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Hiring Skilled Workers and Roles of Free Trade Agreements and Global Production Sharing: Evidence of Thai Manufacturing[1]

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Abstract

The paper examines the extent to which firms hire skilled workers with a view to informing two policy debates about ongoing economic globalization, i.e. the impact of trade liberalization under free trade agreements (FTAs) and that of participating in global production sharing (GPS). Panel data econometric analysis is undertaken using a firm-level panel dataset compiled from three censuses of Thai manufacturing (2006, 2011 & 2016). Our key findings suggest that while competitive pressure from abroad is one crucial factor driving firms to be active in hiring skilled workers and staying competitive, using FTAs to create competitive pressure must be undertaken with caution as its effectiveness hinges on how their commitment has been made. Participating in GPS could influence firms to hire more skilled workers. This points to a mutual benefit to be shared across countries by participating in GPS. Enlarging the pool of skilled workforces must go hand in hand with promoting the use of skilled workers by firms to avoid worsening existing labour mismatching challenges.

Keywords

Global Production Sharing (GPS), Trade liberalization, Free Trade Agreement (FTA) Skilled workers, Thai Manufacturing

JEL: O53, O14, O24, F14, F15

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Introduction

Governments worldwide put great effort into enlarging their pool of skilled workers and encouraging firms to hire participants. Their involvement in production processes not only affects plants' productivity positively, but also allows firms to be in a better position to harness technology advancements elsewhere. This eventually contributes to economic upgrading and sustainable economic development. Interestingly, enlarging the skilled workers pool is necessary, but not sufficient to promote their employment as actual employment also depends on firms' demand. Hence, it's equally important to stimulate the demand for these skilled workers within economies. Otherwise, such enlargement would serve to worsen existing labor mismatching challenges.

Like other primary inputs, labor demand is derived from its contribution to overall firm competence. Changes in the business environment that surrounds firms significantly impacts the demand for skilled workers as businesses often need to adapt to changes in their operating circumstances, such as the introduction of new technologies and regulations or changing market conditions. Each may require a different mix of skills and expertise from within their workforce. As hiring skilled workers is costly, a conducive business environment could either encourage or discourage firms to hire skilled workers.

One factor creating a conducive business environment is trade liberalization. As echoed in empirical studies within the international trade literature (e.g., Levinsohn, 1993; Amiti & Korning, 2007; Chen et al. 2017; Baldwin & Yan, 2021; Gonzalez-Garcia & Yang, 2022), trade liberalization potentially has an impact on the demand for skilled workers. Trade liberalization adds competitive pressures on firms. To survive in business, firms undertake productivity enhancing activities in response. They include using new inputs and higher input quality, adopting new technologies, and hiring more skilled workers. Interestingly, the analyses above are based on trade liberalization committed under the World Trade Organization (WTO). As WTO negotiations have stalled since the new millennium, many countries have continued their liberalization efforts by signing free trade agreements (FTAs) with their trading partners. In theory, FTA- and WTO-committed trade liberalizations are different. The former is discriminatorily in favor of selected countries (i.e., member countries) and selective in favor of certain products. To be eligible for FTA preferential scheme, products must comply with certain criteria to identify their origin (i.e., rules of origin). By contrast, trade liberalization in the latter is non-discriminatory and is offered unconditionally. Despite its immense policy relevance, the FTA-committed trade liberalization effect on the demand for skilled workers has yet to be empirically examined.

Another factor concerns the extent to which industries have engaged in global production sharing (GPS), a phenomenon where different stages of the production process of a product are distributed across multiple countries, based on their comparative advantages in different stages of production. This allows for more efficient production and cost savings, as different countries can specialize in certain stages of production and achieve economies of scale.

GPS is widely regarded as a shortcut into global integration for firms in developing countries as they can specialize in certain tasks within their participation. Participating in GPS also allows them to become familiar with the inherent advanced technology and benefit from technology transfer. As a consequence, many developing countries offer lucrative investment incentives to entice multinational enterprises (MNEs) and participate in GPS in order to maximize the ensuing benefits for their domestic economy.[2] Nonetheless, there is a growing concern that participating in GPS puts the countries involved at risk of being trapped in the low-end segments of value chains, heavily relying on pools of cheap labor to stay competitive. This concern is based on the presumption that GPS-outsourced activities from developed to developing countries are likely to involve unskilled-labor intensive activities in the former. All things being equal, the outsourced activities could increase the demand for unskilled as opposed to skilled workers. The overreliance on unskilled labor can also result in a lack of investment in education and training, which can further hinder efforts to develop a skilled workforce. In turn, this can limit the ability of developing countries to move up the value chain and compete in more sophisticated and high-value-added industries. This potentially runs counterproductive to policies aiming to enlarge skilled worker pools.

Arguably, on the other hand, such outsourced activities might not necessarily involve unskilled-labor intensive activities in the context of developing countries. In fact, firms operating in developing and developed countries face different sets of available inputs (technically referred to as production cones) (Leamer & Levinsohn 1995; Feenstra 2004; Leamer & Schott 2005; Kiyota 2012). To perform tasks within GPS-outsourced activities, suppliers in developing countries might need skilled workers, thereby increasing the demand for such workers. This is regardless of whether the outsourced activities are labor intensive in the developed countries concerned. Therefore, engaging in GPS could induce higher skilled worker demand in developing countries. While there are a number of empirical studies on the effect of participating in GPS and the demand for skilled workers, their focus is on the impact on developed countries.[3] All in all, the effect of participating in GPS on the demand for skilled workers remains a testable hypothesis with immense policy relevance.

To the best of our knowledge, so far there has not been any empirical studies examining these two factors in a single framework with a view to informing prudential policies in the context of developing countries. Most of the empirical studies mentioned above focus on either one (the effect of trade liberalization) or the other (the effect of participating in GPS).

[2] See Taglioni and Winkler (2016); Kano et al (2020); WDR (2020) and WTO (2021) works cited therein.

[3] These studies include Flug and Hercowitz (2000); Silva (2008); Katz and Margo (2013); McGowan and Andrews (2017); Modestino et al. (2020); Sloane and Mavromaras (2020).

However, it is important to note that trade liberalization and participating in GPS are often interconnected. One of the reasons many governments engage in FTA negotiations is to attract foreign investment and encourage multinational enterprises to outsource GPS activities. Against this backdrop, this paper examines the determinants of the skilled workers employed with a view to informing two policy debates about ongoing economic globalization, that is the impact of trade liberalization under FTAs and that the repercussions of participating in GPS.

Our contribution to the existing literature is that while both FTAs and GPS are immensely policy relevant in the context of managing economic globalization, there have not been any systematic empirical studies simultaneously examining them. In this study, these two industry-specific factors are unbundled and incorporated in the empirical model together with other controlling variables.

Thai manufacturing is an excellent case study for the issue at hand because Thailand has long been engaged in GPS since the early 1980s. After a certain time has passed, examining the relative demand for unskilled and skilled workers in nations intensively engaging in GPS provides valuable policy lessons for GPS latecomers. In addition, Thailand is enthusiastic in signing FTAs. Since 2006, tariff changes in Thailand have been largely undertaken through FTA commitments. This allows the effect of FTA-led liberalization pressuring firms to be active in terms of productivity enhancing activities.

The paper is organized as follows; The following section presents the analytical framework used in this study. Section 3 discusses trends and patterns in terms of the skilled workers employed by Thai manufacturing firms. Sections 4 and 5 outline the empirical model and data sets used in the analysis, followed by an examination of the econometric procedures in Section 6. The ensuing results are presented in the next section, with the conclusions and policy inferences in the final section.

