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## **Global Engagement and the Occupational Structure of Firms**

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**Abstract:** Global engagement can impact firm organization and the occupations firms need. We use a simple task-based model of the firm's choice of occupational inputs to examine how that choice varies with global engagement. We reveal a robust and causal relationship between global engagement and the skill mix of occupations within firms, using Swedish matched employer-employee data that link firms and the labor force for 1997-2005. Taking an instrumental variable approach, we find that increased export shares (driven by higher world import demand) skew the labor mix more toward high-skill occupations. Our results suggest that global engagement may require firms to employ more skilled labor to undertake complex tasks embodied in international businesses, which have further implications for the demand for specific occupational skills and overall wage dispersion.

**JEL:** F1, F2

**Keywords:** Occupational structure, Globalization, Multinational Enterprises, Exporters

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## 1. Introduction

It is well documented that multinational firms are more skill intensive than purely local firms,<sup>1</sup> and exporters are more skill intensive than non-exporters.<sup>2</sup> However, less is known about the exact nature of, and the mechanism behind, the differences in skill intensities. Due to data limitations, previous studies usually define production workers as the unskilled and non-production workers as the skilled. Further, although the established evidence suggests a strong correlation between exporters/multinationals and skill intensity, it remains unclear to what extent international activities can affect the skill mix within firms. This is important since the systematic differences in skill mix across firms can have implications for the dynamics of aggregate labor markets as the degree of globalization changes. If the distribution of firms *within* sectors changes in concert with the process of globalization, those cross-firm differences in skill mix may imply changes in the demand for workers with different skills and thus their wages.

In this paper we reveal detailed patterns of the skill mix across firms with different degree of global engagement, and investigate the causal effect of global engagement on the skill mix at the firm level. To this end, our empirical investigation uses comprehensive and detailed Swedish matched employer-employee data spanning 1997 to 2005, which is further merged with Swedish Foreign Trade Statistics that contain information on firms' import and export activities. The data cover all Swedish firms and a representative sample of the labor force, including information on worker occupations at a very detailed level (100 occupations), which allows us to examine labor specialization at a detailed occupational level.

Initial results are displayed in Figure 1 which shows the aggregate distribution of payroll shares by skill levels for three different firm types: MNEs, which are the most globally integrated firms; non-MNEs that do not export (i.e., Local firms), which are the least globally integrated; and non-MNE exporters, which represent an intermediate degree of global integration. The horizontal axis is the skill percentile ranking of occupations based on the average occupational wages for all firms in 1997. The vertical axis is the cumulative payroll share accounted for by the skill category indicated on the horizontal axis. Compared to Local firms, the distribution of payroll share for MNEs and non-MNE exporters is more skewed toward high-skill occupations, e.g.,

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<sup>1</sup> e.g., see Markusen 1995, and Barba-Navaretti and Venables 2004, for a survey; Lipsey and Sjöholm 2004 on Indonesia; Heyman et al. 2007 on Sweden.

<sup>2</sup> e.g., see Bernard and Jensen 1997 on the U.S.; Alvarez and Lopez 2005 on Chile; Munch and Skaksen 2008 on Denmark.

managers, professionals specialized in finance and sales, computing, and engineering. For instance, Local firms allocate roughly 40% of payroll expenditures to occupations above the 60<sup>th</sup> skill percentile. The corresponding figures for MNEs and Exporters are roughly 60% and 50%, respectively.

To guide the empirical investigation, we use a task-based model of the firm's choice of occupational inputs to examine how that choice varies with global engagement. Our model builds on Chaney and Ossa's (2013) framework in which production requires a series of tasks to be completed and firms design their production chain to minimize costs. We depart from Chaney and Ossa by assuming that it is costlier to train workers to perform more complex tasks. Within the structure of our model, firms skew employment and payroll shares toward occupations engaged in more complex tasks. Assuming that increased global engagement is associated with additional fixed costs (e.g., Melitz 2003, Helpman et al. 2014) and the additional fixed cost is intensive in the use of more complex specializations, we derive the main proposition that *for more globalized firms, total payroll expenses will be further skewed towards higher-skilled occupations with specialization in more complex tasks*. In this paper, we quantify this relationship between global engagement and the occupational structure of firms.

Our estimations confirm a robust and causal relationship between the degree of international integration and the skill mix of occupations at the firm level. We measure the skill mix using an index computed as a weighted average of the skill rankings of each occupation, with firm-occupation-year specific payroll shares as the weight. We first focus on a sample of exporters to estimate the impact of increased export shares on the skill mix. Taking an instrumental variable approach, we find that increased export shares, driven by higher world demand for the product that the firm is exporting, lead to a shift of payroll expenses toward more skilled occupations. The 2SLS estimate of the coefficient on export shares is significantly positive, and the magnitude is economically large: the implied skill index differential between exporters at the 75<sup>th</sup> percentile of export shares and those at the 25<sup>th</sup> percentile is more than half of the 75-25 skill index differentials between firms that exported in 1997. We also find that this shift in skill mix (induced by higher export shares) mainly arises from a shift toward more complex specializations *within* non-production categories (e.g., a smaller share of sales workers, and a bigger share of professionals specialized in finance, engineering) and *within* production categories (e.g., a smaller share of transportation operators and a bigger share of machine operators). However, we find less robust evidence for a shift from production to non-production categories, implying that using the

standard classification of worker skills into production and non-production categories may miss substantial shifts in skill mix as a result of increased export shares. We also find that export to markets with higher entry costs (e.g., non-EU markets, lower-income markets) is significantly associated with a higher skill index.

We then look at the full sample of all firms, and compare MNEs, non-MNE exporters and Local firms. Confirming the pattern at the aggregate level as displayed in Figure 1, we find that payroll expenses are most skewed toward high skilled occupations for MNEs, and the least skewed toward skilled for Local firms. More than half of the skill index differential between globally engaged firms and Local firms is associated with a shift toward more complex specializations within non-production categories, while only about one third is associated with a shift from production to non-production categories.

Our results suggest that increased global engagement may lead firms to change their skill mix in order to undertake complex tasks embodied in multinational and export activities. Previous studies document that firms invest in new technology in response to increased market access (see, e.g., Lileeva and Trefler 2010 on Canada, and Bustos 2011 on Argentina). Our paper complements these studies by showing that firms may also need to reorganize their production (in terms of labor specialization) in the process of globalization. In particular, certain occupational skills can constitute an important component of the fixed costs that firms must incur to gain access to global markets. This is a new mechanism that differs from the technology-skill complementarity by Burstein and Vogel (2016) and sorting by product quality within industries by Verhoogen (2008). In Section 4.C we emphasize the importance of this new mechanism by showing that the cross-firm variation in the occupational structure has important implications for the demand for different skills and overall wage dispersion.

Our paper also relates to a small but growing empirical literature on globalization and firm organization. Some of these studies find that trade liberalization makes firms flatter with fewer layers of management (Rajan and Wulf 2006, Guadalupe and Wulf 2010), whereas others find that new exporters are likely to add layers of management (Caliendo et al. 2015). Unlike these empirical studies that focus on organizational hierarchy, our work focuses on the skill mix in firms with different degrees of global engagement.

Furthermore, the richness of our data allows us to deepen our understanding of the relationship between global engagement and skills. Our study presents the most comprehensive analysis to date, with a special focus on differences in the mix of occupations between firms. Our measure of skill mix captures not only the shift

from production to non-production categories, but also the shift from lower skilled to higher skilled occupations within the categories of production or non-production.

While our main interest is in the skill effect of export activities, our analysis also covers the impact of offshoring on the demand for different skills. As documented by Hummels et al. (2014) and others, imports of intermediates may substitute for unskilled labor and thus shift the distribution of employment (and payroll) toward more skilled. We find that the skill effect of export activities is little changed after controlling for offshoring. On the other hand, the skill effect of offshoring varies across occupations within the broad non-production and production groups. We show that higher offshoring shares increase the demand for more skilled occupations within the non-production category, while shifting payroll expenses toward lower skilled occupations within the production category. This result complements previous studies on offshoring and labor markets, e.g., Hummels et al. (2014) and Goos et al. (2014).

Finally, our study covers the whole economy, including both manufacturing and non-manufacturing industries. This is important since manufacturing is declining in many industrialized economies while non-manufacturing industries are playing an increasingly important role in global businesses (see Jensen 2011 for an overview). We find that more globalized firms have payroll more skewed toward high skilled occupations for both manufacturing and non-manufacturing firms.

In the following we sketch out a simple theoretical framework in Section 2, describe the data, measurement and empirical specification in Section 3, turn to detailed empirical analysis in Section 4, and conclude in Section 5.

## **2. A Conceptual Framework**

In this section, we modify the theoretical framework of Chaney and Ossa (2013) to understand why we might expect systematic differences in the occupational structure of employment across firms with different characteristics.<sup>3</sup> In this framework, firms create teams of workers and assign each team a set of tasks to complete. In doing so, the firm trains each team to have a “core competency” or “specialization,” which allows it to complete a certain task at zero cost. The team completes related tasks that are close to its specialization at

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<sup>3</sup> See Davidson et al. (2016) for a complete analysis of the model outlined here. Footnote 6 below clarifies the differences between our analysis here and the one provided in Davidson et al (2016).

positive cost, with the cost increasing in the distance of that task from the team's core competency. Thus, we can think of a firm hiring a group of attorneys and training them in the law that relates specifically to the firm's product market. Those attorneys could also deal with other legal issues within the firm that are somewhat related to their specialization. The firm's goal is to select the number of teams and assign them tasks in a way to produce the desired output as cheaply as possible.

