high capital-intensive industries, including automotive, plastics and chemicals, and electronics and machinery. the impacts of intensity of robot use on employment status/income changes emerge only when individual sectors are analysed. Workers in the automotive and electronics and the plastics and chemical sectors tend to get net negative impacts from the introduction of more robots. The intensity of robot use has less severe effects on the food and beverage sector. Wage/income tends to adjust lower from an increase in ICT use whilst introduction of more robots has a negative but statistically insignificant impact on income.

Comparing the effects of technological advancement and import penetration, our results show less concern for negative impacts induced by imports on employment status, particularly imports of capital and raw materials. By contrast, concerns on employment status is uncovered in imports of final products. Particularly, such imports could shift workers from skilled to unskilled positions and reduce the probability of workers staying at the same job and receiving higher income. Imports of final products dampen the wage/income of workers significantly. Imports of raw materials also negatively impact wage/income but only when ICT use and robots are proxies of technology. However, a negative effect of wage/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 skill improvement of workers, government should act as facilitator to vigorously reduce friction in the labour market and smoothen the transitions of workers from one place to another. Cooperation with private firms is necessary to manage information well – especially that relating to job creation and destruction across firms and industries – and lessen friction in the labour market. Attention should be paid more on capital-intensive industries where higher negative impacts of advanced technology are revealed. Second, wage/income should be properly adjusted by skill improvement. From our study, advanced technology helps workers shift from relatively unskilled to skilled positions in some cases, but such benefits fall on workers whose wage/income does not adjust along with skill improvement. Proper payment schemes, beyond relying on minimum wage, could be developed to fairly treat workers, along with encouraging them to improve skills and be flexible. Third, trade liberalisation could continue in Thailand with less concern on labour market outcomes, as some developed countries worry about, especially in terms of capital goods and raw materials. Although liberalisation in final products could reduce the probability of workers shifting from unskilled to skilled positions, they create a higher probability of bringing unemployed workers back into the job market. The impacts of dampened wage/income induced by imports are minimal, compared to those of technological advancement.

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Appendix I: Multinomial Logistic Regression for Employment Status

ICTUSE				*robot*				*ecommerce*				*total proxies of technology*			
Outcomes/ Variables	**Coef.**	**z**	**P>z**	**Outcomes/ Variables**	**Coef.**	**z**	**P>z**	**Outcomes/Variables**	**Coef.**	**z**	**P>z**	**Outcomes/Variables**	**Coef.**	**z**	**P>z**
1				**1**				**1**				**1**			
*age*i, jt-1,t-1	0,077	4,53	0	*age*i, jt-1,t-1	0,074	4,08	0	*age*i, jt-1,t-1	0,070	3,36	0,001	*age*i, jt-1,t-1	0,066	3,03	0,002
2.*sex*i,j,t	-0,001	0	0,997	2.*sex*i,j,t	0,000	0	0,999	2.*sex*i,j,t	0,061	0,17	0,866	2.*sex*i,j,t	0,203	0,53	0,598
												*education*i, jt-1,t-1			
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1				1	-0,042	-0,1	0,922
1	-0,026	-0,08	0,938	1	0,001	0	0,997	1	-0,141	-0,34	0,733	2	0,721	1,05	0,294
2	0,130	0,27	0,783	2	0,277	0,55	0,584	2	0,674	0,99	0,321	3	12,798	0,01	0,993
3	-1,186	-0,98	0,327	3	-1,025	-0,84	0,403	3	13,865	0,01	0,995	ICTUSEi, jt-1, t-1	1,057	0,99	0,325
												roboti, jt-1, t-1	0,041	0,8	0,425
*ICTUSE*i, jt-1, t-1	0,517	0,61	0,54	*robot*i, jt-1, t-1	-0,005	-0,09	0,924	ecommercei, jt-1, t-1	3,538	0,88	0,377	ecommercei, jt-1, t-1	2,928	0,71	0,475
*IMpen*i, jt-1, t-1	0,086	0,97	0,332	*IMpen*i, jt-1, t-1	0,080	0,91	0,362	*IMpen*i, jt-1, t-1	0,056	0,49	0,624	*IMpen*i, jt-1, t-1	0,020	0,18	0,86
totalincomei, jt-1, t-1	0,000	-0,47	0,635	*totalincomei, jt-1, t-1*	0,000	-0,53	0,597	*ecommerce_Residuali, jt-1, t-1*	-0,252	-0,16	0,871	*ICTUSE_Residuali, jt-1, t-1*	3,139	1,15	0,252
ICTUSE_Residuali, jt-1, t-1	2,475	1,24	0,213	*robot_Residuali, jt-1, t-1*	-0,039	-0,42	0,677					*robot_Residuali, jt-1, t-1*	-0,08397	-0,54	0,591

_cons	2,240	2,77	0,006	_cons	2,500	2,17	0,03	_cons	1,512	1,49	0,137	*ecommerce_Residuali, jt-1, t-1*	0,154	0,08	0,939
												_cons	1,363	1,02	0,306
2				**2**				**2**				**2**			
*age*i, jt-1,t-1	0,108	6,38	0	*age*i, jt-1,t-1	0,104	5,79	0	*age*i, jt-1,t-1	0,101	4,9	0	*age*i, jt-1,t-1	0,095	4,39	0
2.*sex*i,j,t	0,105	0,37	0,713	2.*sex*i,j,t	0,162	0,53	0,595	2.*sex*i,j,t	0,174	0,48	0,631	2.*sex*i,j,t	0,340	0,89	0,376
												*education*i, jt-1,t-1			
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1				1	-0,056	-0,13	0,897
1	-0,006	-0,02	0,986	1	-0,006	-0,02	0,986	1	-0,105	-0,26	0,799	2	0,899	1,31	0,19
2	0,370	0,78	0,434	2	0,470	0,93	0,352	2	0,881	1,3	0,194	3	13,210	0,01	0,993
3	-0,594	-0,49	0,622	3	-0,520	-0,43	0,67	3	14,303	0,01	0,995	ICTUSEi, jt-1, t-1	1,212	1,13	0,258
												roboti, jt-1, t-1	0,046	0,9	0,37
*ICTUSE*i, jt-1, t-1	0,538	0,64	0,522	*robot*i, jt-1, t-1	-0,014	-0,29	0,775	ecommercei, jt-1, t-1	3,514	0,88	0,38	ecommercei, jt-1, t-1	3,218	0,78	0,432
*IMpen*i, jt-1, t-1	0,113	1,29	0,198	*IMpen*i, jt-1, t-1	0,109	1,24	0,215	*IMpen*i, jt-1, t-1	0,093	0,83	0,408	*IMpen*i, jt-1, t-1	0,063	0,56	0,573
totalincomei, jt-1, t-1	0,000	-0,88	0,379	*totalincomei, jt-1, t-1*	0,000	-0,76	0,445	*ecommerce_Residuali, jt-1, t-1*	-0,401	-0,26	0,795	*ICTUSE_Residuali, jt-1, t-1*	2,560	0,94	0,349
ICTUSE_Residuali, jt-1, t-1	2,490	1,25	0,21	*robot_Residuali, jt-1, t-1*	-0,046	-0,49	0,627					*robot_Residuali, jt-1, t-1*	-0,073	-0,47	0,638