Analytical Framework

The role of skilled workers in industrial upgrading has been long acknowledged since the seminal work of by Becker (1965) and Mincer (1974). Its role is also highlighted in the economic development literature as well as within growth empirics (Grilliches, 1969; Berman & Grilliches, 1994; Autor et al, 1998; Hollanders & ter weel, 2002). Skilled workers not only enhance firms' productivity, but also allow them to better cope with changes, disruptions, and especially new technologies. This is crucial amidst the disruptive technology era we are currently experiencing. As a result, the proportion of skilled workers to total workers is often used as a proxy of the ability of economies to move up the quality ladder, from low-value to relatively high-value activities.

Against this backdrop, efforts to promote the use of skilled workers have been lopsided to a certain extent as many governments worldwide put great emphasis on activities aimed at enlarging the pool of skilled workers. In fact, the number of skilled workers employed is jointly determined by both the demand for and supply of skilled workers. Overlooking demand side analysis puts these workers at risk of working in jobs which do not require the skills they have acquired. This can involve overeducation, over-skilling or both[4], which are referred to collectively in this paper as representing labor mismatching.

Like other primary inputs, the demand for skilled workers derives from firms' profit maximization motives. This makes the business environment surrounding firms influence their decision to demand primary factor inputs like skilled workers. It is of immense importance within emerging market economies, which are typically small and open, how an industry participates in the global economy. This has significant influence on the business environment. This is echoed by a number of empirical studies, including Antonelli et al (2009 &2010); Antonioli et al. (2011); Blatter et al. (2012) Blatter et al. (2016), Bustos (2011), Schneider (2015); Jongwanich and Kohpaiboon (2015).

There are two factors impacting how an industry participates in global economy which deserve special research attention. One is the impact of trade liberalization and the other is the extent to which industries have engaged in GPS.

The economic rationale for the impact of trade liberalization is based on the fact that it creates competitive pressures on firms, which can respond by altering their behavior and conducting activities in various ways, including their use of skilled workers. These empirical studies have approached trade liberalization from two perspectives. One is to distinguish the effects of input and output tariffs. Examples of these studies include Amiti and Korning (2007), Harris & Robertson (2013), and Chen et al. (2017). Input tariff cuts induce more intermediate inputs in terms of variety and quality. To fully utilize these inputs, skilled workers are needed to work with the imported intermediates involved, representing complementarity between skills and imported input quality (Amiti & Korning, 2007; Bas & Paunov, 2021). Output tariff cuts also induce tougher competition, thereby promoting productivity improvement activities, one of which is the use of skilled workers. The shortcoming of these studies lies in the fact that input and output tariffs are often taken into consideration simultaneously by firms in deciding on productivity improvement activities. This is in line with the well-established concept of effective rate of protection pioneered by Corden (1963) and Balassa (1963), and further supported by recent theoretical studies (Kugler & Verhoogen, 2012; Hallak & Sivadasan, 2013; Fieler et al., 2018).

Another perspective involves viewing trade liberalization as a collective force pushing firms to remain competitive. It does not matter whether the source of trade liberalization is

[4] The former refers to a situation where workers' education background is more than what is required by the position. In the latter, skills workers provided during their formal education system are not fully utilized (Sloane & Mavromaras 2020).

derived from either input, output or both tariffs. This concept, known as 'import discipline', was pioneered by Levinsohn (1993) and has been explored in recent empirical studies by Baldwin and Yan (2021) and Gonzalez-Garcia and Yang (2022). As hiring skilled workers can be expensive (Blatter et al., 2012), competition is necessary to incentivize firms to invest in them. The key implication is in favor of trade liberalization. As the liberalization induced by input tariff changes might affect firms differently from that involving output tariff changes, such differences cannot be examined under this approach.

It remains inconclusive which approach is more suitable than the other. In fact, it depends on whether effective or nominal (output) protection is used in the political process in protection bargaining (see Caves, 1976, p. 293). If the bargain focuses on effective protection wherein both input and output tariffs are taken into consideration simultaneously, it does not matter whether the liberalization is induced by input or output tariff changes. Otherwise, it is worth distinguishing the effects of input and output tariff changes.

The issue has become more complicated in recent years as the negotiations of the World Trade Organization (WTO), the main driver of trade liberalization in the last three decades of the previous millennium, have stalled. Many countries have carried on with their trade liberalization agenda through introducing FTAs. The number of signed FTAs has mushroomed. Interestingly, trade liberalization impacts under FTAs and the WTO are quite different from each other. The former is discriminatorily in favor of selected countries (member countries) and selective in terms of certain products. To be eligible for FTA preferential schemes, products must comply with certain criteria to identify their origin (known as rules of origin). By contrast, trade liberalization under the latter is non-discriminatory and offered unconditionally. Despite its immense policy relevance, the effect of trade liberalization under FTAs has yet to be examined empirically.

Another factor impacting how an industry participates in the global economy is the extent to which it is engaged in GPS. GPS have become one facet of economic globalization (Athukorala, 2011; Athukorala & Kohpaiboon, 2015). For indigenous firms in developing countries, participating in GPS can be a shortcut to global participation. These indigenous firms no longer have to master each stage in the entire production process of a product. They can specialize in only a segment of the international production process, while reaching sufficient production scale to meet their bottom line. In GPS, they have to work within the vertically integrated systems of production, sharing blueprints, technicians, managerial practices, and productivity-enhancing tools and techniques. GPS also allow these indigenous firms to become familiar with the advanced technology used in GPS and benefit from the technology transfer opportunities. This takes place at a rate unthinkable in traditional trade settings (Taglioni & Winkler, 2016). As a result, many developing countries offer lucrative investment incentives to entice MNEs to participate in GPS (Athukorala, 2011; WDR, 2020; WTO, 2021).

What remains unclear is how engaging in GPS affects skilled worker demand. On the one hand, the GPS-activities outsourced from developed to developing countries are unskilled-labor intensive. Such outsourced activities could, *ceteris paribus*, increase the demand for unskilled workers as opposed to skilled. As a consequence, it is less likely to enhance economic development prospects. Instead, these suppliers can be trapped in the low-end segments of value chains, heavily relying on pools of cheap labor to stay competitive.

On the other hand, such outsourced activities might not necessarily involve unskilled-labor intensive activities in the context of developing countries. In fact, firms operating in developing and developed countries face different cones of production (Leamer & Levinsohn 1995; Feenstra 2004; Leamer & Schott 2005; Kiyota 2012). Suppliers in developing countries might need skilled workers to perform outsourced tasks and to meet all requirements. This is regardless of whether the outsourced activities are unskilled-worker intensive in the developed country. Therefore, engaging in GPS could induce more demand for skilled workers in both developing and developed countries simultaneously. This debatable issue is a part of a broader theme echoed in various international organizations, like the World Bank, WTO, and Asian Development Bank.

There are a number of empirical studies examining the impact of GPS on the demand for skilled workers, but they remain lopsided in their focus on the impact on developed countries. They include Flug and Hercowitz (2000), Silva (2008), Katz and Margo (2013), McGowan and Andrews (2017), Modestino et al. (2020) and, Sloane and Mavromaras (2020). The exceptions are Kohpaiboon and Jongwanich (2014) and Yasar and Rejesus (2020), but only the former addresses the impact of GPS. The latter's research focus is on the impact of foreign direct investment on the demand for skilled workers within the context of Indonesian manufacturing.

These two factors have not been addressed simultaneously in the empirical research literature. Most of the empirical studies mentioned above focus on either one (the effect of trade liberalization) or the other (the effect of participating in GPS). However, it is important to note that trade liberalization and participating in GPS are often interconnected. One of the reasons many governments engage in FTA negotiations is to attract foreign investment and encourage multinational enterprises to outsource GPS activities to their industries. All in all, bringing them together in examining the impact on use of skilled workers is hugely policy relevant, but remains unexamined in the empirical research.

Hiring Skilled Workers in Thai Manufacturing

The trends and patterns involving skilled workers employed by Thai manufacturing firms are revealed in this section. Data from the industrial censuses of Thai manufacturing of

2006 and 2016 is used.[5] They are the only data sources which present patterns within the hiring of workers at the plant level in Thai manufacturing. In these censuses, the data related to total workers within Thai manufacturing can be broken down into two categories, non-operational and operational workers. The former includes employees working in offices, comprising secretarial workers, managerial staff and industrial-specific professionals. The latter is further disaggregated into skilled and unskilled workers. In this study, therefore, skilled workers are defined as representing the sum of non-operational and skilled operational employees. The higher the share, the greater the volume of skilled workers hired by firms.