We measure labor in efficiency units and use  $w$  to represent the wage per efficiency unit of labor. We order tasks by complexity and assume that more complex tasks require more efficiency units of labor. To operationalize the theory, we map teams to occupations by defining an occupation as a specialization combined with the tasks assigned to the team. For example, firms hire teams of attorneys, accountants, mid-level managers, machinists, and so on. This interpretation is consistent with the definition of occupations in the context of ISCO-88 and SSYK96 where occupations are grouped together and aggregated on the basis of the similarity of skills required to fulfill the duties of particular jobs (Hoffman 2004). Given our interpretation, we can then use the terms "occupation" and "teams" interchangeably.

Formally, define the set of tasks  $\omega \in [0,1]$  where  $\omega''$  is more complex than  $\omega'$  for all  $\omega'' > \omega'$  and assume that each task must be completed once to produce one unit of output. Suppose that there are  $n$  occupations indexed by  $k$  and let  $s_k \in [0,1]$  denote the specialization associated with occupation (and team)  $k$ . We further assume that this team is assigned a range of tasks  $[\underline{\omega}_k, \bar{\omega}_k] \subseteq [0,1]$ . We define  $\ell_k$  as the number of efficiency units of labor needed for this team to produce  $y$  units and assume that

$$(1) \quad \ell_k = f + \beta s_k + y \int_{\underline{\omega}_k}^{\bar{\omega}_k} |s_k - \omega| d\omega, \quad f > 0, \quad \beta > 0.$$

The cost of employing occupation  $k$  is  $w\ell_k$ , consisting of both fixed and variable components. Multiplying the first two terms in (1) by  $w$  captures the fixed cost of establishing and training the team, while multiplying the last term by  $w$  represents the variable cost of producing  $y$  units of output.<sup>4</sup>

In writing (1), we treat  $f$  and  $\beta$  as parameters of the technology that may vary across industries and possibly with the degree to which firms within a given industry are globalized. We can think of this as a

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<sup>4</sup> Since different individuals may embody different efficiency units of labor, (1) does not necessarily represent the measured number of workers (headcount or hours) in a particular occupation. For example, a firm might have one manager embodying  $M$  efficiency units of labor, and  $P$  production workers, each embodying one efficiency unit of labor. The payroll share of management will exceed the payroll share of production workers as long as  $M > P$ .

refinement of Melitz (2003) or Helpman, Melitz, and Yeaple (2004), both of which assume additional fixed costs for firms that are more globalized. Our model supposes that the additional fixed cost is intensive in the use of more complex specializations. For example, additional fixed costs associated with exporting might be concentrated in tasks dealing with writing contracts and managing exchange risk rather than product assembly (in which case, task  $s_k$  would be interpreted as ‘writing contracts’ or ‘managing risk’). Thus, an internationally engaged firm would need to train its legal staff to handle contracts that cover aspects of both domestic and international law related to its product. In a sense, this means that internationally engaged firms must train their workers to take on a wider variety of duties (i.e., embody more efficiency units of labor) for a given task  $s_k$ . Under this scenario,  $\beta$  would be larger for more globalized firms. As such, the degree of globalization would exert a *direct globalization effect* on the design of the optimal production chain.

In addition to the direct effect, global engagement may also exert an indirect effect on the design of the optimal production chain. The indirect effect emerges since more globalized firms tend to be larger than less globalized firms. That effect, which we reference as the *size effect*, is captured by  $y$  in equation (1). As we show below, the direct globalization effect and size effect are partially offsetting.<sup>5</sup>

The firm’s objective is to design its production chain to minimize cost. Specifically, it must decide how many teams to form ( $n$ ), the location of each team’s specialization ( $s_k$ ) on the task continuum, and the set of tasks to assign each team ( $\underline{\omega}_k$  and  $\bar{\omega}_k$ ). Formally:

$$(2) \quad \underset{n, s_k, \underline{\omega}_k, \bar{\omega}_k}{\text{minimize}} \quad w \sum_{k=1}^n \left\{ f + \beta s_k + y \int_{\underline{\omega}_k}^{\bar{\omega}_k} |s_k - \omega| d\omega \right\}.$$

Solving the firm’s problem is done via backwards induction. Taking the number of teams as given, we first solve for the optimal specialization ( $s_k$ ) given that team’s assigned set of tasks (defined by  $\underline{\omega}_k$  and  $\bar{\omega}_k$ ). We then solve for the optimal set of tasks to assign to each team.<sup>6</sup>

The first insight that we obtain is that for a given set of tasks, the firm will select a specialization closer

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<sup>5</sup> Thus, we are following Helpman et al. (2004) in assuming increased global engagement is associated with firms that are bigger (as captured through changes in  $y$ ) and that have additional fixed costs of production and market entry (as captured by changes in  $\beta$ ) when compared to their domestic counterparts.

<sup>6</sup> There are two main differences between this analysis and what is presented in Davidson et al (2016). First, in the latter paper, we present the details behind all of our derivations, while here we only summarize our results. Second, for concreteness, we take the number of teams to be fixed in this paper. In Davidson et al (2016) we treat  $n$  as endogenous, solve for the optimal number of teams and show that the analysis is qualitatively the same as when  $n$  is exogenous.



to the least complex task than it is to the most complex task. Using an asterisk to represent the cost-minimizing choice, it can be shown that  $s_k^* = \frac{1}{2}(\underline{\omega}_k + \bar{\omega}_k - \frac{\beta}{y}) < \frac{1}{2}(\underline{\omega}_k + \bar{\omega}_k)$ . The intuition for this result, which we refer to as the *specialization bias*, is as follows. If  $\beta = 0$  so that the fixed component in (1) is independent of the team's specialization, the firm would choose  $s_k$  at the mid-point of the range of tasks in order to minimize the variable cost needed to complete the tasks. However, this is not the case if the fixed labor requirement increases with complexity. In this case, the firm can save on fixed costs by marginally reducing the specialization that it uses, but doing so increases variable cost. A given reduction in  $s_k$  results in a larger reduction in fixed costs relative to the increase in variable cost when  $\beta$  is large or  $y$  is small. Thus, an increase in  $\beta$  makes the specialization bias more pronounced while an increase in  $y$  moderates the specialization bias by increasing the relative importance of variable costs. Much of what follows hinges on the tradeoff between fixed and variable costs and how that tradeoff might be affected by global engagement.

The second insight concerns the range of tasks assigned to each team. Since the fixed cost of establishing a team is increasing in the complexity of that team's specialization, *the firm will assign teams with less complex specializations a narrower range of tasks than those with more complex specializations*. To show this, we first note that since each task must be completed, the most complex task assigned to the team with specialization  $s_k$  must be the same as the least complex task assigned to the team with specialization  $s_{k+1}$  (i.e.,  $\bar{\omega}_k = \underline{\omega}_{k+1}$ ). With this in mind, if we substitute  $s_k^*$  into (2), fix  $n$ , and optimize over  $\underline{\omega}_k$  and  $\bar{\omega}_k$  we can show that  $\bar{\omega}_k^* = \underline{\omega}_{k+1}^* = \frac{k}{n} - k(n-k)\frac{\beta}{y}$ . We can now solve for the range of tasks assigned to team  $k$ :  $\bar{\omega}_k^* - \underline{\omega}_k^* = \frac{1}{n} - [n - 2k + 1]\frac{\beta}{y}$ , which is increasing in  $k$ .

We can push the analysis further by substituting the optimal cut-off values back into  $s_k^*$  to obtain  $s_k^* = \frac{2k-1}{2n} - \left\{ \frac{n}{2} + (n-k)(k-1) \right\} \frac{\beta}{y}$ , implying that  $s_{k+1}^* - s_k^* = \frac{1}{n} - [n - 2k + 2]\frac{\beta}{y}$ , which is increasing in  $k$  – that is, the distance between specializations is increasing in the complexity of the task, so that *the design of the production chain is skewed towards less complex occupations*. The skewness is positively related to the direct globalization effect and inversely related to the size effect. Intuitively, this stems from the fact that the relative cost of using more complex occupations rises as  $\beta$  increases, leading firms to use relatively more occupations with less complex specializations and assigning them a narrower range of tasks, therefore increasing the

skewness of the distribution of specializations. The size effect works in the opposite direction, since any increase in  $y$  makes variable costs relatively more important and decreases the firm's incentive to shade each team's specialization towards low-skilled tasks.

We can now derive the theoretical analog of Figure 1. If we substitute the optimal cut-off values and specializations back into (1), we can derive the payroll expense for occupation  $k$ :  $w\ell_k = w\left\{f + \frac{y}{4}\left(\frac{1}{n}\right)^2 + \frac{\beta^2}{y}\left\{\frac{n^2+4n+2}{4}\right\} - \frac{\beta(n+2)}{2n} + \left\{\frac{2\beta}{n} - \frac{2\beta^2(1+n)}{y}\right\}k + \frac{2\beta^2}{y}k^2\right\}$ . Differentiate with respect to the occupation index to get:

$$(3) \quad w \frac{\partial \ell_k}{\partial k} = w \left\{ \frac{2\beta}{n} \left( 1 - \frac{\beta n^2}{y} \right) + \frac{2\beta^2}{y} (2k - 1) \right\}.$$

The second-order condition for the firm's optimization problem is  $n^2 < y/\beta$  so that  $\beta > 0$  implies that  $\frac{\partial \ell_k}{\partial k} > 0$  and  $\frac{\partial^2 \ell_k}{\partial k^2} > 0$  for all  $k \geq 1$  (see Davidson et al. 2016). Occupation-specific payroll is increasing and convex in the occupation index. Moreover, since occupation-specific payroll *share* is simply occupation-specific payroll divided by the firm's total payroll, *convexity of occupation-specific payroll implies that the cumulative distribution function for payroll shares is also convex*. In addition, the Arrow-Prat measure of convexity is increasing in  $\beta$  and decreasing in  $y$ .<sup>7</sup>

These results come directly from our earlier findings on the skewness of the specialization distribution and the manner in which the specialization bias depends on  $\beta$  and  $y$ . To see this, first note that since less-skilled workers are assigned tasks that are near their specialization, the amount of variable cost involved is minimal. In contrast, more-skilled workers are assigned a wide range of tasks, some of which are quite distant from their specialization. This entails the need for a substantial amount of variable cost. Combined with the assumption that more complex occupations entail more fixed costs, we conclude that the payroll share tied to more complex occupations is larger than the payroll share tied to less complex occupations. In other words, *total payroll expenses will be skewed towards high-skilled occupations*. Moreover, the degree of skewness is increasing in  $\beta$  since the specialization bias becomes more pronounced as  $\beta$  rises. The reverse is true for changes in  $y$ . We can address this prediction in our empirical work by explicitly including firm size and degree of global

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<sup>7</sup> This is seen by using (3) to solve for  $\frac{\partial^2 \ell_k}{\partial k^2} / \frac{\partial \ell_k}{\partial k}$ . After some simplification,  $\frac{\partial^2 \ell_k}{\partial k^2} / \frac{\partial \ell_k}{\partial k} = \frac{2n}{y/\beta - n^2 - n + 2nk}$ .

engagement as explanatory variables.