_cons	1,792	2,22	0,026	_cons	1,665	1,44	0,149	_cons	1,001	0,99	0,324	*ecommerce_Residuali, jt-1, t-1*	0,069	0,03	0,973
												_cons	0,147	0,11	0,912
3				**3**				**3**				**3**			
*age*i, jt-1,t-1	0,083	4,78	0	*age*i, jt-1,t-1	0,081	4,41	0	*age*i, jt-1,t-1	0,079	3,75	0	*age*i, jt-1,t-1	0,075	3,36	0,001
2.*sex*i,j,t	0,049	0,17	0,867	2.*sex*i,j,t	0,068	0,22	0,828	2.*sex*i,j,t	0,092	0,25	0,805	2.*sex*i,j,t	0,239	0,6	0,547
												*education*i, jt-1,t-1			
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1				1	0,298	0,66	0,509
1	0,171	0,49	0,623	1	0,169	0,45	0,649	1	0,284	0,66	0,509	2	1,480	2,11	0,035
2	0,843	1,75	0,081	2	0,962	1,87	0,062	2	1,500	2,17	0,03	3	13,441	0,01	0,993
3	-1,063	-0,84	0,4	3	-0,912	-0,71	0,475	3	14,684	0,01	0,995	ICTUSEi, jt-1, t-1	0,998	0,92	0,358
												roboti, jt-1, t-1	0,032	0,58	0,559
*ICTUSE*i, jt-1, t-1	0,665	0,78	0,436	*robot*i, jt-1, t-1	-0,020	-0,39	0,7	ecommercei, jt-1, t-1	2,947	0,73	0,466	ecommercei, jt-1, t-1	2,123	0,51	0,609
*IMpen*i, jt-1, t-1	0,089	1	0,318	*IMpen*i, jt-1, t-1	0,083	0,93	0,353	*IMpen*i, jt-1, t-1	0,072	0,62	0,534	*IMpen*i, jt-1, t-1	0,038	0,33	0,743
totalincomei, jt-1, t-1	0,000	-0,09	0,926	*totalincomei, jt-1, t-1*	0,000	-0,15	0,878	*ecommerce_Residuali, jt-1, t-1*	-0,246	-0,16	0,876	*ICTUSE_Residuali, jt-1, t-1*	4,747	1,69	0,091
ICTUSE_Residuali, jt-1, t-1	2,586	1,3	0,194	*robot_Residuali, jt-1, t-1*	-0,036	-0,38	0,706					*robot_Residuali, jt-1, t-1*	-0,084	-0,53	0,598
_cons	-1,061	-1,27	0,205	_cons	0,042	0,04	0,972	_cons	-1,449	-1,35	0,179	*ecommerce_Residuali, jt-1, t-1*	0,165	0,08	0,936

												_cons	-1,142	-0,82	0,411
4				**4**				**4**				**4**			
*age*i, jt-1,t-1	0,095	5,46	0	*age*i, jt-1,t-1	0,092	5,01	0	*age*i, jt-1,t-1	0,095	4,47	0	*age*i, jt-1,t-1	0,092	4,13	0
2.*sex*i,j,t	0,228	0,78	0,437	2.*sex*i,j,t	0,300	0,95	0,34	2.*sex*i,j,t	0,289	0,77	0,444	2.*sex*i,j,t	0,477	1,2	0,231
												*education*i, jt-1,t-1			
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1				1	0,366	0,81	0,42
1	0,247	0,71	0,48	1	0,294	0,78	0,433	1	0,307	0,71	0,479	2	1,789	2,55	0,011
2	1,137	2,35	0,019	2	1,274	2,47	0,014	2	1,771	2,56	0,011	3	14,009	0,01	0,992
3	-0,191	-0,15	0,878	3	-0,099	-0,08	0,937	3	15,038	0,01	0,995	ICTUSEi, jt-1, t-1	0,639	0,58	0,561
												roboti, jt-1, t-1	0,041	0,73	0,466
*ICTUSE*i, jt-1, t-1	0,011	0,01	0,99	*robot*i, jt-1, t-1	-0,006	-0,12	0,904	ecommercei, jt-1, t-1	3,988	0,99	0,32	ecommercei, jt-1, t-1	3,429	0,83	0,404
*IMpen*i, jt-1, t-1	0,156	1,75	0,08	*IMpen*i, jt-1, t-1	0,150	1,69	0,091	*IMpen*i, jt-1, t-1	0,152	1,33	0,185	*IMpen*i, jt-1, t-1	0,121	1,06	0,289
totalincomei, jt-1, t-1	0,000	0,24	0,807	*totalincomei, jt-1, t-1*	0,000	0,26	0,798	*ecommerce_Residuali, jt-1, t-1*	-0,462	-0,29	0,77	*ICTUSE_Residuali, jt-1, t-1*	2,754	0,98	0,328
ICTUSE_Residuali, jt-1, t-1	2,408	1,21	0,227	*robot_Residuali, jt-1, t-1*	-0,032	-0,33	0,738					*robot_Residuali, jt-1, t-1*	-0,059	-0,37	0,709
_cons	-1,130	-1,35	0,176	_cons	-1,082	-0,9	0,366	_cons	-1,867	-1,74	0,081	*ecommerce_Residuali, jt-1, t-1*	-0,059	-0,03	0,977