Table 1 presents both indicators at the 2-digit disaggregated level of the International Standard of Industrial Classification (ISIC Rev. 3) for 2006 and 2016. On average, the share of skilled to total workers in Thai manufacturing was 13.6 per cent in 2006, slightly dropping to 12.8 per cent in 2016.

The skilled worker share varies substantially across industries, ranging from 5.2 to 30.8 per cent in 2006. Such variation across industries narrowed down to 9 to 20 per cent in 2016. Such a variation is due to a large extent to differences in the capital-labor ratio across industries. In 2016, the five industries exhibiting the highest skilled worker shares were (1) manufacture of other transports (ISIC 35), (2) manufacture of other non-metallic mineral products (ISIC 26), (3) manufacture of chemicals and chemical products (ISIC 24), (4) manufacturing of radio, television and communication equipment and apparatus (ISIC 32), and (5) manufacture of medical, precision, and optical instruments, watches and clocks (ISIC 33). Their shares were 20, 18.8, 17.5, 16.6, and 13.4 per cent, respectively. All but the manufacture of chemicals and chemical products exhibited an increasing trend in their share from 2006 to 2016.

Interestingly, these top-five industries in terms of their skilled worker share have two common features, that is they are highly domestic-oriented and involve high capital intensity. This is different from major export-oriented industries like processed foods (ISIC 15), manufacture of office, accounting, and computing machinery (ISIC 30), manufacture of electrical machinery and apparatus (ISIC 31) and manufacture of motor vehicles, trailers and semi-trailers (ISIC 34), within which the role of skilled workers in their establishments were moderate and had slightly declined over the period in question.

Such features suggest that competing import industries are relatively capital intensive and skilled workers are hired to be complementary with capital. By contrast, export-oriented industries still rely on the availability of labor in handling mass production. In fact, over the past two decades, Thailand has exhibited trade deficit in parts and components, but surplus in terms

[5] While there are three industrial censuses available (2006, 2011, & 2016), only two censuses are used here due to space limitations.

of finished manufacturing products (Athukorala, 2011; Athukorala & Kohpaiboon, 2015). Such a pattern is also similar to China, the world assembly factory, to a certain extent. In other words, Thailand seems to be another assembly center in addition to China. To perform assembling tasks, unskilled and skill workers complement each other so that the extent to which firms hire skilled workers changes slightly over the years.

Figure 1 illustrates the kernel density distribution in terms of the extent to which firms in the Thai manufacturing sector hired skilled workers. Figure 1.1 shows the distribution in the 2006 and 2016 industrial censuses. They are virtually identical so the following discussion involves the 2016 industrial census. In addition, it has long tailed at the right end with the average ratio of skilled to total workers at 12.8 per cent in 2016. Foreign owned firms[6] tend to hire more skill workers as opposed to their local counterparts (Figure 1.2). In addition, global participating firms (either exporting, importing or both), exhibit the higher share of white-collar workers (Figures 1.3 and 1.4, respectively).

Empirical Model

The empirical model in this study is designed to examine the share of skilled to total workers as a function of a set of firm- and industry-specific variables guided by sound economic theories, as well as previous empirical studies. The dependent variable in the model is the share of skilled to total workers, as defined in Section 3.

To examine the impact of trade liberalization on the demand for skilled workers, the effective rate of the protection of industry *j* ($ERP_{j,t}$) is introduced as expressed in Equation 1;

$$ERP_{j,t} = \frac{t_{j,t}^{MFN} - \sum_{i=1}^{n} a_{ij}^{*} t_{k,t}^{MFN}}{1 - \sum_{i=1}^{n} a_{ij}^{*}} \qquad (1)$$

where $t_{k,t}^{MFN}$= most favored nation (MFN) tariff of product *k* (*i* and *j*) at time *t*

a_{ij}^{*}= (value) share of product *i* used for producing product *j* at time *t* at the world price

The higher the ERP, the greater the protection. The expected effect of $ERP_{j,t}^{W}$ on skilled workers is negative. The more the protection granted, the less the share of skilled workers.

To further examine the possible factor that trade liberalization under FTAs is different from that under WTO, $ERP_{j,t}^{FTA}$ is introduced as in Equation 2;

$$ERP_{j,t}^{FTA} = \frac{t_{j,t}^{*} - \sum_{i=1}^{n} a_{ij}^{*} t_{i,t}^{*}}{1 - \sum_{i=1}^{n} a_{ij}^{*}} \qquad (2)$$

[6] Registered foreign ownership share greater than or equal 20 per cent is used to identify foreign firms.

where $t^*_{k,t}$ = the weighted tariff of product *k (i and j)* between MFN and FTA tariffs at time *t*

$$t^*_{k,t} = \left(1 - \sum_{g=1}^{h} \theta_g\right) t^{MFN}_{k,t} + \sum_{g=1}^{h} \theta_g \, t^{FTA}_{k,t}$$

$t^{FTA}_{k,t}$ = FTA preferential tariff of product *k* (*i* and *j*) from Thailand offered to Country *g* at time *t*

θ_g = import share of Country *g* to total imports at time *t*

The coefficient corresponding to $ERP^{FTA}_{j,t}$ presents the effects of trade liberalization under FTAs on skilled worker demand over and above the effect of $ERP_{j,t}$. The expected sign is negative. Whether it is different statistically from that associated with $ERP_{j,t}$ is examined to shed light on whether the trade liberalization under FTAs is different from that under the WTO.

To examine the impact of participating in GPS, the ratio of parts and components to total trade $(Network_{j,lag\_t})$ is employed as a proxy of the extent to which industries are involved in GPS. Note that the lagged values (*t-1* and *t-2*) are used to minimize the risk of simultaneity issues from this variable. Equation 3 presents the formula:

$$Network_{j,lag\_t} = \frac{PCX_{j,lag\,t} + PCM_{j,lag\_t}}{X_{j,lag\_t} + M_{j,lag\_t}} \qquad (3)$$

where PCX_{j,lag_t} = the lag value of parts and components exports of industry *j averaging* at time *t-1 and t-2*

PCM_{j,lag_t} = the lag value of parts and components imports of industry *j averaging* at time *t-1 and t-2*

X_{j,lag_t} = the lag total export value of industry *j averaging* at time *t-1 and t-2*

M_{j,lag_t} = the lag total import value of industry *j averaging* at time *t-1 and t-2*

The definition of parts and components used here is based on Athukorala and Kohpaiboon (2010) and Kohpaiboon (2010) which are based on careful analysis of SITC Revision 3 at the 5-digit level of disaggregation, as well as on firm interview evidence. As argued above, the impact of $Network_{j,lag\_t}$ is ambiguous. It can be either positive or negative.

In addition, GPS participation impact is further examined as it interacts with firms either exporting or importing raw materials. In particular, $Network_{j,lag_t} * \; expd_{i,j,t}$ and $Network_{j,lag_t} * imp_{di,j,t}$ are introduced over and above $Network_{j,lag_t}$ where $expd_{i,j,t}$ and $imp_{di,j,t}$ are 0-1 binary dummy variables (i.e., 1 indicates firms exporting and importing, respectively, and zero otherwise). The rationale of these two interacting terms is that the impact of GPS participation would be greater for those who are globally integrated. Hence, the coefficients associated with these two interacting terms are expected to be positive.

Over and above these variables, a series of firm- and industry-specific factors are included as controlling variables.