To tie the model more closely to our empirical results, we note that our empirical work uses the language of “skill” when referring to occupations in contrast to the language of “complexity” in the theoretical model. In our context, more skilled workers are those who embody more efficiency units of labor. Further, in our empirical work, we have direct measures of firm size, but we do not have direct measures of  $\beta$ . Rather, as described in the next section, we proxy for  $\beta$  using measures that capture the degree to which a firm is globally engaged, e.g., export shares, and indicator variables for MNEs, non-MNE exporters and Local firms.

### 3. Data, Measurement, and Empirical Specification

#### A. Data

We use register-based matched employer-employee data from Statistics Sweden covering the period 1997-2005. The firm data contain detailed information on all Swedish firms, including variables such as value added, capital stock (book value), number of employees, wages, ownership status, sales, and industry. Moreover, the Regional Labor Market Statistics (RAMS) provide plant-level information on education and demographics, which we aggregate to the firm level. RAMS include data on all Swedish plants. The worker data cover detailed information on a representative sample of the labor force, including full-time equivalent wages, education, occupation, and gender.<sup>8</sup> Occupations are based on the *Swedish Standard Classification of Occupations (SSYK96)* which in turn is based on the *International Standard Classification of Occupations (ISCO-88)*. Occupations in ISCO-88 and SSYK96 are grouped based on the similarity of skills required to fulfill the duties of the jobs (Hoffmann, 2004).<sup>9</sup> Appendix A provides details on the occupation classification.

Firm level data on exports and imports by products and countries originate from the Swedish Foreign Trade Statistics, collected by Statistics Sweden. Based on compulsory registration at Swedish Customs, the data

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<sup>8</sup> The worker data originate from the Swedish annual salary survey (*Lönestrukturstatistiken*). The survey’s sampling units consist of firms included in Statistics Sweden’s firm data base (FS). A representative sample of firms is drawn from FS and stratified according to industry affiliation and firm size (number of employees). The sample size consists of between 8,000 and 11,000 firms. The Central Confederation of Private Employers then provides employee information to Statistics Sweden on all its member firms that have (i) at least ten employees and (ii) are included in the sample. Firms with at least 500 employees are examined with probability one. The final sample includes information on around 50% of all employees within the private sector and is representative of the Swedish labor force. See [www.scb.se](http://www.scb.se) for more details on the data.

<sup>9</sup> As part of the Swedish annual salary survey, data on occupations are also collected. In the instructions to firms, Statistics Sweden are asking for the main job duties for those who work at the firm during the current year, or who have worked at the firm during the previous year. There is an obligation to provide information for this survey according to the Official Statistics Act. The coverage of our occupation data is very good. Out of 8.3 million worker-year observations in firms with at least 20 employees, only 238,000 observations have missing information on occupation status.

cover all trade transactions from outside the EU.<sup>10</sup> Trade data for EU countries are available for all firms with a yearly import or export of around 1.5 million SEK and above. According to the figures from Statistics Sweden, the data cover around 92% of total goods trade within the EU. Material imports are defined at the 5-digit level according to NACE Rev 1.1 and grouped into Main Industrial Groupings (MIGs) based on intended use.<sup>11</sup> Based on the MIGs definition of intermediate inputs we identify offshoring using import data at the firm and product level.<sup>12</sup>

Multinationals consist of both Swedish and foreign owned firms. Information on foreign MNEs operating in Sweden comes from the Swedish Agency for Economic and Regional Growth (Tillväxtanalys). The Agency uses definitions that are in accordance with definitions in similar data from the OECD and Eurostat. A firm is classified as a foreign-owned MNE if more than 50% of the equity is foreign-owned. Finally, firms reporting trade with foreign firms in the same corporation are defined as Swedish MNEs.

All data sets are matched by unique identification codes. To make the sample of firms consistent across the time periods, we restrict our analysis to firms with at least 20 employees in the non-agricultural private sector, which are available throughout the period.

### *B. Measurement*

The goal of our empirical analysis is to quantify the relationship between global engagement and the occupational structure of firms. Below we describe how we measure the two key variables in our analysis: a firm's degree of global engagement (a proxy for  $\beta$  in the model), and the occupational structure of employment (or skill mix of occupations) within a firm.

#### *Global engagement*

We construct various measures to capture the different degree of global engagement by firms. On the extensive margin, we follow Helpman et al. (2004) and classify firms into three exclusive categories: (1) multinationals (MNEs); (2) non-MNE exporters; and (3) Local firms, i.e., non-MNEs that do not export. In our

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<sup>10</sup> Many firms in the non-manufacturing sector export goods as defined in our Customs data. Since the Customs data do not include service trade, firms that only export services are classified as non-exporters. However, as we show in Section 4.B, our results differ little between manufacturing and non-manufacturing industries.

<sup>11</sup> The Main Industrial Grouping (MIG) is a European Community classification of products. Based on intended use, there are five broad categories: Intermediate goods, capital goods, consumer durables, consumer non-durables, and energy. See [http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Main\\_industrial\\_grouping\\_\(MIG\)](http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Main_industrial_grouping_(MIG)) for more detail.

<sup>12</sup> See Hummels et al. (2016) for an overview of different measures of offshoring.

sample, 34.4% of firms are MNEs, 31.7% are non-MNE exporters, and 33.9% are Local firms. Our data reveal that the shares of professionals, especially in financing, marketing, and engineering, are the highest in MNEs, and lowest in Local firms. Those professionals may represent an important component of the fixed costs required for gaining access to foreign markets (Matsuyama, 2007). To map onto our model, MNEs have the largest  $\beta$  while Local firms have the smallest  $\beta$ . This is consistent with the Helpman et al. (2004) assumption that the fixed costs of production and market entry are the highest for MNEs but the lowest for Local firms.

On the intensive margin, we use the value of exports as a share of total sales to capture the variation in export intensity across both MNEs and non-MNE exporters. As firms export more, they may need to reach out for new consumers in foreign markets, which could imply additional costs of marketing, financing, and engineering. Thus,  $\beta$  is increasing in export shares.

We note that offshoring is an additional aspect of global engagement. In our sample 80% of MNEs are engaged in both exporting and offshoring, and more than two-thirds of non-MNE exporters also offshore. On the other hand, 91% of offshorers export. These statistics suggest that offshoring tends to be bundled with export decisions when firms expand globally. However, offshoring presents an alternative mechanism through which global expansion affects the occupational structure of employment. Unlike our model that associates global entry with skill-biased fixed costs, offshoring may reduce the demand for unskilled labor if imported intermediates are substitutes for the unskilled (Hummels et al. 2014). Thus, in the following analysis we control for offshoring (see Section 4.A for details).

#### Occupational structure:

In our model tasks are ranked by complexity. Teams (occupations) that specialize in more complex tasks (e.g., writing contracts) require more skills. Empirically, we rank occupations using average occupation-specific wages as proxies for skills.<sup>13</sup> Table A1 in the online appendix lists the 100 occupations ranked by the average occupational wages. On the top of the list are occupations that tend to require more education/training such as managers, research/business professionals, and technicians.

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<sup>13</sup> An alternative approach is to impute the task content of occupations (see e.g. the seminal work by Autor et al. 2003, and Acemoglu and Autor 2011 for an overview). Two studies that look at how globalization affects the relative demand for different job tasks are Becker et al. (2013) (analyzing the impact of offshoring) and Hakkala et al. (2014) (studying multinational activity and inward FDI). However, the data patterns presented in the online appendix suggest that the skill content of occupations may better characterize the cross-firm difference in labor mix in our sample.

The main proposition of our model is that total payroll expenses will be more skewed towards high-skilled occupations for more globalized firms. To capture the cross-firm difference in occupational structure, we use two measures. Our main measure is a skill index that captures the average skill level of the occupational structure. We also use a measure that captures the skewness of the occupational structure. Below we describe these two measures.

We first construct a skill index for firm  $j$  in year  $t$  as

$$(4) \quad S_{jt} = \sum_k \lambda_{jkt} s_k$$

where  $s_k$  represents the skill percentile ranking of occupation  $k$  and  $\lambda_{jkt}$  is the payroll share of occupation  $k$  at firm  $j$  in year  $t$ . This index is similar to the one used by Zhu and Trefler (2005) to measure the skill content of a country's exports. Since  $s_k$  is fixed for a specific occupation  $k$ , the difference in the skill index reflects the difference in distribution of payroll shares across firms. The skill index is higher if payroll is allocated more toward higher skilled occupations. The index is bounded between zero and one, and a value of 0.5 indicates that payroll is evenly distributed across all occupations.<sup>14</sup> We note that payroll expenditures are used to capture employment in efficiency units, as in our model. A manager could have more efficiency units than a production worker. To back out the efficiency units of employment, we use data on worker wages. For example, a manager who is twice as productive as a production worker should earn twice as much as that production worker. It is straightforward to show that the payroll share equals the share of employment in efficiency units.<sup>15</sup> Table A2 in the online appendix reports descriptive statistics on the skill index and on other firm characteristics. Consistent with our expectation, MNEs have the highest skill index on average while local firms have the lowest skill index. Compared to local firms, globalized firms are also larger, older, and more productive.