												_cons	-2,572	-1,81	0,071
5				**5**				**5**				**5**			
*age*i, jt-1,t-1	0,079	4,49	0	*age*i, jt-1,t-1	0,076	4,11	0	*age*i, jt-1,t-1	0,074	3,43	0,001	*age*i, jt-1,t-1	0,071	3,15	0,002
2.*sex*i,j,t	0,313	1,05	0,293	2.*sex*i,j,t	0,319	1,01	0,315	2.*sex*i,j,t	0,230	0,6	0,547	2.*sex*i,j,t	0,362	0,9	0,369
												*education*i, jt-1,t-1			
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1				1	0,130	0,28	0,777
1	0,241	0,68	0,496	1	0,229	0,6	0,546	1	0,042	0,1	0,923	2	1,390	1,97	0,049
2	0,973	1,99	0,047	2	1,087	2,09	0,037	2	1,333	1,91	0,056	3	-0,641	0	1
3	-2,232	-1,42	0,155	3	-2,074	-1,31	0,189	3	-0,271	0	1	ICTUSEi, jt-1, t-1	1,258	1,14	0,255
												roboti, jt-1, t-1	0,047	0,85	0,396
*ICTUSE*i, jt-1, t-1	0,683	0,79	0,432	*robot*i, jt-1, t-1	0,002	0,04	0,966	ecommercei, jt-1, t-1	2,897	0,71	0,476	ecommercei, jt-1, t-1	2,209	0,53	0,599
*IMpen*i, jt-1, t-1	0,057	0,63	0,53	*IMpen*i, jt-1, t-1	0,047	0,52	0,601	*IMpen*i, jt-1, t-1	0,040	0,35	0,728	*IMpen*i, jt-1, t-1	0,003	0,02	0,981
totalincomei, jt-1, t-1	0,000	-0,7	0,482	*totalincomei, jt-1, t-1*	0,000	-0,82	0,412	*ecommerce_Residuali, jt-1, t-1*	-0,863	-0,51	0,61	*ICTUSE_Residuali, jt-1, t-1*	3,476	1,22	0,223
ICTUSE_Residuali, jt-1, t-1	2,679	1,34	0,18	*robot_Residuali, jt-1, t-1*	-0,038	-0,39	0,698					*robot_Residuali, jt-1, t-1*	-0,093	-0,58	0,559
_cons	-1,412	-1,64	0,101	_cons	-0,163	-0,14	0,892	_cons	-1,590	-1,43	0,154	*ecommerce_Residuali, jt-1, t-1*	-0,382	-0,18	0,858
												_cons	-1,343	-0,95	0,345

6				**6**				**6**				**6**			
*age*i, jt-1,t-1	0,095	5,48	0	*age*i, jt-1,t-1	0,091	4,96	0	*age*i, jt-1,t-1	0,095	4,49	0	*age*i, jt-1,t-1	0,092	4,14	0
2.*sex*i,j,t	0,330	1,13	0,258	2.*sex*i,j,t	0,332	1,07	0,287	2.*sex*i,j,t	0,378	1,01	0,311	2.*sex*i,j,t	0,493	1,25	0,212
												*education*i, jt-1,t-1			
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1				1	0,235	0,52	0,601
1	-0,001	0	0,998	1	0,048	0,13	0,897	1	0,115	0,27	0,789	2	1,783	2,56	0,011
2	0,928	1,93	0,053	2	1,030	2,01	0,044	2	1,718	2,5	0,013	3	13,820	0,01	0,993
3	-1,102	-0,89	0,375	3	-1,087	-0,86	0,388	3	14,900	0,01	0,995	ICTUSEi, jt-1, t-1	0,903	0,83	0,406
												roboti, jt-1, t-1	0,035	0,65	0,516
*ICTUSE*i, jt-1, t-1	0,308	0,36	0,719	*robot*i, jt-1, t-1	-0,018	-0,36	0,717	ecommercei, jt-1, t-1	3,723	0,93	0,354	ecommercei, jt-1, t-1	3,079	0,75	0,454
*IMpen*i, jt-1, t-1	0,136	1,53	0,126	*IMpen*i, jt-1, t-1	0,133	1,5	0,134	*IMpen*i, jt-1, t-1	0,108	0,94	0,345	*IMpen*i, jt-1, t-1	0,080	0,7	0,483
totalincomei, jt-1, t-1	0,000	0,85	0,397	*totalincomei, jt-1, t-1*	0,000	0,84	0,404	*ecommerce_Residuali, jt-1, t-1*	-0,405	-0,26	0,797	*ICTUSE_Residuali, jt-1, t-1*	3,870	1,39	0,165
ICTUSE_Residuali, jt-1, t-1	2,130	1,07	0,286	*robot_Residuali, jt-1, t-1*	-0,052	-0,55	0,585					*robot_Residuali, jt-1, t-1*	-0,087	-0,55	0,584
_cons	-1,254	-1,51	0,132	_cons	-0,453	-0,38	0,701	_cons	-1,474	-1,4	0,162	*ecommerce_Residuali, jt-1, t-1*	-0,047	-0,02	0,982
												_cons	-1,758	-1,27	0,204
7				**7**	**(base outcome**			**7**	**(base outcome**			**7**	**(base outcome**		
8				**8**				**8**				**8**			