Firm-specific controlling factors

The first firm-specific factor introduced is firm size $(size_{i,j,t})$. As argued studies within the innovation literature, such as Pavitt *et al.* (1987), Vaona and Pianta (2008), the decision to innovate is positively related to firm size. This is because larger establishments are in a better position to cover the fixed costs incurred in innovative activities (Schumpeter, 1942). This seems to be applicable where hiring skilled workers is concerned. Similar to installing machinery and equipment, hiring skilled workers incurs fixed and sunk costs to firms as recruiting processes are rather complicated and costly. Once a candidate is hired, it still takes time and possibly extra training for him or her to become fully productive. As a result, it is expected that the larger a firm's size, the more likely it is to hire skilled workers (Blatter et al. 2012; Ejarque and Nilsen, 2008; Manning, 2006; Merz and Yashiv, 2007). In our study, firms' size is measured by (real) sales values (in natural logarithms).

The second firm-specific factor is capital-labor ratio $\left(\frac{K}{L}\right)_{i,j,t}$ reflecting firms' capital deepening. Many empirical studies in the labor economics literature point to complementarity between skilled workers and physical capital (Griliches, 1969; Krusell, et al. 2000), so that a positive relationship is expected.

The third factor is related to the extent to which firms globally participate. This would influence their decision to hire skilled workers. In principle, firms are involved in international trade through either exports, imports or both. These firms are likely to hire more skilled workers. Exporting firms are faced with more intense competition, so that they are potentially more likely to hire skilled workers to enhance their productivity and survival prospects as opposed to domestic-oriented firms (Greenaway et al, 1999; Milner and Wright, 1998; Hine and Wright, 1997; Roberts and Skoufias, 2007).

Imported intermediates are often embedded within advanced technology. To fully utilize them, skilled workers are needed to work with the imported intermediates. In other words, skilled workers and imported input quality are complementary (Amiti & Korning, 2007; Bas & Paunov, 2021). In addition, importing often involves complicated procedures, ranging from selecting suppliers, negotiating price and quality, and understanding the technology embedded into imported products, together with dealing with documentation with custom officials from different countries. Hence, importing firms are also likely to hire more skilled workers.

To measure the extent to which firms are involved in international trade, export-output ratios $(exp_{i,j,t})$ and the proportion of imported to total inputs (raw materials and intermediates) $(imp_{i,j,t})$ are used. Their expected signs are both positive.

The next firm-specific factor is firm ownership $(own_{i,j,t})$. Foreign firms are more likely to hire skilled workers as investing aboard is often associated with some proprietary assets (Caves, 2007). This is done to ensure the established affiliates can compete with their indigenous counterparts which are more familiar with the local business environment in host investment-receiving countries. To harness the associated advanced technology, skilled workers are needed. A positive sign is expected.

The last firm-specific factor is firms' research and development efforts $(RD_{i,j,t})$. As R&D activities by nature are skilled-worker intensive, firms committing to R&D activities are likely to involve hiring more skilled workers. $RD_{i,j,t}$ is measured by the ratio of R&D expenses to total sales. The more the firms commit to R&D activities, the more the demand for skilled workers increases. The expected sign is positive.

Industry-specific controlling variables

The first industry-specific controlling variable involves market structure. In line with the structure-conduct-performance (S-C-P) paradigm in the industrial economics literature, competition pressure tends to be less in a market structure where there are few firms operating and competing with each other (i.e. high market concentration). In this environment, firms are less active in any productivity-enhancing activities. The theoretical expected sign of the coefficient associated with market concentration is negative. Hirschman-Herfindahl of industry *j* $HHI_{j,t}$ is used to reflect the producer concentration in the domestic market. The formula of $HHI_{j,t}$ is expressed in Equation 4.

$$HHI_{j,t} = \sum_{i=1}^{n} s_{i,j,t}^2 \quad (4)$$

where $s_{i,j,t}$ = an establishments' share of firm *i* in industry *j*

In addition, the interaction between $HHI_{j,t}$ and $ERP_{j,t}$, is also introduced into the empirical model. The rationale is based on the fact that in many developing countries, including Thailand, a highly concentrated market structure is likely to occur naturally due to the small domestic market. Whether a high market concentration allows firms to be inactive in productivity enhancing activities could be conditioned by cross-border protection. That is, when cross-border protection is high and the import threat is slight, the negative effect of high market concentration could be enlarged. A negative coefficient of the interaction term is expected.

Another industry-specific controlling variable is the annual growth of gross output over the past two years (OG_{j,lag_t}) to capture the growth potential of the industry involved. The inherent rationale is in line with the argument that hiring skilled workers incurs fixed and sunk costs for firms. The expected demand observed from the past output growth is likely to be a factor influencing firms' decision to hire skilled workers. The greater the output growth, the higher the share of skilled workers hired. Hence, the coefficient associated with OG_{j,lag_t} is expected to be positive.

All in all, the empirical model used in this study is shown in Equation 5;

$$skill_{i,j,t} = \beta_0 + \beta_1 size_{i,j,t} + \beta_2 \left(\frac{K}{L}\right)_{i,j,t} + \beta_3 exp_{i,j,t} + \beta_4 imp_{i,j,t} + \beta_5 own_{i,j,t} + \beta_6 RD_{i,j,t}$$
$$+\gamma_1 ERP_{j,t} + \gamma_2 ERP_{j,t}^{FTA} + \gamma_3 Network_{j,lag} + \gamma_4 Network_{j,lag} * expd_{i,j,t}$$
$$+\gamma_5 Network_{j,lag} * impd_{i,j,t} + \gamma_6 HHI_{j,t} + \gamma_7 HHI_{j,t} * ERP_{j,t} + \gamma_8 OG_{j,lag\_t} + \varepsilon_{i,j,t} \quad (5)$$

Dependent variable

$skill_{i,j,t}$ = The share of skilled to total workers in firm *i* in industry *j* at time *t,*

Explanatory variables

$size_{i,j,t}$ (?) = Size of establishment *i* in industry *j* at time *t,* proxied by (real) sale value (in natural log)

$\left(\frac{K}{L}\right)_{i,j,t}$ (?) = Capital-labor ratio of establishment *i* in industry *j* at time *t* (in natural log)

$exp_{i,j,t}$ (+) = Export-output ratio of establishment *i* in industry *j* at time *t*

$expd_{i,j,t}$ = Zero-one binary dummy which equals one when firms export, and zero otherwise

$imp_{i,j,t}$ (+) = Ratio of imported to total raw materials and intermediates of establishment *i* in industry *j* at time *t*

$impd_{i,j,t}$ = Zero-one binary dummy which equals one when firms import raw materials and intermediates, and zero otherwise

$own_{i,j,t}$ (+) = Foreign ownership of establishment *i* in industry *j* at time *t*

$RD_{i,j,t}$ (+) = Ratio of R&D expenses to total sales of establishment *i* in industry *j* at time *t*

$ERP_{j,t}$ (-) = Trade protection of industry *j* at time *t* , measured by effective rate of protection (see the formula in Equation 1)

$ERP_{j,t}^{FTA}$ (-) = Trade protection of industry *j* at time *t* , measured by effective rate of protection (see the formula in Equation 2)

$Network_{j,lag\_t}$ (?) = GPS participation of industry *j* at time *t* , proxied by the ratio of parts and components to total trade in the past two years (as in Equation 3)

$HHI_{j,t}$ (-) = Industrial concentration of industry *j* at time *t* , proxied by Hirschman-Herfindahl index (see the formula in Equation 4).

$OG_{j,lag}$ (+) = Annual growth of gross output over the past two years

$\varepsilon_{i,j,t}$ = Disturbance term of establishment *i* in industry *j* at time *t*

(Expected signs are expressed in the parenthesis)

Data and Variable Measurement

The data set used in this study is compiled from Thailand's industrial censuses, conducted by the National Statistical Office. So far, four censuses are available (1996, 2006, 2011, & 2016). The econometric analysis within this paper uses a panel data of 9,912 observations constructed using the three latest censuses, 2006, 2011, & 2016.