It is worth pointing out that since our skill index is constructed using a detailed classification of occupations, it can capture skill differentiation within the broader categories of production and non-production workers. In order to gain additional insights into labor specialization within firms, below we decompose the skill index into components that capture the shift from lower skilled to higher skilled occupations within the

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<sup>14</sup> This is a limiting result as the number of occupations tends to infinity. For a finite number of occupations ( $n$ ), the lower limit of the index is  $1/n$ , and  $S_{jt} = \frac{1}{2} \frac{n+1}{n}$  when  $\lambda_{jkt} = \frac{1}{n}$  for all  $k$ .

<sup>15</sup> Some other empirical work on globalization and labor demand also uses changes in payroll shares as the dependent variable (e.g. Hakkala et al., 2014).

broader categories of production or non-production, and the shift from production to non-production categories (equivalent to the traditional measure of the share of non-production workers). Specifically, let  $\bar{s}_{NP}$  be the average of  $s_k$  for all non-production occupations ( $NP$ ), and  $\bar{s}_P$  be the average of  $s_k$  for all production occupations ( $P$ ). Our skill index can then be decomposed as

$$(5) \quad S_{jt} = \sum_{k \in NP} \lambda_{jkt} (s_k - \bar{s}_{NP}) + \sum_{k \in P} \lambda_{jkt} (s_k - \bar{s}_P) + [(\bar{s}_{NP} - \bar{s}_P) \sum_{k \in NP} \lambda_{jkt} + \bar{s}_P].$$

To understand this decomposition, consider two firms  $j$  and  $j'$ . The difference in their skill index  $S_{jt} - S_{j't}$  equals

$$\sum_{k \in NP} (\lambda_{jkt} - \lambda_{j'kt}) (s_k - \bar{s}_{NP}) + \sum_{k \in P} (\lambda_{jkt} - \lambda_{j'kt}) (s_k - \bar{s}_P) + (\bar{s}_{NP} - \bar{s}_P) \sum_{k \in NP} (\lambda_{jkt} - \lambda_{j'kt}).$$

The first term is positive if on average  $\lambda_{jkt} > \lambda_{j'kt}$  for occupations with  $s_k > \bar{s}_{NP}$ , that is, if firm  $j$  allocates more payroll expenses toward higher skilled occupations in the non-production category, as compared to firm  $j'$ . Similarly, the second term captures the shift from less skilled to more skilled occupations in the production category. The third term is positive if  $\sum_{k \in NP} \lambda_{jkt} > \sum_{k \in NP} \lambda_{j'kt}$ , that is, firm  $j$  has a higher payroll share of the non-production category, as compared to firm  $j'$ .

In order to analyze higher moments of the distribution of skills across occupations, we apply a transformation of the Groeneveld-Meeden skewness measure (Groeneveld and Meeden, 1984). Let  $v_{jt}$  be the median of the payroll distribution, i.e., half of the payroll expenses are allocated to occupations with a skill percentile above  $v_{jt}$ , and the other half to occupations with a skill percentile below  $v_{jt}$ . We capture the skewness of the payroll distribution as

$$(6) \quad SK_{jt} = \frac{v_{jt} - S_{jt}}{\sum_k \lambda_{jkt} |s_k - v_{jt}|}.$$

A positive  $SK_{jt}$  (i.e.  $v_{jt} > S_{jt}$ ) implies that the payroll distribution is more skewed toward higher skilled occupations. Note that the skill index  $S_{jt}$  is the mean of the payroll distribution.

Finally, we use various alternative ways to measure the skill level of occupations as a robustness check, including the share of college graduates among workers in a particular occupation, the mean wage for each occupation using the sample of non-MNE firms (taking into account the dominant effect of MNEs on wages), or using the estimates from Mincer wage regressions that combine the returns to schooling and training required for a specific occupation. Since there are very high correlations between different ranking measures (over 95%),

our results are unchanged when these alternative measures are used. To save space, in what follows we only report results that use average occupational wages to rank occupations by skill content.

### C. Empirical specification

We use the following specification to examine our prediction that more globally engaged firms (with a larger  $\beta$ ) have a distribution of employment more skewed toward higher skilled occupations:

$$(7) \quad S_{jt} = \alpha \cdot Global_{jt} + Z_{jt}\gamma + D_i + D_t + \varepsilon_{jt}$$

where  $i, j$  and  $t$  index industries, firms, and years, respectively;  $S_{jt}$  is the skill index for firm  $j$  in year  $t$ ;  $Global_{jt}$  measures the extent of global engagement by firm  $j$  in year  $t$ ;  $Z_{jt}$  is a vector of firm characteristics that might affect the skill mix, including firm size (the number of employees), capital intensity (capital-labor ratio), labor productivity (value added per worker), and firm age;  $D_i$  represents industry fixed effects to control for e.g. technology differences across industries;  $D_t$  is year fixed effects that control for common macro-level shocks that may affect firm-level employment; and  $\varepsilon_{jt}$  is the error term.

Our model predicts a positive relationship between global engagement and skill mix, i.e.,  $\alpha > 0$ . Although our specification controls for various firm characteristics, it is still possible that some unobserved factors (e.g., firm-specific technology shocks) could be correlated with both global engagement and skill mix. Furthermore, firms with a higher share of professionals specialized in marketing, financing, and engineering might be able to expand trade more and have a higher export share. As a result, our estimates could be biased due to the possible endogeneity problem arising from omitted variables or reverse causality. Below we describe how we tackle these issues.

#### Instruments for export shares:

In the following analysis we first focus on a sample of exporters, which account for nearly two-thirds of the firms and more than 80% of employment in our sample. To overcome the potential endogeneity problem with the OLS estimates, we need to construct instruments that are positively correlated with a firm's export shares, but do not directly affect the occupational structure of the firm. Following Hummels et al. (2014), we instrument for export shares using the weighted averages of world import demand ( $WID$ ). Specifically, for firm  $j$  in year  $t$ , it is computed as:

$$(8) \quad WID_{jt} = \sum_{cg} tS_{jcg} * WID_{cgt},$$



where  $WID_{cgt}$  is country  $c$ 's total purchases of product  $g$  (at the 6-digit HS level) from the world market (less purchases from Sweden) in year  $t$  and  $ts_{jcg}$  is the share of firm  $j$ 's export of product  $g$  to country  $c$  in firm  $j$ 's total export.<sup>16</sup> Thus, the instrument  $WID_{jt}$  captures the fluctuations in world demand conditions that are time varying and specific to firm  $j$ . The variation in  $WID_{jt}$  stems from the fact that different firms export different products to different destination countries and hence firms will be differentially affected by changes in world demand. At the same time, the shocks to world import demand are external to Swedish firms and unlikely to be correlated with unobserved firm characteristics that may affect the firm-level labor mix.

An important issue with aggregating trade shocks at the firm level is the choice of weights. Trade shares for different product-destination pairs will vary over time in response to current market conditions. To avoid endogeneity, Hummels et al. (2014) use trade shares for the year prior to the sample period. Then introducing new products or expanding to new destination markets will have no effect on the instrument. Hence, if firms' production and export structure change over time, the explanatory power of the instrument would decrease over time because these new products or new destinations are not captured by the pre-sample trade shares.<sup>17</sup> To deal with this issue, we have experimented with five different versions of trade shares. First, following Hummels et al. (2014), we use trade shares for the pre-sample year (1997) and run regressions for the period 1998-2005. In the second version we use trade shares for 1998 instead as the pre-sample year and then run regressions for 1999-2005. One problem with using the pre-sample years is that we (and Hummels et al.) have observations where trade for a specific combination of destinations and products is equal to zero for the first year (1997), resulting in many missing observations.<sup>18</sup> To deal with this problem, we have also used different lags (at one, two or three years) to construct the trade shares. Our results are robust to different weights used to construct the trade shocks.

#### 4. Empirical Results

Our following analysis provides a comprehensive view of the relationship between global engagement and the skill mix within firms. We first focus on a sample of exporters and estimate the effect of increased

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<sup>16</sup> World import demand ( $WID$ ) is constructed using COMTRADE bilateral trade data.

<sup>17</sup> However, Hummels et al. (2014) argue that typically a large share of export revenue for Danish manufacturing firms is accounted for by a small set of stable product-destinations. Hence for most firms, the instrument will remain strong over time as long as the core products of a firm in the pre-sample remain an important part of their export activities in later years as well.

<sup>18</sup> See discussions in Hummels et al. (2014) on p. 1611.

export shares on the skill index and skewness of the occupational structure. We then use a full sample of firms to compare MNEs, non-MNE exporters, and Local firms.

#### *A. Intensive margin*

##### *The skill effect of export shares:*

The sample of exporters, including both MNE and non-MNE exporters, account for more than 80% of employment. We use export shares of total sales to capture the variation in export intensity among these exporters. Table 1 presents the regression results where the dependent variable is the skill index defined in (4). Column 1 shows that firms with a larger export share have a higher skill index.

In column 2 we report the two-stage least square (2SLS) estimates where the export share is instrumented using world demand shocks with weights for 1997 ( $WID_{97}$ ). Since the regressions include only firms that exported in 1997, the sample is reduced. The first-stage estimate shows that  $\text{Log}(WID_{97})$  is significantly and positively correlated with export shares, implying that Swedish firms tend to have a higher export share when the world demand is stronger for the products they export. The 2SLS estimate of the coefficient on export shares is significantly positive, and the magnitude is economically large. For the sample of firms that exported in 1997, a coefficient of 0.209 implies that compared to exporters at the 25<sup>th</sup> percentile of export shares (0.03), exporters at the 75<sup>th</sup> percentile of export shares (0.55) have a higher skill index by  $0.209 \times (0.55 - 0.03) = 0.11$ . This implied skill index differential is more than half of the 75-25 skill index differentials between firms that exported in 1997 ( $0.68 - 0.50 = 0.18$ ).