*age*i, jt-1,t-1	-0,021	-0,8	0,421	*age*i, jt-1,t-1	-0,025	-0,91	0,361	*age*i, jt-1,t-1	-0,008	-0,23	0,815	*age*i, jt-1,t-1	-0,012	-0,36	0,719
2.*sex*i,j,t	0,247	0,55	0,585	2.*sex*i,j,t	0,395	0,83	0,407	2.*sex*i,j,t	0,293	0,54	0,589	2.*sex*i,j,t	0,436	0,78	0,434
												*education*i, jt-1,t-1			
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1				1	0,174	0,25	0,8
1	1,410	2,28	0,022	1	1,207	1,9	0,057	1	0,135	0,2	0,842	2	0,842	0,89	0,372
2	1,288	1,66	0,097	2	1,284	1,6	0,109	2	0,871	0,93	0,353	3	-0,013	0	1
3	-11,784	-0,02	0,985	3	-11,621	-0,02	0,983	3	0,283	0	1	ICTUSEi, jt-1, t-1	0,203	0,11	0,909
												roboti, jt-1, t-1	0,015	0,17	0,865
*ICTUSE*i, jt-1, t-1	-0,721	-0,48	0,633	*robot*i, jt-1, t-1	0,120	1,58	0,114	ecommercei, jt-1, t-1	1,495	0,32	0,752	ecommercei, jt-1, t-1	1,233	0,24	0,807
*IMpen*i, jt-1, t-1	-0,013	-0,11	0,915	*IMpen*i, jt-1, t-1	-0,042	-0,32	0,745	*IMpen*i, jt-1, t-1	0,112	0,76	0,447	*IMpen*i, jt-1, t-1	0,097	0,66	0,507
totalincomei, jt-1, t-1	-0,001	-5,88	0	*totalincomei, jt-1, t-1*	-0,001	-5,95	0	*ecommerce_Residuali, jt-1, t-1*	-8,184	-1,15	0,249	*ICTUSE_Residuali, jt-1, t-1*	3,639	0,69	0,487
ICTUSE_Residuali, jt-1, t-1	2,284	1,08	0,281	*robot_Residuali, jt-1, t-1*	0,094	0,62	0,536					*robot_Residuali, jt-1, t-1*	0,637	1,45	0,146
_cons	0,763	0,56	0,577	_cons	2,524	1,41	0,157	_cons	-15,141	-0,02	0,988	*ecommerce_Residuali, jt-1, t-1*	-6,309	-0,76	0,448
												_cons	-0,898	-0,42	0,676

Industry dummy for all outcomes	Yes	Industry dummy for all outcomes	Yes	Industry dummy for all outcomes	Yes	Industry dummy for all outcomes	Yes
Year dummy for all outcomes	Yes	Year dummy for all outcomes	Yes	Year dummy for all outcomes	Yes	Year dummy for all outcomes	Yes
Number of obs	16.275	Number of obs	14.252	Number of obs	9.344	Number of obs	8.820
LR chi2	2.372	LR chi2	2.043	LR chi2	963,35	LR chi2	950,56
Prob > chi2	0,00	Prob > chi2	0,00	Prob > chi2	0,00	Prob > chi2	0,00
Pseudo R2	0,0553	Pseudo R2	0,0534	Pseudo R2	0,0408	Pseudo R2	0,0425
Log likelihood	-20255.424	Log likelihood	-18107.519	Log likelihood	-11310.391	Log likelihood	-10708.156

Source: Authors' estimation.

Appendix II: Multinomial Logistic Regression for Employment Status, by Sector

ICTUSE				***robot***				***ecommerce***			
Outcomes/Variables	**Coef.**	**z**	**P>z**	**Outcomes/Variables**	**Coef.**	**z**	**P>z**	**Outcomes/Variables**	**Coef.**	**z**	**P>z**
1				**1**				**1**			
*age*i, jt-1,t-1	0,077	4,48	0	*age*i, jt-1,t-1	0,074	4,09	0	*age*i, jt-1,t-1	0,068	3,25	0,001
2.*sex*i,j,t	0,007	0,02	0,982	2.*sex*i,j,t	0,024	0,08	0,938	2.*sex*i,j,t	0,102	0,28	0,779
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1			
1	-0,017	-0,05	0,96	1	-0,013	-0,04	0,97	1	-0,140	-0,34	0,734
2	0,137	0,29	0,772	2	0,257	0,51	0,611	2	0,706	1,04	0,299
3	-1,069	-0,87	0,386	3	-0,999	-0,81	0,418	3	19,366	0	1
*ICTUSE*i, jt-1, t-1	0,914	0,73	0,465	*robot*i, j, t	5,835	0,43	0,667	*ecommerce*i, j, t	7,216	0,92	0,358
*ICTUSE*i, j, t***dumfood*	-4,873	-1,73	0,084	*roboti, j, t*dumfood*	-5,000	-0,36	0,716	*ecommercei, j, t*dumfood*	-6150,1	-0,01	0,99
*ICTUSE*i, j, t***dumcloth*	-5,602	-1,29	0,198	*roboti, j, t*dumcloth*				*ecommercei, j, t*dumcloth*	-20,571	-1,03	0,303
*ICTUSE*i, j, t***dumplas*	2,863	0,37	0,71	*roboti, j, t*dumplas*	-3,627	-0,26	0,794	*ecommercei, j, t*dumplas*	-13,482	-1,55	0,12
*ICTUSE*i, j, t***dumelec*	1,381	0,17	0,868	*roboti, j, t*dumelec*	-5,962	-0,44	0,66	*ecommercei, j, t*dumelec*	33,967	0,44	0,657
*ICTUSE*i, j, t***dumauto*	1,084	0,24	0,813	*roboti, j, t*dumauto*	-5,808	-0,43	0,668	*ecommercei, j, t*dumauto*	56,161	0,76	0,448
*IMpen*i, j, t	0,076	0,86	0,389	*IMpen*i, j, t	0,090	0,99	0,32	*IMpen*i, jt-1, t-1	0,003	0,03	0,978