The data cleaning starts with examining the possibility of duplicated observations, that is when samples with different plants' identification numbers report the same value of key variables. Presumably, this is largely driven by multi-plant cases where all affiliates fill in the questionnaire using company-level information where all affiliates are included. Seven key variables are used to identify duplication: (i) years in operation, (ii) total employment, (iii) wage compensation, (iv) raw materials, (v) initial raw material stocks, (vi) initial finished product stocks, and (vii) initial fixed assets. When duplicated samples are found, only one is kept in the sample and the others are removed.

The next step is to examine whether samples provide reliable information in the questionnaire. To do so, we drop observations which report annual sales less than ฿12,000 (less than \$400), annual value added less than ฿10,000, and/or less than ฿10,000 of initial fixed assets. There are small/micro enterprises, defined as plants with less than 20 workers (involving 3,342 observations) whose employees totalled less than ten workers. They are excluded as they would behave differently from the others and might serve local market niches that are not participating directly with larger firms. Another feature in Thai manufacturing censuses is that there are samples whose industrial classification is not the same over the period covered. Generally, all samples are categorized according to the 4 digit International Standard of Industrial Classification (ISIC) Revision 3. There are 2,780 cases where the ISIC code assigned to a given plant identification changed between these three censuses, perhaps because firms changed in terms of product coverage, but used the same firm IDs across these three censuses. They are excluded because comparing them across these censuses could be misleading. The final cleaning procedure is to turn all the nominal value variables (e.g., sales, raw materials expenses, and inventory) into the real (2001 price) values. The price deflator at the 4-digit ISIC disaggregation was employed.

All variables related to an establishments' characteristics are derived directly from the censuses. They include $skill_{i,j,t}$, $size_{i,j,t}$, $exp_{i,j,t}$, $imp_{i,j,t}$, $own_{i,j,t}$, and $RD_{i,j,t}$., all of which are from the same time period. While undertaking econometric analysis of these variables could raise concerns in terms of simultaneity, the test conducted in Jongwanich and Kohpaiboon (2020) suggests that the simultaneity problem is not statistically significant.[7]

To calculate $ERP_{j,t}$, the inter-industry linkage relationship is derived from Thailand's input–output tables compiled by the National Economic and Social Development Board (NESDB).[8] The latest input–output table (2010) is used for all three years of the ERP calculation. This is done to ensure that any changes in $ERP_{j,t}$ reflect those in tariffs, instead of changes in the input–output relationship.

In calculating $ERP_{j,t}^{FTA}$, preferential tariffs in four FTAs are used. They are ASEAN-China FTA (ACFTA), Thailand-Australia FTA (TAFTA), Japan-Thailand Economic Partnership Agreement (JTEPA), and ASEAN Economic Community (AEC) where substantial tariff commitments took place after 2006. In particular, 90 per cent in 2010 for the ACFTA, 93 per cent of tariff lines in 2010 for the TAFTA, and 100 per cent in 2010 for the AEC. In the case of the JTEPA, there are two tariff cuts, that is, before and after 2011. As the tariff cuts of these FTAs took place after 2006, Equation 2 will be estimated using the 2011 and 2016 censuses.

$HHI_{j,t}$ is calculated using information from each census disaggregated at the 4 digit of ISIC classification. The formula is expressed in Equation 4. Before using it, we cleaned the data using the same criteria used with the panel data set, that is, removing duplicated observations and dropping observations that provide unreliable information. The trade data used to construct $Network_{j,lag\_t}$ is from the UNComtrade database, whereas gross output series at the four-digit ISIC are collected by NESDB. Tables 2 and 3 present the statistical summary and correlation matrix of all variables used in the analysis.

[7] In particular, Jongwanich and Kohpaiboon (2020) employed the Blundell and Bond (1998) panel system generalized method of moments (GMM) regression to guard against any possible simultaneity bias, the lag value of endogenous variables was not statistically significant.

Econometric Analysis

Our econometric analysis starts with the standard panel data analysis where fixed- and random-effect models (FE and RE models, respectively) are estimated. As the dependent variable in our analysis, the share of white-collar workers, is truncated being between zero and one, estimates of the standard panel data models, which assumed a linear relationship, could be biased.

Two alternative estimation methods are employed to handle the truncated dependent variable. One is the Fixed-effect Poisson Pseudo Maximum Likelihood (PPML) models proposed by Silva and Tenreyro (2006), and the other is the random effect Tobit model. While both could handle the truncated dependent variable, the PPML estimator is better when heteroskedasticity of error is observed. Based on the Monte-Carlo simulations in Silva and Tenreyro (2006), the PPML estimator produces estimates with the lowest bias for different patterns of heteroskedasticity. Even thought the limited-dependent variable bias might be pronounced when a significant part of the observations is censored, this could not be severe in our case where the number of skilled workers varies substantially across observations. The PPML model is popularly used to handle cases where excessive zero observations are found. A clear example is the gravity model estimation. Note that in at least one third of the samples the share of skilled to total workers is zero, so the fractional response model is not applicable.

On the other hand, the random effect Tobit model relies on the assumptions of normality and homoskedasticity of errors, (Herrera, 2013; Turkson, 2016). Such assumptions do not hold in many occasions. Nonetheless, estimates of the Tobit model are reported as robustness checks of our results.

Results

Table 4 reports the estimation results, whereas Table 5 presents the robustness check of Table 4. The first two columns of Table 4 show the results based on FE and RE models, respectively. The model's overall fit is statistically significant at the one per cent level. The results based on FE PPML (henceforth referred to as PPML in short) and Tobit model estimation are in Column 3 of Table 4.

Overall, the results are not sensitive to estimation methods, except for a few variables such as $exp_{i,j,t}$ and $ERP_{j,t}^{FTA}$ in the PPML model (Column 4.3). Hence, the following discussion concerns the PPML model estimation (Column 4.3) because it is more suitable for handling excessive zero dependent variable circumstances. The coefficient associated to $size_{i,j,t}$ is positive and statistically significant at one per cent. The role of size determining the extent to which firms hire skilled workers has been well documented in the labor economics literature (e.g. Blatter et al., 2012; Muehlemann and Leiser, 2018). In the context of developing countries, it would either reflects the presence of fixed and sunk costs to the establishment in hiring these workers, the preferences of these skilled workers who want to work in the larger establishments with brighter career paths, or both.

The coefficient corresponding to $\left(\frac{K}{L}\right)_{i,j,t}$ is positive and statistically different from zero at the one per cent level. This reflects the complementarity between skilled workers and capital. This finding is consistent with that in previous studies (e.g. Kohpaiboon and Jongwanich, 2015; Jongwanich, 2022). Agruably, the positive coefficient could be driven by simultaneity bias as total workers appear in both the share of skilled workers and $\left(\frac{K}{L}\right)_{i,j,t}$ simulatenously. To examine whether the positive coefficient is the result of bias, $\left(\frac{K}{L}\right)_{i,j,t}$ is replaced by $K_{i,j,t}$. Presented in Column 5.1 of Table 5, the results are not sensitve to choices between $\left(\frac{K}{L}\right)_{i,j,t}$ and $K_{i,j,t}$.

The coefficient corresponding to $exp_{i,j,t}$ turns out to be negative, but statistically insignificant. Note that in other models in Table 4, the coefficient is negative and statistically significant at the conventional level (i.e. 5 per cent). The weak statistical significance could be due to the rather high collinearity with $imp_{i,j,t}$ (its correlation is 0.4: Table 3). The negative coefficient would reflect the nature of Thai exports which is largely involved in original equipment manufacutring (OEM) activities and its order volumne is large. In this circumstance, the number of unskilled workers must be large to a certain extent. All other things being equal, this would lower the share of skilled to total workers.