In column 3 we present OLS estimates for the same reduced sample to facilitate the comparison between OLS and IV estimates. We find that the IV estimate is about 4 times larger than the corresponding OLS estimate.<sup>19</sup> This suggests that the observed positive association between export shares and skill mix is not driven by reverse causality (or simultaneity) since the OLS estimates would be biased upward if a higher share of skilled occupations makes it easier for firms to export more. On the other hand, the OLS estimates could be biased downward due to some unobserved firm-level shocks that may be positively related to the skill mix, but negatively related to export shares. For example, some unobserved firm-specific technology shocks might

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<sup>19</sup> As a comparison, the corresponding differences in Hummels et al. (2014) are much larger between OLS (FE) and IV estimates. Comparing columns 1 and 3 (or columns 2 and 4) of Table 5 in Hummels et al. (2014) we find differences that are of factor 9 (or 16).

reduce the use of unskilled labor while allowing the firm to expand domestic sales faster than foreign sales. The OLS estimates could also be biased downward toward zero due to measurement errors in export shares. One possible source of measurement errors in export shares could arise from the fact that small trade flows to the EU are not included. The IV approach can solve the problem of omitted variables bias and attenuation bias, leading to larger estimates of the skill effect. Furthermore, it is important to note that the IV estimates capture the average effect of export shares on the skill index for the subsample of firms that exported more because of the positive world import demand shocks but would not have exported more otherwise (e.g., see Imbens and Angrist 1994 for discussions about the local average treatment effect). It is possible that the skill effect of export shares is stronger for this subsample of firms (“compliers”) than for other firms.

Column 4 shows the IV estimates when export shares are instrumented by world import demand constructed by using trade weights at a one-year lag. The regression sample includes firms that exported in two consecutive years. The coefficient for export shares is significantly positive, and slightly larger than the one reported in column 2.

We have also experimented with alternative trade weights when constructing the instrument for export shares, including weights for 1998, and weights at a lag of two years or three years. We obtained estimates that are very similar to those reported in columns 2 and 4. In particular, the alternative instruments are significantly and positively correlated with export shares. The IV estimates of export shares are statistically significant and very stable across different samples. Hence, we find strong evidence that firms with higher export shares (driven by stronger world demand) have significantly higher skill levels.

We also run regressions with firm fixed effects. The estimates of the skill effect remain positive, although they are less significant and the magnitudes are smaller. Note that since both our dependent variable and export shares are normalized, they do not change much over time. With firm fixed effects, measurement errors can amplify and reduce estimation precision. In addition, the specification with firm fixed effects addresses a different question: the extent to which an increase in export shares within a firm can affect its skill mix over time. This differs from the main focus of the paper: we are interested in the cross-firm comparison.

#### Controlling for offshoring:

As mentioned above, offshoring offers an alternative channel through which global engagement affects the labor market. Some previous studies have examined the impact of imports of intermediate goods on the

labor market (see e.g. Goos et al. 2009 for European countries, Liu and Trefler 2011 for the U.S., Baumgarten et al. 2013 for Germany, and Hummels et al. 2014 for Denmark). We note that in our sample nearly 80% of exporters are engaged in offshoring. It is possible that part of the estimated exporting effect could be attributable to offshoring. Hence, in columns 5-7 we control for offshoring shares, which are measured by import of intermediate goods as a share of total sales. To account for endogeneity of offshoring, we again follow Hummels et al. (2014) and instrument offshoring shares using the world export supply (*WES*). Specifically, for firm  $j$  in year  $t$ , it is computed as:

$$(9) \quad WES_{jt} = \sum_{cg} ts_{jcg} * WES_{cgt},$$

where  $WES_{cgt}$  is country  $c$ 's total supply of product  $g$  (at the 6-digit HS level) to the world market (less exports to Sweden) in year  $t$  and  $ts_{jcg}$  is the share of firm  $j$ 's import of product  $g$  from country  $c$  in firm  $j$ 's total import for 1997. We also construct an additional instrument for offshoring shares by replacing  $WES_{cgt}$  in (9) with Swedish tariffs imposed on imports of input  $g$  (at the 6-digit HS level) from country  $c$  in year  $t$ .

Column 5 reports the IV estimates where export shares and offshoring shares are instrumented by  $WID_{97}$  and  $WES_{97}$ . Now the sample includes firms that both exported and offshored in 1997. The IV estimate of export shares is close to that reported in column 2 when offshoring shares are excluded. Offshoring shares have significantly positive coefficients. A coefficient of 0.439 implies that compared to firms at the 25<sup>th</sup> percentile of offshoring shares (0.006), firms at the 75<sup>th</sup> percentile of offshoring shares (0.14) have a higher skill index by  $0.439*(0.145-0.006) = 0.06$ . This implied skill index differential is around a third of the 75-25 skill index differentials between firms that both exported and offshored in 1997 ( $0.69 - 0.50 = 0.19$ ).

The bottom of column 5 reports the first-stage estimates of the coefficients on instruments. Both instruments have expected signs, implying that firms tend to have a higher export share when they experience a higher world import demand, and have a higher offshoring share when they experience a higher world export supply.

As a comparison, column 6 reports the OLS estimates on the same sample of firms that exported and offshored in 1997. The coefficient on export shares remains statistically significant and positive. The magnitude is close to that of OLS estimates reported in column 3 when offshoring shares are excluded. However, the OLS estimate of the coefficient on offshoring shares is statistically insignificant.

In column 7 we include Swedish tariffs on imports of inputs as an additional instrument for offshoring shares. The sample is the same as in columns 5-6. As shown in the bottom of column 7, the instrument of world export supply ( $WES_{97}$ ) remains strong. Swedish tariffs on imports of inputs are negatively correlated with offshoring shares, indicating that firms tend to have a higher offshoring share when facing a lower tariff on imports of inputs.

The second-stage estimates are little changed when Swedish tariffs are used as an additional instrument. The IV estimates suggest that increased offshoring activities (driven by higher world export supply) may shift the distribution of employment toward high-skill occupations among firms that offshore. On the other hand, controlling for offshoring shares has very little impact on our estimates of the effect of export shares on the skill mix within firms. The coefficients on export shares remain significantly positive and stable across different samples. The magnitude of the estimates is very similar to those when offshoring is excluded.

#### Decomposing the skill effect

The above analysis has provided strong evidence that higher export shares significantly increase the average skill level of exporters. To provide further insights into this skill effect, we now use equation (5) to decompose the skill index into three components: (i) a shift within the non-production category; (ii) a shift within the production category; and (iii) a shift between the production and non-production categories (equivalent to the traditional measure of the share of non-production workers).<sup>20</sup> We then re-run the regression equation (7) by using each of the three components as the dependent variable separately. The results are shown in Table 2.

In panel A, we use the benchmark specification where the export share is the variable of interest, and detailed firm characteristics, industry and year fixed effects are included as controls. Columns 2-4 display the OLS results.<sup>21</sup> As comparison, column 1 carries over the baseline result from Table 1 column 3. These results show that nearly half of the skill effect is associated with a shift from lower skilled to higher skill occupations within the non-production category, e.g., a smaller share of sales and service workers, but a higher share of

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<sup>20</sup> Workers are classified into non-production or production category based on their detailed occupation information. The non-production category includes managers, professionals, technicians, clerks, sales and service workers. The production category includes operators, craft, and laborers. See Table A1 in the online appendix for details on the occupation classification.

<sup>21</sup> Note that the sum of the estimated coefficients for the three terms in the decomposition is equal to the estimated coefficient for the aggregated index (see e.g. columns 1-4 for the OLS results).

professionals specialized in finance and engineering. The other half is associated with a shift from less skilled to more skilled occupations within the production category: a smaller share of transportation operators and laborers, but a higher share of machine operators. On the other hand, there is no evidence for a significant shift from production to non-production. Therefore, using the traditional measure of the share of non-production workers can miss the significant changes within both categories of non-production and production.

Columns 5-8 of Table 2 give the corresponding IV estimates. As comparison, column 5 repeats the baseline result from Table 1 column 2. To save space, the first-stage results are not reported since they are the same as shown in column 2 of Table 1. These IV estimates confirm the observation that the skill effect mainly arises from shifts *within* the broader categories of non-production and production.

In panel B, we include offshoring shares as an additional control. We note that the results on the skill effect of export shares are largely similar to those without controlling for offshoring, but with some minor differences. For instance, the IV results in column 7 shows a relatively small and only marginally significant increase in the skill mix within production workers from higher export shares, suggesting that shifts toward higher skills are perhaps more important within non-production workers than within production workers.

The skill effect of offshoring shares appears interesting. Like export shares, higher offshoring shares contribute to a shift toward more skilled occupations within the nonproduction category. However, unlike export shares, higher offshoring shares shift payroll expenses toward lower skilled occupations within the production category. Compared to higher skilled production occupations (e.g., machine operators), those lower skilled production occupations (e.g., laborers, transportation operators) tend to be more intensive in non-routine tasks and thus less offshorable. Hence, our result implies that increased offshoring shares may contribute to a higher share of lowest skilled occupations at the expense of mid-skilled ones, which is consistent with previous studies on job polarization, e.g., Goos et al. (2009).