totalincomei, jt-1, t-1	0,000	-0,55	0,583	*totalincomei, jt-1, t-1*	0,000	-0,62	0,533	*ecommerce_Residuali, jt-1, t-1*	-0,982	-0,5	0,617
ICTUSE_Residuali, jt-1, t-1	3,013	1,21	0,228	*robot_Residuali, jt-1, t-1*	0,138	0,94	0,345				
_cons	2,182	2,68	0,007	_cons	1,830	1,71	0,088	_cons	1,490	1,41	0,158
2				**2**				**2**			
*age*i, jt-1,t-1	0,108	6,33	0	*age*i, jt-1,t-1	0,105	5,81	0	*age*i, jt-1,t-1	0,100	4,79	0
2.*sex*i,j,t	0,111	0,39	0,696	2.*sex*i,j,t	0,184	0,6	0,548	2.*sex*i,j,t	0,220	0,6	0,546
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1			
1	0,006	0,02	0,987	1	-0,023	-0,06	0,95	1	-0,099	-0,24	0,81
2	0,381	0,81	0,42	2	0,449	0,89	0,374	2	0,918	1,35	0,176
3	-0,471	-0,38	0,702	3	-0,502	-0,41	0,683	3	19,807	0	1
*ICTUSE*i, jt-1, t-1	0,968	0,77	0,439	*robot*i, j, t	9,986	0,74	0,461	*ecommerce*i, j, t	7,281	0,93	0,354
*ICTUSE*i, j, t**dumfood*	-6,162	-2,19	0,029	*roboti, j, t*dumfood*	-9,166	-0,67	0,504	*ecommercei, j, t*dumfood*	-6138,4	-0,01	0,99
*ICTUSE*i, j, t**dumcloth*	-2,948	-0,69	0,493	*roboti, j, t*dumcloth*				*ecommercei, j, t*dumcloth*	-27,718	-1,39	0,164
*ICTUSE*i, j, t**dumplas*	2,831	0,37	0,713	*roboti, j, t*dumplas*	-7,899	-0,57	0,568	*ecommercei, j, t*dumplas*	-10,396	-1,21	0,227
*ICTUSE*i, j, t**dumelec*	1,224	0,15	0,883	*roboti, j, t*dumelec*	-10,111	-0,75	0,455	*ecommercei, j, t*dumelec*	45,304	0,59	0,553
*ICTUSE*i, j, t**dumauto*	0,227	0,05	0,961	*roboti, j, t*dumauto*	-9,972	-0,74	0,461	*ecommercei, j, t*dumauto*	50,175	0,68	0,498
*IMpen*i, j, t	0,102	1,16	0,245	*IMpen*i, j, t	0,122	1,34	0,179	*IMpen*i, jt-1, t-1	0,042	0,35	0,723

totalincomei, jt-1, t-1	0,000	-0,95	0,342	*totalincomei, jt-1, t-1*	0,000	-0,84	0,402	*ecommerce_Residuali, jt-1, t-1*	-1,071	-0,55	0,585
ICTUSE_Residuali, jt-1, t-1	3,056	1,22	0,221	*robot_Residuali, jt-1, t-1*	0,127	0,86	0,388				
_cons	1,733	2,13	0,033	_cons	1,033	0,96	0,335	_cons	1,055	1	0,316
3				**3**				**3**			
*age*i, jt-1,t-1	0,082	4,73	0	*age*i, jt-1,t-1	0,081	4,44	0	*age*i, jt-1,t-1	0,078	3,66	0
2.*sex*i,j,t	0,059	0,2	0,841	2.*sex*i,j,t	0,084	0,27	0,789	2.*sex*i,j,t	0,142	0,38	0,705
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1			
1	0,177	0,51	0,609	1	0,154	0,41	0,679	1	0,290	0,67	0,501
2	0,847	1,75	0,079	2	0,939	1,83	0,068	2	1,547	2,23	0,025
3	-0,965	-0,75	0,453	3	-0,878	-0,68	0,494	3	20,190	0	1
*ICTUSE*i, jt-1, t-1	1,022	0,81	0,418	*robot*i, j, t	3,679	0,27	0,789	*ecommerce*i, j, t	6,855	0,87	0,384
*ICTUSE*i, j, t**dumfood*	-4,433	-1,52	0,129	*roboti, j, t*dumfood*	-2,885	-0,21	0,836	*ecommercei, j, t*dumfood*	-6156,4	-0,01	0,99
*ICTUSE*i, j, t**dumcloth*	-5,679	-1,13	0,257	*roboti, j, t*dumcloth*				*ecommercei, j, t*dumcloth*	-30,464	-1,35	0,175
*ICTUSE*i, j, t**dumplas*	3,133	0,41	0,685	*roboti, j, t*dumplas*	-0,574	-0,04	0,967	*ecommercei, j, t*dumplas*	-10,214	-1,16	0,245
*ICTUSE*i, j, t**dumelec*	5,862	0,69	0,492	*roboti, j, t*dumelec*	-3,789	-0,28	0,783	*ecommercei, j, t*dumelec*	33,248	0,43	0,668
*ICTUSE*i, j, t**dumauto*	-0,138	-0,03	0,977	*roboti, j, t*dumauto*	-3,679	-0,27	0,789	*ecommercei, j, t*dumauto*	55,038	0,74	0,46
*IMpen*i, j, t	0,083	0,92	0,355	*IMpen*i, j, t	0,087	0,94	0,346	*IMpen*i, jt-1, t-1	0,022	0,18	0,857