It is less likely that the negative coefficient associated with $exp_{i,j,t}$ suggests Thailand to be trapped in the low end segments of value chains, heavily relying on pools of cheap labor to stay competitive. This is because the coefficient's magnitude of $exp_{i,j,t}$ is small (i.e. -0.098) and much smaller in comparison with those associated with $imp_{i,j,t}$, and $RD_{i,j,t}$. which are 0.4 and 0.509, respectively. Our interpretation is that skilled workers are also needed in exporting activities to stay globally competitive, although they are not growing proportionately with unskilled ones. This is especially true for middle income countries like Thailand whose comparative advantage is moving away from unskilled labor-intensive products.

The coefficient associated with $imp_{i,j,t}$ is positive and statistically significant, suggesting skilled workers are needed to work with the imported intermediates, that is to say reflecting complementarity between skills and imported input quality. This is in line with empirical studies based on the experiences of other developing countries, such as Amiti and

Korning (2007) for Indonesia, Bas and Paunov (2021) for Ecuador, and Chen et al. (2017) for China.

Foreign firms tend to hire more skilled workers than indigneous, reflected by the positive and statistically signficant coefficient corresponding to $own_{i,j,t}$. The coefficient associated with $RD_{i,j,t}$ is positive and statistically significant, reflecting firms intensively committing in R&D activities hiring more skilled workers, all other things being equal.

The effect of $ERP_{j,t}$ is negative and statistically significant at the one per cent level in all of the estimation methods in Table 4. This is in line with is the ideas hypothesized above. When trade protection is high (high $ERP_{j,t}$values), firms tend to hire less skilled workers, all things considered. This seems to be consistent with the result above that there are fixed costs associated with hiring skilled workers. In order to incur these costs, competitive pressure is needed to motivate firms to do so. The role of competitive pressure is also supported by the negative and statistically significant coefficients corresponding to $HHI_{j,t}$ and their interaction term ($HHI_{j,t}$and $ERP_{j,t}$). Creating competitive pressure plays a role in forcing firms to hire skilled workers, regardless of whether the pressure comes from abroad or from domestic markets.

Interestingly, the coefficient corresponding to $ERP_{j,t}^{FTA}$ turns out to be positive, but statistically insignificant in the PPML model. In the other estimation models in Table 4, it is statistically significant at 5 per cent. This suggests that tariff cuts under FTAs and their induced competitive pressure do not work in the same way as those under the WTO. This is perhaps due to the nature of tariff cut commitments under FTAs, which are selective. Exemptions under WTO commitments are likely to also be exempted under FTAs. In addition, utilizing FTA preferential trade schemes incurs dollar costs to firms and many firms have benefited from tariff exemption schemes long available before the signed FTAs. Hence, Thai firms have actively not utilized FTA schemes. In particular, Kohpaiboon and Jongwanich (2019) found that FTA preferential schemes accounted for less than 30 per cent of total imports between 2006 and 2017. Note that the results are not significantly affected when $ERP_{j,t}^{FTA}$ is dropped from the estimation (See Column 5.2 of Table 5).

Another hypothesis to be examined in this paper is the impact of participating in GPS. Firms in GPS intensive industries tend to hire more skilled workers. Note that in the PPML model, the coefficient associated with $Network_{j,lag}$ is positive, but not statistically significant (Column 4.3 of Table 4). It is also notable that in the other models in Table 4, the coefficient is positive and statistically significant. Interestingly, only the coefficient corresponding to its interaction term with $impd_{i,j,t}$ is positive and statistically significant. The statistical insignificance of $Network_{j,lag}$ could be largely driven by introducing the two interaction terms (collinearity with each other). When the two interaction terms are dropped, the coefficient turns to be statistically significant at the 5 per cent rate (See Column 5.3 of Table 5).

All results, therefore, suggest firms in GPS intensive industries tend to hire more skilled workers. The need to hire skilled workers is statistically greater when firms rely on imported intermediates. These intermediates are often embedded with advanced technology, so that skilled workers are required. The statistical insignificance of the interaction term with $expd_{i,j,t}$ suggests that there is no additional requirement of skilled workers for exporting firms. This finding is consistent with previous studies (i.e. Kohpaiboon and Jongwanich, 2015 whose analysis concerns wage premiums). This suggests that outsourced activities from developed to developing countries are relatively skilled labor intensive as opposed to other activities in the developing countries concerned, all other things being equal.

Conclusions and Policy Inferences

The paper examines the hiring of skilled workers at the plant level of Thai manufacturing with a view to informing two policy debates concerning ongoing economic globalization, that is whether trade liberalization under FTAs is complementary to that under the WTO, and whether participating in GPS makes firms in developing countries become trapped in low-end segments of value chains.A firm-level panel dataset compiled from three censuses of Thai manufacturing (2006, 2011 and 2016) is used in the econometric analysis. Guided by relevant economic theories, the empirical model is nested in an eclectic manner where two policy debates are included over and above firm-specific factors.

Our key findings suggest that so far competition pressure is one crucial factor driving firms to be active in hiring skilled workers and staying competitive. While WTO negotiations have stalled and many countries, including Thailand, advance their trade liberalization agenda through FTAs, the competition created by the latter is not adequately strong enough in motivating firms to hire more skilled workers. Our results suggest that participating in GPS influences firms to hire more skilled workers. This is especially true for those importing intermediates. While GPS outsourced activities are often unskilled-labour intensive in the developed country context, they can be skilled-intensive in the developing country context. The evidence from Thai manufacturing does not support the concern regarding being trapped in low-end segments of value chains, heavily relying on pools of cheap labor to stay competitive.

Three policy inferences can be drawn. Firstly, solely enlarging a pool of skilled workers without promoting demand within their respective employment fields is likely to exacerbate existing problems in terms of quality mismatching. Promoting the use of skilled workers by firms must first go hand in hand. Secondly, installing competitive pressure is one key determinant influencing firms to hire more skilled workers. This can be done by advancing trade liberalization agendas. Using FTAs in forwarding trade liberalization agendas must be undertaken with caution. Whether they can be an effective tool hinges on how their commitment has been made and how they have been implemented. Thirdly, there is mutual benefit to be derived from participating in GPS to be shared between developed and developing countries.

Table 1 Share of White-collar Workers across Industries between 2006 and 2016

ISIC	Description	2006	2016
15	Manufacture of food products and beverages	16.7	14
17	Manufacture of textiles	8.8	11.2
18	Manufacture of wearing apparel; dressing and dyeing of fur	7.3	9.3
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness, and footwear	9.5	10.7
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	10.1	8.2
21	Manufacture of paper and paper products	13.9	13.6
22	Publishing, printing and reproduction of recorded media	21.1	12.3
23	Manufacture of coke, refined petroleum products and nuclear fuel	30.8	12.6
24	Manufacture of chemicals and chemical products	24.9	17.5
25	Manufacture of rubber and plastics products	12.8	10.7
26	Manufacture of other non-metallic mineral products	14.1	18.8
27	Manufacture of basic metals	13.1	11.9
28	Manufacture of fabricated metal products, except machinery and equipment	13.2	11
29	Manufacture of machinery and equipment n.e.c.	13.9	11.4
30	Manufacture of office, accounting, and computing machinery	10.3	7.9

Table 1 Share of White-collar Workers across Industries between 2006 and 2016 (continued)

ISIC	Description	2006	2016
31	Manufacture of electrical machinery and apparatus n.e.c.	17	8.4
32	Manufacture of radio, television and communication equipment and apparatus	13.1	16.6
33	Manufacture of medical, precision, and optical instruments, watches and clocks	5.2	13.4
34	Manufacture of motor vehicles, trailers, and simi-trailers	14.3	10.3
35	Manufacture of other transport equipment	15.7	20
36	Manufacture of furniture; manufacturing n.e.c.	10.8	10.1
	All manufacturing	13.6	12.8

Source: Author's compilation from 2006 and 2016 industrial censuses.