#### *Skewness of the occupational structure*

Columns 9-10 of Table 2 look at the effect of export shares on the skewness of the occupational structure. The dependent variable is the skewness measure defined in equation (6). The estimated coefficients on export shares are significantly positive, indicating that firms with high export shares have a distribution of occupations more skewed toward higher skilled ones. This pattern holds for both OLS and IV estimates, and is not changed after offshoring shares are included as a control. On the other hand, we find some indications that

offshoring shares have the opposite effect: large shares of offshoring correspond to a distribution of occupations skewed towards less skilled ones.

*The skill effect by destination markets*

Our model emphasizes the role of fixed costs involved in global engagement. To provide more direct evidence for this mechanism, we now study the variation in skill mix across firms that export to different destination markets. The literature has pointed out that different export markets imply different costs of entry (Blanes-Cristóbal et al. 2008; Arkolakis 2010; Gullstrand 2011). Therefore, in Table 3 we examine the extent to which the skill mix varies between firms that export to different markets.

We first separate destination markets into EU vs. non-EU.<sup>22</sup> Compared to the EU markets, exporting to non-EU markets is likely to involve higher tariffs, higher transport costs, and other types of trade barriers including the border effect. We divide the total export share from Table 1 into the share of export to EU and that to non-EU markets, and examine whether the skill effect of export shares differs between these two destination markets. The OLS estimate in column 1 shows that export to non-EU markets has a stronger positive effect on the skill mix, suggesting that more skilled occupations tend to be associated with higher entry costs. In column 2 we treat the export shares as endogenous and instrument for export shares using component-specific instruments. Specifically, we instrument the share of export to EU markets using  $WID_{jt}^{EU} = \sum_{g,c \in EU} ts_{jcg} * WID_{cgt}$ , and instrument the share of export to non-EU markets using  $WID_{jt}^{non-EU} = \sum_{g,c \in non-EU} ts_{jcg} * WID_{cgt}$ , where  $WID_{cgt}$  is country  $c$ 's total purchases of product  $g$  (at the 6-digit HS level) from the world market (less purchases from Sweden) in year  $t$  and  $ts_{jcg}$  is the share of firm  $j$ 's export of product  $g$  to country  $c$  in firm  $j$ 's total export. The bottom of column 2 shows the first stage regressions. As expected,  $\log WID_{jt}^{EU}$  is significantly and positively correlated with the share of export to EU markets, and  $\log WID_{jt}^{non-EU}$  is significantly and positively correlated with the share of export to non-EU markets. The IV estimate in column 2 confirms the result that given the same share of export to EU markets, an increased share of export to non-EU markets can raise the skill index even higher.

In columns 3-4, we group destination markets into high-income vs. middle- or low-income based on

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<sup>22</sup> The EU-15 countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom.

the World Bank classification of countries by income levels. Unlike the comparisons in columns 1-2, the division based on income levels is less related to the geographic distance from Sweden since the group of high-income countries ranges from Europe, Asia and Oceania, to North America. Compared to high-income countries, export to lower-income countries may involve higher costs given the larger difference from Sweden in consumer preferences, business practices, and rule of law. Both OLS and IV estimates show that the skill index is even higher for firms with a higher share of export to lower-income countries. This result is distinct from the mechanism of sorting by product quality proposed by Verhoogen (2008) to explain skill upgrading by Mexican exporters in response to exchange rate shocks. Similar to column 2, export shares in column 4 are instrumented using weighted average of world import demand shocks where the weight is specific to the export destination markets. The first-stage results show strong correlations between instruments and export shares.

In columns 5-6, we separate Sweden's top ten trading partners from other destination markets.<sup>23</sup> This distinction may capture the difference in market size for Swedish exporters. Compared to larger markets, breaking into smaller and less familiar markets may impose a higher entry cost. The results in columns 5-6 again confirm the pattern that entering a more difficult market requires a higher share of skilled occupations.

Overall, the results in Table 3 provide strong evidence supporting the key mechanism in our paper: fixed entry costs are skill biased and entering markets that involve higher costs can significantly shift the occupational structure toward more skilled occupations.

### *B. Extensive margin*

The above analysis has shown that increased export shares may shift the occupational structure toward higher-skilled occupations for a sample of exporters. In this section, we complement the above analysis by looking at the full sample of all firms, including those that solely serve the domestic markets. Our focus is on the relationship between firm types, or the extensive margin of global engagement, and the skill mix at the firm level. Unlike the above analysis focusing on causality, the extensive margin analysis is of a descriptive nature and does not control for the possibility of a self-selection bias.

### *Full sample:*

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<sup>23</sup> The top ten trading partners (ranked by export value in 1998) include Germany, United Kingdom, United States, Norway, Denmark, the Netherlands, Finland, France, Belgium, and Italy. Note that United States and Norway are not in the EU-15 markets.



Table 4 shows how the skill mix differs across firm types. All regressions control for firm characteristics (firm size, productivity, capital-labor ratio, and age) and industry and year fixed effects. Column 1 includes indicators for MNEs, non-MNE exporters, and offshorers. The excluded group is non-MNEs that neither export nor offshore. Compared to firms that are not globally engaged, both MNEs and non-MNE exporters have a significantly higher skill index. Further, the skill index is even higher for MNEs than for non-MNE exporters: the estimated coefficient for MNE is statistically larger based on standard  $t$ -tests. This sorting pattern is consistent with our model's assumption that FDI involves the highest fixed costs (i.e., the largest  $\beta$ ) and serving the domestic market involves the lowest fixed costs. It also aligns well with the pattern of sorting by firm productivity in Helpman et al. (2004): MNEs and non-MNE exporters are more productive than firms that solely serve the domestic market, and MNEs are the most productive. The coefficient on export shares is significantly positive, and the magnitude is similar to that reported in Table 1 for the sample of exporters. Note that the export share is zero for non-exporters. Column 1 also shows that the coefficient on the offshoring dummy is significantly positive, indicating that offshoring activities are associated with a shift toward more skilled occupations at the firm level. However, the coefficient on offshoring shares is statistically insignificant, which is similar to the OLS results for the sample of offshorers (column 6 of Table 1).

In columns 2-4, we use equation (5) to decompose the skill index into three components and run regressions using these three components separately as the dependent variable. We find that more than half of the higher skill index for MNEs and non-MNE exporters is associated with a shift toward higher skilled occupations within the category of non-production, and just about a quarter to one third of the difference in skill index is related with a shift from production to non-production categories.<sup>24</sup>

#### Manufacturing vs. non-manufacturing:

While data limitations force most studies to focus on manufacturing, our sample is more comprehensive, allowing us to study non-manufacturing as well. We therefore divide our sample into manufacturing and non-manufacturing firms. Results are presented in Table 5. Because manufacturing industries have very few Local firms (i.e., non-MNEs that do not export), in columns 1-4 we compare MNEs with non-MNEs (most of which

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<sup>24</sup> We also studied how the skill mix evolves before and after a firm switches from being Local to Global. We found significant and persistent shifts in payroll toward more skilled occupations after firms begin to export or become multinational. These results are available upon request.

are exporters).<sup>25</sup> MNEs have a more skilled labor mix than non-MNEs. The difference in skill index between MNEs and non-MNEs is 0.029 in column 1. The magnitude is similar to the difference in the estimated coefficients on MNE and non-MNE exporter dummies as reported in column 1 of Table 4 for all industries. In columns 2-4 we decompose the difference into three components based on the decomposition in equation (5). The results suggest that most of the difference arises from a shift toward higher skilled occupations within the non-production category, and a shift from production to non-production categories. These results are also similar to those reported in Table 4 for the difference in the estimated coefficients on MNE and non-MNE exporter dummies.

The result for non-manufacturing, where we have more firms in the category of Local firms, is also in line with previous results. Compared to the estimates for all industries, MNEs and non-MNE exporters have an even higher skill levels than Local firms. The decomposition results in columns 6-8 suggest that more than half of the difference in skill index stems from a shift toward more skilled occupations within the non-production category, and about a quarter to one third is associated with a shift from production to non-production categories.

### *C. Implications for skill upgrading and wage dispersion*

Our firm-level results have presumably important implications for skill upgrading and wage dispersion on the aggregate level. To examine the implications for skill upgrading, we modify the standard decomposition in the literature on wage inequality (e.g., Berman et al., 1994), and decompose the change in skill index on the aggregate level into within- and between-industry changes. We then decompose the within-industry change into three components: (1) a change of skill index in globalized firms (MNEs and non-MNE exporters); (2) a change of skill index in Local firms; and (3) a change due to the compositional shift from local to globalized firms and the difference in skill index between globalized firms and their local counterparts (see Appendix B for technical details). Figure 2 plots these changes relative to 1997. The aggregate level the skill index rises over the sample period as shown in panel A. This is mainly driven by skill upgrading within industries, which is similar to the pattern documented in previous studies, e.g., Berman et al. (1994) on the U.S. economy. Panel B displays the three components of the within-industry change in skill index. It is clear that the within-industry change mainly

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<sup>25</sup> For instance, only in Printing and Publishing do we have a more substantial share of Local firms (24 percent). In other manufacturing industries the share of employees in Local firms ranges from 0 percent (Basic Metals) to 4 percent (Food, Beverages and Tobacco).

stems from skill upgrading by globalized firms and the compositional shift from local to globalized firms. These two components of changes correspond to our earlier estimates of the skill effect of global engagement. As reported in Table 1, higher export shares raise the skill index. Thus, skill upgrading by globalized firms may arise from skill upgrading within the same firm due to increased export shares or from a compositional shift from firms with a lower export share to those with a higher export share within the same industry. Furthermore, as shown in Table 4, globalized firms have a significantly higher skill index than local firms. Hence, as the share of globalized firms increases within industries, the demand for more skilled workers rise, leading to within-industry skill upgrading.