totalincomei, jt-1, t-1	0,000	-0,18	0,857	*totalincomei, jt-1, t-1*	0,000	-0,27	0,788	*ecommerce_Residuali, jt-1, t-1*	-0,751	-0,38	0,705
ICTUSE_Residuali, jt-1, t-1	3,163	1,26	0,206	*robot_Residuali, jt-1, t-1*	0,122	0,82	0,412				
_cons	-1,131	-1,34	0,181	_cons	-0,506	-0,46	0,647	_cons	-0,996	-0,91	0,362
4				**4**				**4**			
*age*i, jt-1,t-1	0,095	5,43	0	*age*i, jt-1,t-1	0,093	5,03	0	*age*i, jt-1,t-1	0,094	4,37	0
2.*sex*i,j,t	0,238	0,81	0,418	2.*sex*i,j,t	0,319	1,01	0,311	2.*sex*i,j,t	0,332	0,88	0,379
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1			
1	0,254	0,73	0,467	1	0,276	0,74	0,461	1	0,311	0,72	0,472
2	1,146	2,37	0,018	2	1,253	2,43	0,015	2	1,806	2,6	0,009
3	-0,066	-0,05	0,958	3	-0,077	-0,06	0,952	3	20,528	0	1
*ICTUSE*i, jt-1, t-1	0,318	0,25	0,804	*robot*i, j, t	11,833	0,85	0,397	*ecommerce*i, j, t	7,688	0,98	0,328
*ICTUSE*i, j, t**dumfood*	-4,129	-1,41	0,159	*roboti, j, t*dumfood*	-11,012	-0,78	0,436	*ecommercei, j, t*dumfood*	-6127,5	-0,01	0,99
*ICTUSE*i, j, t**dumcloth*	0,221	0,05	0,963	*roboti, j, t*dumcloth*				*ecommercei, j, t*dumcloth*	-31,967	-1,41	0,158
*ICTUSE*i, j, t**dumplas*	2,218	0,29	0,775	*roboti, j, t*dumplas*	-9,381	-0,66	0,511	*ecommercei, j, t*dumplas*	-8,922	-1,02	0,307
*ICTUSE*i, j, t**dumelec*	2,909	0,33	0,738	*roboti, j, t*dumelec*	-11,940	-0,86	0,393	*ecommercei, j, t*dumelec*	30,698	0,39	0,695
*ICTUSE*i, j, t**dumauto*	1,650	0,34	0,731	*roboti, j, t*dumauto*	-11,815	-0,85	0,398	*ecommercei, j, t*dumauto*	44,676	0,59	0,552
*IMpen*i, j, t	0,148	1,67	0,095	*IMpen*i, j, t	0,163	1,78	0,075	*IMpen*i, jt-1, t-1	0,099	0,83	0,406

totalincomei, jt-1, t-1	0,000	0,2	0,84	*totalincomei, jt-1, t-1*	0,000	0,19	0,846	*ecommerce_Residuali, jt-1, t-1*	-1,182	-0,59	0,552
ICTUSE_Residuali, jt-1, t-1	2,970	1,19	0,236	*robot_Residuali, jt-1, t-1*	0,135	0,89	0,374				
_cons	-1,198	-1,42	0,155	_cons	-1,678	-1,49	0,136	_cons	-1,866	-1,7	0,089
5				**5**				**5**			
*age*i, jt-1,t-1	0,078	4,43	0	*age*i, jt-1,t-1	0,077	4,15	0	*age*i, jt-1,t-1	0,072	3,34	0,001
2.*sex*i,j,t	0,316	1,06	0,29	2.*sex*i,j,t	0,332	1,04	0,297	2.*sex*i,j,t	0,280	0,73	0,465
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1			
1	0,252	0,71	0,477	1	0,222	0,58	0,559	1	0,050	0,11	0,909
2	0,985	2,01	0,044	2	1,073	2,06	0,039	2	1,387	1,99	0,047
3	-2,061	-1,3	0,194	3	-2,024	-1,28	0,202	3	-0,382	0	1
*ICTUSE*i, jt-1, t-1	1,303	1,03	0,305	*robot*i, j, t	-3,460	-0,25	0,806	*ecommerce*i, j, t	6,421	0,81	0,416
*ICTUSE*i, j, t**dumfood*	-6,285	-2,02	0,043	*roboti, j, t*dumfood*	4,336	0,3	0,761	*ecommercei, j, t*dumfood*	-6163,4	-0,01	0,99
*ICTUSE*i, j, t**dumcloth*	-14,273	-2,16	0,031	*roboti, j, t*dumcloth*				*ecommercei, j, t*dumcloth*	-24,444	-1,08	0,279
*ICTUSE*i, j, t**dumplas*	1,281	0,17	0,869	*roboti, j, t*dumplas*	5,847	0,41	0,685	*ecommercei, j, t*dumplas*	-8,516	-0,97	0,333
*ICTUSE*i, j, t**dumelec*	-5,330	-0,6	0,546	*roboti, j, t*dumelec*	3,408	0,24	0,809	*ecommercei, j, t*dumelec*	0,229	0	0,998
*ICTUSE*i, j, t**dumauto*	0,259	0,05	0,957	*roboti, j, t*dumauto*	3,472	0,25	0,806	*ecommercei, j, t*dumauto*	66,718	0,9	0,369
*IMpen*i, j, t	0,042	0,47	0,641	*IMpen*i, j, t	0,043	0,46	0,645	*IMpen*i, jt-1, t-1	-0,010	-0,08	0,937

totalincomei, jt-1, t-1	0,000	-0,72	0,474	*totalincomei, jt-1, t-1*	0,000	-0,95	0,342	*ecommerce_Residuali, jt-1, t-1*	-1,299	-0,63	0,528
ICTUSE_Residuali, jt-1, t-1	3,235	1,29	0,197	*robot_Residuali, jt-1, t-1*	0,158	1,05	0,295				
_cons	-1,444	-1,67	0,096	_cons	-0,612	-0,54	0,589	_cons	-1,118	-1	0,317
6				**6**				**6**			
*age*i, jt-1,t-1	0,094	5,42	0	*age*i, jt-1,t-1	0,091	4,99	0	*age*i, jt-1,t-1	0,093	4,38	0
2.*sex*i,j,t	0,339	1,16	0,246	2.*sex*i,j,t	0,346	1,1	0,269	2.*sex*i,j,t	0,423	1,13	0,258
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1			
1	0,013	0,04	0,97	1	0,031	0,08	0,934	1	0,126	0,29	0,769
2	0,948	1,97	0,049	2	1,010	1,97	0,049	2	1,761	2,56	0,011
3	-0,950	-0,75	0,452	3	-1,063	-0,84	0,401	3	20,38	0	1
*ICTUSE*i, jt-1, t-1	0,734	0,58	0,562	*robot*i, j, t	14,457	1,04	0,298	*ecommerce*i, j, t	7,144	0,91	0,363
*ICTUSE*i, j, t**dumfood*	-6,543	-2,15	0,032	*roboti, j, t*dumfood*	-13,664	-0,97	0,331	*ecommercei, j, t*dumfood*	-6170,2	-0,01	0,99
*ICTUSE*i, j, t**dumcloth*	-8,986	-1,66	0,098	*roboti, j, t*dumcloth*				*ecommercei, j, t*dumcloth*	-29,895	-1,33	0,184
*ICTUSE*i, j, t**dumplas*	2,231	0,29	0,773	*roboti, j, t*dumplas*	-11,731	-0,83	0,408	*ecommercei, j, t*dumplas*	-8,267	-0,95	0,34
*ICTUSE*i, j, t**dumelec*	3,943	0,46	0,646	*roboti, j, t*dumelec*	-14,543	-1,05	0,295	*ecommercei, j, t*dumelec*	21,292	0,27	0,785
*ICTUSE*i, j, t**dumauto*	2,801	0,6	0,549	*roboti, j, t*dumauto*	-14,459	-1,04	0,298	*ecommercei, j, t*dumauto*	27,607	0,37	0,713
*IMpen*i, j, t	0,126	1,42	0,157	*IMpen*i, j, t	0,146	1,6	0,11	*IMpen*i, jt-1, t-1	0,056	0,47	0,637