Table 2 Statistical Summary of Variables in the Regression Analysis

Variable	Obs	Mean	Std. dev.	Min	Max
$skill_{i,j,t}$	14,585	0.1	0.1	0.0	1.0
$(K/L)_{i,j,t}$	14,616	12.4	1.6	4.4	21.5
$size_{i,j,t}$	14,616	17.5	2.1	10.1	25.6
$own_{i,j,t}$	14,616	0.1	0.2	0.0	0.7
$exp_{i,j,t}$	14,616	0.1	0.2	0.0	0.7
$imp_{i,j,t}$	14,616	0.1	0.2	0.0	0.7
$RD_{i,j,t}$	14,616	0.0	0.1	0.0	3.4
$ERP_{j,t}$	14,596	-0.1	0.3	-1.7	0.7
$\Delta ERP_{j,t}$	14,596	0.03	0.95	-3.25	3.34
$HHI_{j,t}$	14,600	-3.4	1.0	-5.5	-0.01
$Network_{j,lag}$	13,972	0.1	0.2	0.0	1.0
OG_{j,lag_t}	14,341	1.9	-13.4	50.6	112.3

Source: Author's Calculations

Table 3 Correlation Matrix of Variables in the Regression Analysis

	$skill_{i,j,t}$	$(K/L)_{i,j,t}$	$size_{i,j,t}$	$own_{i,j,t}$	$exp_{i,j,t}$	$imp_{i,j,t}$	$RD_{i,j,t}$	$ERP_{j,t}$	$\Delta ERP_{j,t}$	$HHI_{j,t}$	$Network_{j,lag}$
$(K/L)_{i,j,t}$	0.13	1.00									
$size_{i,j,t}$	0.15	0.41	1.00								
$own_{i,j,t}$	0.06	0.13	0.31	1.00							
$exp_{i,j,t}$	0.01	0.06	0.34	0.40	1.00						
$imp_{i,j,t}$	0.09	0.10	0.29	0.36	0.41	1.00					
$RD_{i,j,t}$	0.07	0.03	0.05	0.02	0.06	0.05	1.00				
$ERP_{j,t}$	0.05	-0.05	-0.02	0.01	0.03	0.03	0.10	1.00			
$\Delta ERP_{j,t}$	0.05	-0.05	-0.02	0.01	0.03	0.03	0.09	0.95	1.00		
$HHI_{j,t}$	0.01	0.02	0.05	0.07	0.04	0.10	0.03	0.01	-0.03	1.00	
$Network_{j,lag}$	0.01	0.03	0.14	0.19	0.08	0.13	-0.01	0.02	0.01	0.12	1.00
OG_{j,lag_t}	0.07	0.08	0.08	0.07	0.01	0.02	0.03	0.01	0.00	0.01	0.25

Source: Author's Calculations

Table 4 Estimation Results

VARIABLES	4.1 (FE)	4.2 (RE)	4.3 (PPML)	4.4 (Tobit)
$size_{i,j,t}$	0.00394**	0.00716***	0.0401***	0.00714***
	(0.00153)	(0.000805)	(0.0151)	(0.000758)
$(K/L)_{i,j,t}$	0.00411***	0.00507***	0.0423***	0.00506***
	(0.00116)	(0.000914)	(0.0118)	(0.000895)
$own_{i,j,t}$	0.0510***	0.0180*	0.417***	0.0182**
	(0.0138)	(0.0101)	(0.121)	(0.00909)
$exp_{i,j,t}$	-0.0220**	-0.0336***	-0.0984	-0.0336***
	(0.0108)	(0.00798)	(0.101)	(0.00782)
$imp_{i,j,t}$	0.0474***	0.0409***	0.400***	0.0409***
	(0.0129)	(0.00991)	(0.109)	(0.00884)
$RD_{i,j,t}$	0.0703***	0.0634***	0.509***	0.0635***
	(0.0168)	(0.0146)	(0.12)	(0.0121)
$ERP_{j,t}$	-0.0512***	-0.0528***	-0.598***	-0.0527***
	(0.0103)	(0.0103)	(0.0992)	(0.0108)
$ERP_{j,t}^{FTA}$	0.0328**	0.0322**	0.257	0.0322**
	(0.0165)	(0.0161)	(0.162)	(0.0148)
$HHI_{j,t}$* $ERP_{j,t}$	-0.0293***	-0.0301***	-0.330***	-0.0301***
	(0.00319)	(0.00317)	(0.0324)	(0.0033)
$HHI_{j,t}$	-0.0313***	-0.0287***	-0.283***	-0.0287***
	(0.00362)	(0.00349)	(0.033)	(0.00336)
$Network_{j,lag\_t}$	0.0937*	0.0991**	0.746	0.0991**
	(0.0488)	(0.0469)	(0.496)	(0.0489)
$Network_{j,lag\_t} * expd_{i,j,t}$	-0.00368	-0.0261*	-0.0907	-0.0259*
	(0.0192)	(0.0139)	(0.166)	(0.014)

Table 4 Estimation Results (continued)

VARIABLES	**4.1 (FE)**	**4.2 (RE)**	**4.3 (PPML)**	**4.4 (Tobit)**
i$Network_{j,lag_t} * imp_{di,j,t}$	0.0381**	0.0595***	0.386***	0.0593***
	(0.0189)	(0.0149)	(0.147)	(0.0138)
OG_{j,lag_t}	0.000729***	0.000678***	0.00720***	0.000678***
	(9.18e-05)	(8.60E-05)	(0.000795)	(9.88E-05)
Constant	0.00158	-0.188***		-0.187***
	-0.053	-0.0196		-0.0211
Observations	13,868	13,868	12,068	13,868
R-squared	0.048			
Number of Observation	4,755	4,755	4,069	4,755
Industry dummies	Yes	Yes	Yes	Yes

Note: ***,**, and * indicate statistical significance at 1 5 and 10 per cent; the numbers in parentheses are robust standard errors; FE= Fixed-effect, RE= Random-effect, PPML = Fixed-effect Poisson Pseudo Maximum Likelihood and Tobit= the random effect Tobit model

Source: Author's Estimation

Table 5 Results' Robustness Checks (with PPML estimations)

	5.1	5.2	5.3
	Simultaneity bias	Drop $ERP_{j,t}^{FTA}$	Drop interaction terms with $Network_{j,lag\_t}$
$size_{i,j,t}$	0.0349**	0.0397***	0.04***
	(0.0159)	(0.015)	(0.015)
$(K/L)_{i,j,t}$		0.0425***	0.042***
		(0.0117)	(0.0117587)
$K_{i,j,t}$	0.0376***		
	(0.0124)		
$own_{i,j,t}$	0.422***	0.417***	0.44***
	(0.121)	(0.121)	(0.12)
$exp_{i,j,t}$	-0.108	-0.0949	-0.1
	(0.102)	(0.101)	(0.099)
$imp_{i,j,t}$	0.400***	0.405***	0.481***
	(0.109)	(0.109)	(0.103)
$RD_{i,j,t}$	0.504***	0.513***	0.511***
	(0.12)	(0.121)	(0.12)
$ERP_{j,t}$	-0.600***	-0.553***	-0.597***
	(0.099)	(0.0982)	(0.099)
$ERP_{j,t}^{FTA}$	0.267*		0.24*
	(0.161)		(0.161)
$HHI_{j,t}$* $ERP_{j,t}$	-0.328***	-0.327***	-0.333***
	(0.0324)	(0.0326)	(0.032)
$HHI_{j,t}$	-0.284***	-0.283***	-0.283***
	(0.033)	(0.033)	(0.033)

Table 5 Results' Robustness Checks (with PPML estimations) (continued)

	5.1	5.2	5.3
	Simultaneity bias	Drop $ERP_{j,t}^{FTA}$	Drop interaction terms with $Network_{j,lag\_t}$
$Network_{j,lag\_t}$	0.771	0.811	0.923**
	(0.498)	(0.502)	(0.48)
$Network_{j,lag\_t} * expd_{i,j,t}$	-0.0838	-0.0867	
	(0.167)	(0.166)	
$Network_{j,lag_t} * imp_{di,j,t}$	0.389***	0.373**	
	(0.148)	(0.148)	
OG_{j,lag_t}	0.00722***	0.00720***	0.00687***
	(0.000795)	(0.000792)	(0.0007)
Observations	12,068	12,068	12,068
Industry Dummies	Yes	Yes	Yes