To further illustrate the economic significance of our results, we now turn to the implications of the cross-firm differences in skill mix for wage dispersion. The overall wage dispersion can be decomposed into dispersion within firms (each firm has a mix of workers in different occupations) and dispersion between firms (average wages vary across firms). Between-firm wage dispersion comes from three sources: (1) *the between-occupation component* – given the same occupational wages, firms have a different labor mix; (2) *the within-occupation component* – given the labor mix, firms pay different wages to workers with the same occupation; and (3) *the cross-term* – the covariance between the difference in labor mix and within-occupation wage differentials. The cross term is positive when higher-wage firms employ a higher share of skilled workers than lower-wage firms. So a positive sign of the cross term reflects some degree of assortative matching between firms and workers (see Appendix C for technical details).

Figure 3 displays the three components of between-firm wage dispersion as a share of overall wage dispersion. An increasing share of the overall wage dispersion is attributable to the between-firm dispersion (27.1% in 1997, 34.4% in 2005). This pattern is consistent with what Lazear and Shaw (2009) report for many countries. Figure 3 also reveals that the contribution of the within-occupation component to overall wage dispersion is relatively small and constant (7.7% in 1997, 8.3% in 2005). By contrast, the between-occupation component is relatively large and increasing over time (15% in 1997, 19.3% in 2005). Moreover, the cross term is positive and increasing (4.5% in 1997, 6.7% in 2005), indicating that there is increasingly assortative matching between firms and workers.<sup>26</sup> Overall, the cross-firm difference in labor mix and a higher share of

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<sup>26</sup> See also Davidson et al. (2012 and 2014) for evidence of an increase over time in assortative matching.

skilled workers in higher-wage firms contributed to 19.4% of overall wage dispersion in 1997 and 26% in 2005.<sup>27</sup> Furthermore, the vast majority of this is due to globally engaged firms: as shown in Figure 3, the between-occupation component and positive assortative matching (i.e., the cross term) by global firms contributed to 15.2% of overall wage dispersion in 1997 and 22.1% in 2005. Thus, our results could have further implications for the effect of globalization on overall wage dispersion.

## 5. Concluding Remarks

The availability of firm level data has transformed the field of international trade over the past 20 years. Focus has shifted away from industry analysis and now rests squarely on the firm. While we have learned a great deal (see Melitz and Redding 2014 for a survey) there is still much to explore. We know very little about the nature of the fixed costs that firms must overcome to gain access to global markets and we are just beginning to explore how the organizational structure of the firm is affected by globalization. Moreover, one would expect that changes in organizational structure (as documented by Rajan and Wulf 2006 and Guadalupe and Wulf 2010) would lead firms to alter the occupational mix of workers that they employ. For example, a firm that begins to export will likely need to hire new employees in occupations such as logistics and marketing. Or, a firm that sells goods on world markets through foreign affiliates will require information on foreign preferences, laws, regulations, distribution networks and a host of similar issues; and collecting such information requires a different set of occupations than producing for the domestic market. Examining such organizational changes requires quite detailed firm-level data that includes information about the occupation of workers employed by each firm.

In this paper we made use of an extensive, remarkably rich data set to examine one of these issues. In particular, we provided compelling evidence that a more skilled labor mix (with a higher share of professionals specialized in finance and sales, computing, and engineering) is necessary for a firm to overcome costs of entry into foreign markets. Our investigation also revealed that increased global engagement can have a causal impact on the skill mix. Taking an instrumental variable approach, we find that increased export shares (driven by higher world import demand) shift the labor mix more toward high-skill occupations, e.g., professionals

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<sup>27</sup> This is consistent with the finding by Card et al. (2013) that increasing plant-level heterogeneity and rising assortativeness in the assignment of workers to establishments explain a large share of the rise in wage inequality in Germany for the period 1985-2009.

specialized in finance and sales, computing, and engineering.

Our results have important implications for the impact of globalization on the demand for workers with different skills and their wages. To the extent that trade costs fall and more firms increasingly engage in export and multinational activities, we expect to see increased demand for high skilled occupations relative to low skilled occupations with the consequent change in their relative rewards. Hence, our study points at one possible mechanism behind globalization and increased wage inequality.

### References

Acemoglu, Daron and David H. Autor (2011), “Skills, Tasks and Technologies: Implications for Employment and Earnings,” in *Handbook of Labor Economics*, Volume 4, Part B, Orley Ashenfelter and David E. Card (eds.), Amsterdam: Elsevier.

Alvarez, Roberto and Ricardo A. López (2005), “Exporting and Performance: Evidence from Chilean Plants,” *Canadian Journal of Economics*, Vol. 38(4), pp. 1384-1400.

Arkolakis, Costas (2010), “Market Penetration Costs and the New Consumers Margin in International Trade,” *Journal of Political Economy*, Vol. 118(6), pp. 1151-1199.

Autor, David H., Frank Levy, and Richard J. Murnane (2003). “The Skill Content of Recent Technological Change: An Empirical Exploration”. *Quarterly Journal of Economics*, Vol. 118 (4), pp. 1279-1333.

Barba-Navaretti, Giorgio and Anthony J. Venables (2004), *Multinational Firms in the World Economy*, Princeton: Princeton University Press.

Baumgarten, Daniel, Ingo Geishecker, and Holger Görg (2013), “Offshoring, tasks, and the skill - wage pattern”. *European Economic Review*, Vol. 61, pp. 132 - 152.

Becker, S.O., K. Ekholm, and M-A Muendler (2013), “Offshoring and the Onshore Composition of Occupations, Tasks and Skills,” *Journal of International Economics*, Vol. 90, pp. 91-106.

Berman, Eli, John Bound, and Zvi Griliches (1994), “Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers,” *Quarterly Journal of Economics*, Vol. 109 (2), pp. 367-397.

Bernard, Andrew B., and J. Bradford Jensen (1997), “Exporters, Skill Upgrading, and the Wage Gap,” *Journal of International Economics*, Vol. 42, pp. 3-31.

Blanes-Cristobal, J, M. DAVIS, J. Milgram-Baleix, and A. Moro-Egido (2008), “Do Sunk Exporting Costs Differ Among Markets? Evidence from Spanish Manufacturing Firms,” *Economic Letters*, Vol. 101(2), pp. 110-112.

Burstein, Ariel and Jonathan Vogel (2016), “International Trade, Technology, and the Skill Premium,” *Journal of Political Economy*, forthcoming.

Bustos, Paula (2011), “Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms,” *American Economic Review*, Vol. 101, pp. 304-340.

Card, David, Jörg Heining, and Patrick Kline (2013), “Workplace heterogeneity and the rise of West German wage inequality”, *Quarterly Journal of Economics*, Vol. 128 (3), pp. 967-1015.

- Caliendo, Lorenzo, Ferdinando Monte, and Esteban Rossi-Hansberg (2015), “The Anatomy of French Production Hierarchies,” *Journal of Political Economy*, Vol. 123(4), pp. 809-852.
- Chaney, Thomas and Ralph Ossa (2013), “Market Size, Division of Labor, and Firm Productivity,” *Journal of International Economics*, Vol. 90 (1): 177-80.
- Davidson, Carl, Fredrik Heyman, Steven Matusz, Fredrik Sjöholm, and Susan Chun Zhu (2012), “Liberalized Trade and Worker Firm Matching”, *American Economic Review Papers & Proceedings*, Vol. 102(3), pp. 1-8.
- Davidson, Carl, Fredrik Heyman, Steven Matusz, Fredrik Sjöholm, and Susan Chun Zhu (2014), “Globalization and Imperfect Labor Market Sorting”, *Journal of International Economics*, Vol. 94(2), pp. 177-194.
- Davidson, Carl, Fredrik Heyman, Steven Matusz, Fredrik Sjöholm, and Susan Chun Zhu (2016), “Global Engagement, Complex Tasks and the Distribution of Occupational Employment,” *Review of International Economics*, Vol. 24(4), pp. 717-736.
- Goos, Maarten, Alan Manning, and Anna Salomons (2009), “Job Polarization in Europe,” *American Economic Review*, Vol. 99(2), pp. 58-63.
- Groeneveld, Richard A. and Glen Meeden (1984), “Measuring Skewness and Kurtosis,” *The Statistician*, Vol. 33, pp. 391-399.
- Guadalupe, Maria, and Julie Wulf (2010), “The Flattening Firm and Product Market Competition: The Effect of Trade Liberalization on Corporate Hierarchies,” *American Economic Journal: Applied Economics*, Vol. 2(4), pp.105-127.
- Gullstrand, Joakim (2011), “Firm and Destination-Specific Export Costs: The Case of Swedish Food Sector,” *Food Policy*, Vol. 36(1), pp. 204-213.
- Hakkala Nilsson, Katariina, Fredrik Heyman and Fredrik Sjöholm (2014), “Multinational Firms, Acquisitions and Job Tasks,” *European Economic Review*, Vol. 66, pp. 248–265.
- Helpman, Elhanan, Marc J. Melitz, and Stephen R. Yeaple (2004), “Export Versus FDI with Heterogeneous Firms,” *American Economic Review*, Vol. 94(1), pp. 300-316.
- Heyman, Fredrik, Fredrik Sjöholm, and Patrik Gustavsson Tingvall (2007), “Is There Really a Foreign Ownership Wage Premium? Evidence from Matched Employer-Employee Data,” *Journal of International Economics*, Vol. 73(2), pp. 355-376.
- Hoffmann, Eivind (2004), “International Statistical Comparisons of Occupational and Social Structures: Problems, Possibilities and the Role of ISCO-88”, International Labor Office, Geneva.
- Hummels, D., R. Jørgensen, J. Munch, and C. Xiang (2014), “The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data,” *American Economic Review*, 104(6): 1597-1629.
- Hummels, D., J. R. Munch and C. Xiang (2016), “Offshoring and Labor Markets,” NBER Working Paper, No. 22041.
- Imbens, Guido W., and Joshua D. Angrist (1994), Identification and Estimation of Local Average Treatment Effects, *Econometrica*, Vol. 62(2), pp. 467-475.
- Jensen, J.B. (2011), *Global Trade in Services: Fear, Facts, and Offshoring*, Peterson Institute for International Economics, Washington, DC.
- Lazear, Edward and Kathryn Shaw (eds.) (2009), *The Structure of Wages: An International Comparison*, Chicago: University of Chicago Press.