totalincomei, jt-1, t-1	0,000	0,8	0,421	*totalincomei, jt-1, t-1*	0,000	0,78	0,433	*ecommerce_Residuali, jt-1, t-1*	-1,128	- 0,57	0,57
ICTUSE_Residuali, jt-1, t-1	2,717	1,08	0,278	*robot_Residuali, jt-1, t-1*	0,103	0,69	0,49				
_cons	-1,302	- 1,55	0,12	_cons	-0,979	- 0,89	0,374	_cons	-1,355	- 1,25	0,212
7	**(base outcome)**			**7**	**(base outcome)**			**7**	**(base outcome)**		
8				**8**				**8**			
*age*i, jt-1,t-1	-0,021	- 0,83	0,408	*age*i, jt-1,t-1	-0,026	- 0,95	0,341	*age*i, jt-1,t-1	-0,009	- 0,27	0,788
2.*sex*i,j,t	0,258	0,57	0,57	2.*sex*i,j,t	0,441	0,92	0,357	2.*sex*i,j,t	0,339	0,62	0,533
*education*i, jt-1,t-1				*education*i, jt-1,t-1				*education*i, jt-1,t-1			
1	1,438	2,32	0,02	1	1,165	1,84	0,066	1	0,097	0,14	0,886
2	1,277	1,63	0,102	2	1,221	1,52	0,129	2	0,871	0,93	0,354
3	-10,925	- 0,03	0,978	3	-10,922	- 0,03	0,979	3	0,276	0	1
*ICTUSE*i, jt-1, t-1	-0,820	- 0,39	0,696	*robot*i, j, t	16,296	0,58	0,56	*ecommerce*i, j, t	7,267	0,91	0,363
*ICTUSE*i, j, t**dumfood*	0,606	0,1	0,92	*roboti, j, t*dumfood*	-16,015	- 0,57	0,568	*ecommercei, j, t*dumfood*	-6088	- 0,01	0,99
*ICTUSE*i, j, t**dumcloth*	11,307	1,22	0,221	*roboti, j, t*dumcloth*	0 (omitte			*ecommercei, j, t*dumcloth*	-10830	- 0,01	0,991
*ICTUSE*i, j, t**dumplas*	10,495	0,99	0,323	*roboti, j, t*dumplas*	-12,637	- 0,45	0,653	*ecommercei, j, t*dumplas*	-592,443	-0,7	0,484
*ICTUSE*i, j, t**dumelec*	1,293	0,09	0,927	*roboti, j, t*dumelec*	-15,978	- 0,57	0,568	*ecommercei, j, t*dumelec*	-56,367	- 0,52	0,603

*ICTUSE*i, j, t**dumauto*	-1,664	-0,22	0,825	*roboti, j, t*dumauto*	-16,179	-0,58	0,563	*ecommercei, j, t*dumauto*	14,797	0,17	0,863
*IMpen*i, j, t	-0,006	-0,05	0,961	*IMpen*i, j, t	-0,071	-0,5	0,618	*IMpen*i, jt-1, t-1	0,044	0,29	0,772
totalincomei, jt-1, t-1	-0,001	-5,88	0	*totalincomei, jt-1, t-1*	-0,001	-6	0	*ecommerce_Residuali, jt-1, t-1*	-3,019	-0,56	0,578
ICTUSE_Residuali, jt-1, t-1	2,738	1,05	0,295	*robot_Residuali, jt-1, t-1*	0,068	0,3	0,762				
_cons	0,712	0,52	0,605	_cons	2,635	1,61	0,107	_cons	-0,716	-0,43	0,664
Industry dummy for all outcomes	Yes			Industry dummy for all outcomes	Yes			Industry dummy for all outcomes	Yes		
Year dummy for all outcomes	Yes			Year dummy for all outcomes	Yes			Year dummy for all outcomes	Yes		
Number of obs	16.275			Number of obs	14.169			Number of obs	9.344		
LR chi2	2.426,36			LR chi2	2094			LR chi2	1.023		
Prob > chi2	0,00			Prob > chi2	0,00			Prob > chi2	0,00		
Pseudo R2	0,0566			Pseudo R2	0,0547			Pseudo R2	0,0434		
Log likelihood	-20228.191			Log likelihood	-18082.257			Log likelihood	-11280.568		

Source: Authors' estimation.