Note: ***,**, and * indicate statistical significance at 1, 5 and 10 per cent; the numbers in parentheses are robust standard errors

Source: Author's Estimations

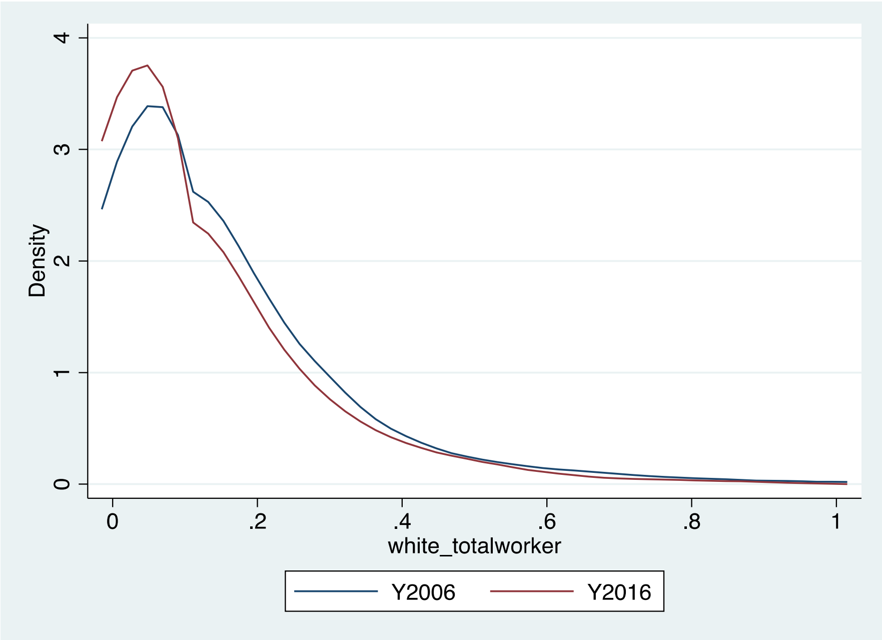

Figure 1.1 Comparing 2006 and 2016 industrial censuses

Kernel Distribution of the Share of White-collar to Total Workers

Source: Author

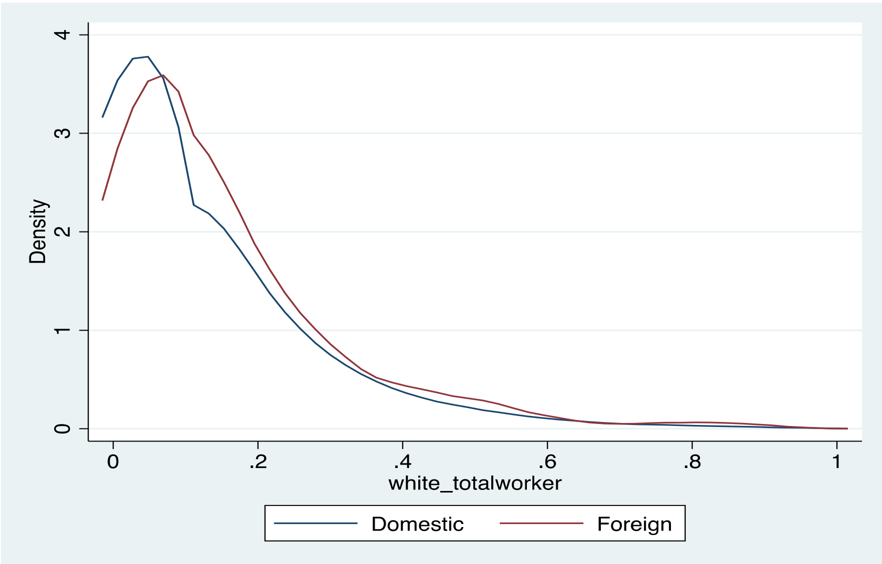

Figure 1.2 Firms' ownership

Kernel Distribution of the Share of White-collar to Total Workers

Source: Author

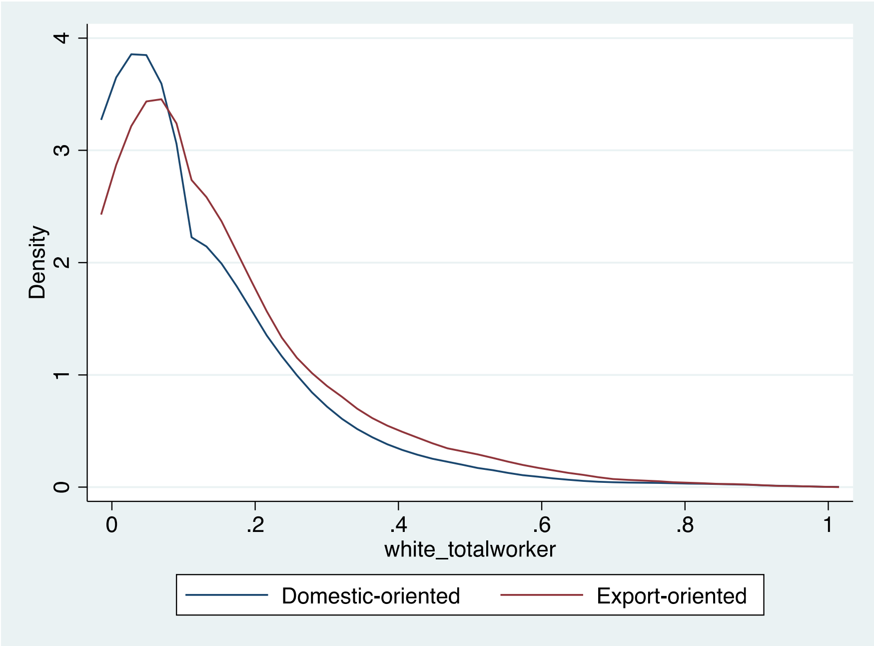

Figure 1.3 Market orientation

Kernel Distribution of the Share of White-collar to Total Workers

Source: Author

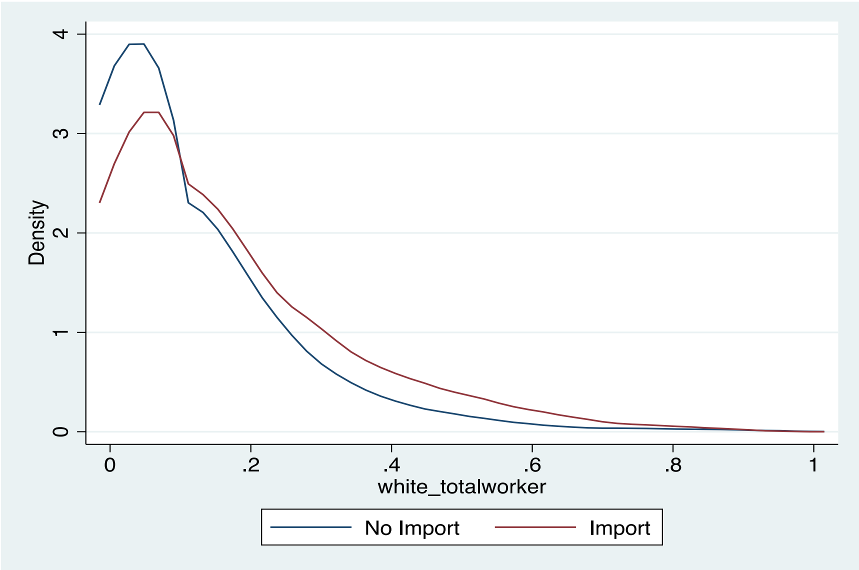

Figure 1.4 Import sourcing

Kernel Distribution of the Share of White-collar to Total Workers

Source: Author

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