Appendix III: Multinomial Logistic Regression for Employment Status, by Different Imported Products

Outcomes/Variables	Coef.	Std. Err.	z	P>z	Outcomes/Variables	Coef.	Std. Err.	z	P>z
1					**5**				
*age*i, jt-1,t-1	0,075	0,018	4,15	0	*age*i, jt-1,t-1	0,077	0,019	4,14	0
2.*sex*i,j,t	0,050	0,307	0,16	0,871	2.*sex*i,j,t	0,356	0,318	1,12	0,264
*education*i, jt-1,t-1					*education*i, jt-1,t-1				
1	-0,003	0,362	-0,01	0,994	1	0,222	0,379	0,59	0,558
2	0,267	0,505	0,53	0,598	2	1,067	0,520	2,05	0,04
3	-1,010	1,234	-0,82	0,413	3	-2,069	1,586	-1,3	0,192
*robot*i, jt-1, t-1	0,014	0,049	0,29	0,774	*robot*i, jt-1, t-1	0,019	0,051	0,38	0,706
*IMpen_raw*jt-1, t-1	-0,002	0,004	-0,57	0,569	*IMpen_raw*jt-1, t-1	-0,002	0,004	-0,41	0,682
*IMpen_capital*jt-1, t-1	0,026	0,025	1,04	0,301	*IMpen_capital*jt-1, t-1	0,027	0,025	1,1	0,273
*IMpen_finish*jt-1, t-1	-0,073	0,038	-1,94	0,053	*IMpen_finish*jt-1, t-1	-0,056	0,045	-1,23	0,218
totalincomei, jt-1, t-1	0,000	0,000	-0,64	0,524	*totalincomei, jt-1, t-1*	0,000	0,000	-0,89	0,372
robot_Residuali, jt-1, t-1	-0,025	0,092	-0,27	0,789	*robot_Residuali, jt-1, t-1*	-0,023	0,095	-0,25	0,805
_cons	2,286	1,124	2,03	0,042	_cons	-0,383	1,177	-0,33	0,745
2					**6**				
*age*i, jt-1,t-1	0,104	0,018	5,79	0	*age*i, jt-1,t-1	0,091	0,018	4,97	0
2.*sex*i,j,t	0,188	0,306	0,61	0,54	2.*sex*i,j,t	0,369	0,313	1,18	0,238
*education*i, jt-1,t-1					*education*i, jt-1,t-1				
1	-0,010	0,361	-0,03	0,977	1	0,047	0,371	0,13	0,899
2	0,460	0,504	0,91	0,362	2	1,026	0,512	2	0,045

3	-0,524	1,228	-0,43	0,669
*robot*i, jt-1, t-1	-0,001	0,049	-0,03	0,978
*IMpen_raw*jt-1, t-1	0,001	0,004	0,19	0,849
*IMpen_capital*jt-1, t-1	0,024	0,025	0,98	0,327
*IMpen_finish*jt-1, t-1	-0,016	0,037	-0,43	0,666
totalincomei, jt-1, t-1	0,000	0,000	-0,79	0,431
robot_Residuali, jt-1, t-1	-0,036	0,092	-0,39	0,698
_cons	1,529	1,123	1,36	0,173
3				
*age*i, jt-1,t-1	0,081	0,018	4,43	0
2.*sex*i,j,t	0,102	0,314	0,32	0,746
*education*i, jt-1,t-1				
1	0,161	0,372	0,43	0,664
2	0,952	0,514	1,85	0,064
3	-0,892	1,286	-0,69	0,488
*robot*i, jt-1, t-1	-0,002	0,050	-0,04	0,965
*IMpen_raw*jt-1, t-1	0,000	0,004	0,09	0,931
*IMpen_capital*jt-1, t-1	0,026	0,025	1,06	0,29
*IMpen_finish*jt-1, t-1	-0,059	0,042	-1,41	0,159
totalincomei, jt-1, t-1	0,000	0,000	-0,21	0,837
robot_Residuali, jt-1, t-1	-0,021	0,094	-0,23	0,819
_cons	-0,154	1,154	-0,13	0,894
4				

3	-1,079	1,268	-0,85	0,395
*robot*i, jt-1, t-1	-0,002	0,050	-0,05	0,961
*IMpen_raw*jt-1, t-1	0,002	0,004	0,37	0,714
*IMpen_capital*jt-1, t-1	0,027	0,025	1,07	0,285
*IMpen_finish*jt-1, t-1	-0,025	0,038	-0,66	0,509
totalincomei, jt-1, t-1	0,000	0,000	0,83	0,408
robot_Residuali, jt-1, t-1	-0,040	0,093	-0,43	0,669
_cons	-0,612	1,152	-0,53	0,595
7	**(base outcome)**			
8				

*age*i, jt-1,t-1	0,092	0,018	5,02	0	*age*i, jt-1,t-1	-0,023	0,027	-0,84	0,403
2.*sex*i,j,t	0,354	0,315	1,12	0,262	2.*sex*i,j,t	0,380	0,478	0,8	0,427
*education*i, jt-1,t-1					*education*i, jt-1,t-1				
1	0,299	0,375	0,8	0,424	1	1,235	0,635	1,95	0,052
2	1,268	0,515	2,46	0,014	2	1,243	0,802	1,55	0,121
3	-0,073	1,264	-0,06	0,954	3	-10,892	408,890	-0,03	0,979
*robot*i, jt-1, t-1	0,017	0,051	0,33	0,744	*robot*i, jt-1, t-1	0,120	0,074	1,64	0,102
*IMpen_raw*jt-1, t-1	0,003	0,004	0,69	0,49	*IMpen_raw*jt-1, t-1	-0,010	0,007	-1,43	0,153
*IMpen_capital*jt-1, t-1	0,029	0,025	1,18	0,239	*IMpen_capital*jt-1, t-1	0,015	0,035	0,44	0,663
*IMpen_finish*jt-1, t-1	-0,068	0,043	-1,59	0,113	*IMpen_finish*jt-1, t-1	0,028	0,052	0,53	0,597
totalincomei, jt-1, t-1	0,000	0,000	0,22	0,828	*totalincomei, jt-1, t-1*	-0,001	0,000	-5,92	0
robot_Residuali, jt-1, t-1	-0,014	0,094	-0,15	0,88	*robot_Residuali, jt-1, t-1*	0,095	0,148	0,64	0,523
_cons	-1,291	1,171	-1,1	0,27	_cons	2,384	1,733	1,38	0,169
Industry dummy for all outcomes	Yes								
Year dummy for all outcomes	Yes								
Number of obs	14.151								
LR chi2(126)	2128,26								
Prob > chi2	0								
Pseudo R2	0,0557								
Log likelihood	-18037.456								

Note: Results of import penetration when *ICTUSE* or e-commerce used are the same as in the case of robots.
Source: Authors’ estimation.

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