Lileeva, Alla, and Daniel Trefler (2010), “Improved Access to Foreign Markets Raises Plant-level Productivity... For Some Plants,” *Quarterly Journal of Economics*, Vol. 125, pp. 1051-1099.

Lipsey, Robert E. and Fredrik Sjöholm (2004), “Foreign Direct Investment, Education, and Wages in Indonesian Manufacturing”, *Journal of Development Economics*, Vol. 73, pp. 415-422.

Liu, Runjuan, and Daniel Trefler (2011), “A Sorted Tale of Globalization: White Collar Jobs and the Rise of Service Offshoring,” NBER Working Papers No. 17559.

Markusen, James R. (1995), “The Boundaries of Multinational Enterprises and the Theory of International Trade,” *Journal of Economic Perspective*, Vol. 9, pp. 169-189.

Matsuyama, K. (2007), “Beyond Icebergs: Towards a Theory of Biased Globalization,” *The Review of Economic Studies*, Vol. 74, pp. 237-253.

Melitz, Marc (2003), “The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity,” *Econometrica*, Vol.71, pp. 1695-1725.

Melitz, Marc J. and Stephen J. Redding (2014), “Heterogeneous Firms and Trade” in *Handbook of International Economics*, 4<sup>th</sup> edition, 4:1-54. Elsevier.

Munch, Jacob and Jan Skaksen (2008), “Human Capital and Wages in Exporting Firms”, *Journal of International Economics*, Vol. 75, pp. 363-372.

Rajan, Raghuram G., and Julie Wulf (2006), “The Flattening Firm: Evidence from Panel Data on the Changing Nature of Corporate Hierarchies,” *Review of Economics and Statistics*, 88(4), pp. 759-773.

Verhoogen, Eric (2008), “Trade, Quality Upgrading and Wage Inequality in the Mexican Manufacturing Sector,” *Quarterly Journal of Economics*, Vol. 123, pp. 489-530.

Zhu, Susan C. and Daniel Trefler (2005), “Trade and Inequality in Developing Countries: a General Equilibrium Analysis,” *Journal of International Economics*, Vol. 65, pp. 21-48.

### **Appendix A: Occupation classification**

Occupations in our data are based on the *Swedish Standard Classification of Occupations (SSYK96)* which in turn is based on the *International Standard Classification of Occupations (ISCO-88)*. SSYK3 and ISCO88 are more or less identical at the 3-digit level with only a few exceptions. A conversion key between SSYK96 and ISCO88 are available at Statistics Sweden:

[http://www.scb.se/Grupp/Hitta\\_statistik/Forsta\\_Statistik/Klassifikationer/\\_Dokument/oversattningsnyckel.pdf](http://www.scb.se/Grupp/Hitta_statistik/Forsta_Statistik/Klassifikationer/_Dokument/oversattningsnyckel.pdf).

In the context of ISCO-88 and SSYK96 a “job” is defined as “a set of tasks and duties which are (or can be assigned to be) carried out by one person.” Occupations are grouped together and aggregated on the basis of the similarity of skills required to fulfill the tasks and duties of the jobs (see e.g. Hoffmann, 2004). Detailed descriptions of occupations can be seen from the *International Labor Organization (ILO)* website: <http://www.ilo.org/public/english/bureau/stat/isco/isco88/major.htm>. Appendix Table A1 lists the 3-digit occupations. As shown in Table 1 in Hoffmann (1994), Managers, Professionals, and Technicians require higher skill levels, and Clerks, Sales and service workers, Craft, Operators, and Laborers require lower skill levels.

### **Appendix B: Decomposition of the aggregate skill upgrading**

We modify the standard decomposition in the literature on skill upgrading and wage inequality (e.g., Berman et al., 1994) and decompose the aggregate change in skill index into a change in skill index within- and

between-industries. Specifically, let  $l_{jkt}$  be the payroll of occupation  $k$  in firm  $j$  in year  $t$ . The aggregate skill index is computed as  $S_t = \sum_k \lambda_{kt} s_k$ , where  $\lambda_{kt} = \frac{\sum_j l_{jkt}}{\sum_k \sum_j l_{jkt}}$  is the aggregate payroll share of  $k$  in year  $t$  and  $s_k$  is the skill percentile ranking of  $k$ . The average skill index for industry  $i$  is defined as  $S_{it} = \sum_k \lambda_{kit} s_k$  where  $\lambda_{kit} = \frac{\sum_{j \in i} l_{jkt}}{\sum_k \sum_{j \in i} l_{jkt}}$  is the payroll share of  $k$  in industry  $i$  in year  $t$ . Let  $B_{it}$  be the total payroll in industry  $i$  as a share of total payroll for the whole economy in year  $t$ . Then the change of aggregate skill index between  $t$  and  $t+1$  can be decomposed as

$$S_{t+1} - S_t = \sum_i (S_{i,t+1} - S_{it}) \frac{B_{i,t+1} + B_{it}}{2} + \sum_i (B_{i,t+1} - B_{it}) \frac{S_{i,t+1} + S_{it}}{2},$$

where the first term represents skill upgrading within industries, and the second term represents skill upgrading between industries.

We further decompose the within-industry change into three components: (1) a change in globalized firms (MNEs and non-MNE exporters); (2) a change in Local firms; and (3) a change due to the compositional shift from local to globalized firms. Specifically, the skill index for globalized firms in industry  $i$  is defined as  $S_{it}^G = \sum_k \lambda_{kit}^G s_k$  where  $\lambda_{kit}^G = \frac{\sum_{j \in i, j \in G} l_{jkt}}{\sum_k \sum_{j \in i, j \in G} l_{jkt}}$  is the payroll share of  $k$  in globalized firms in industry  $i$  in year  $t$ .

The skill index for local firms in industry  $i$  is defined as  $S_{it}^L = \sum_k \lambda_{kit}^L s_k$  where  $\lambda_{kit}^L = \frac{\sum_{j \in i, j \in L} l_{jkt}}{\sum_k \sum_{j \in i, j \in L} l_{jkt}}$ . Let  $B_{it}^G$  and  $B_{it}^L$  be the total payroll in globalized firms and local firms, respectively, as a share of total payroll of all firms in industry  $i$  in year  $t$ . Then the within-industry change in the skill index can be decomposed as

$$\begin{aligned} \sum_i (S_{i,t+1} - S_{it}) \frac{B_{i,t+1} + B_{it}}{2} &= \sum_i (S_{i,t+1}^G - S_{it}^G) \frac{B_{i,t+1}^G + B_{it}^G}{2} \frac{B_{i,t+1} + B_{it}}{2} + \sum_i (S_{i,t+1}^L - S_{it}^L) \frac{B_{i,t+1}^L + B_{it}^L}{2} \frac{B_{i,t+1} + B_{it}}{2} \\ &+ \sum_i (B_{i,t+1}^G - B_{i,t+1}^L) \frac{(S_{i,t+1}^G - S_{i,t+1}^L) + (S_{it}^G - S_{it}^L)}{2} \frac{B_{i,t+1} + B_{it}}{2} + \sum_i \frac{S_{i,t+1}^L + S_{it}^L}{2} \frac{B_{i,t+1}^2 - B_{it}^2}{2}, \end{aligned}$$

where the first term represents skill upgrading in globalized firms, the second term is skill upgrading in local firms, and the third term captures skill upgrading due to the shift from local to globalized firms and the difference in skill index between local and globalized firms. To implement the above decompositions, we use 1997 as the base year and look at the change of all the other years relative to 1997. Figure 2 displays the results of these decompositions. We note that in our sample the fourth term in the decomposition of within-industry changes is very small (i.e., of the order  $10e-5$ ).

### Appendix C: Decomposition of wage dispersion

We start with a standard decomposition of the overall wage dispersion into dispersion within firms and dispersion between firms:

$$\sum_j \sum_h (w_{h(j),j} - \bar{w})^2 = \sum_j \sum_h (w_{h(j),j} - w_j)^2 + \sum_j E_j (w_j - \bar{w})^2$$

where  $w_{h(j),j}$  is the log wage of worker  $h$  employed at firm  $j$ ,  $w_j$  is the average log wage at firm  $j$ ,  $E_j$  is employment at  $j$ , and  $\bar{w}$  is the average log wage for the whole economy. The first term represents within-firm wage dispersion, and the second term represents between-firm wage dispersion.

The between-firm wage dispersion can be further decomposed as

$$\sum_j E_j (w_j - \bar{w})^2 = \sum_j E_j (w_j^* - \bar{w})^2 + \sum_j E_j (w_j - w_j^*)^2 + 2 \sum_j E_j [(w_j^* - \bar{w})(w_j - w_j^*)]$$

where  $w_j^* = \sum_k w_k \lambda_{jk}$  is the hypothetical average log wage at firm  $j$  if  $j$  pays  $w_k$  (the average log wage of all firms for occupation  $k$ ) to workers with occupation  $k$ , given the labor mix captured by  $\lambda_{jk}$ . We note that  $w_j^*$  corresponds to the skill index defined in equation (4) and computed using average log wages of all firms as a proxy for skills. Since  $w_j^* - \bar{w} = \sum_k w_k (\lambda_{jk} - \lambda_k)$ , the first term captures the contribution of varying labor mix to wage dispersion (with occupational wages being held constant at  $w_k$ ), and is thus referred to as the *between-occupation component*. Since  $w_j = \sum_k w_{jk} \lambda_{jk}$  (where  $w_{jk}$  is the log wage paid by firm  $j$  to workers with occupation  $k$ ) and thus  $w_j - w_j^* = \sum_k (w_{jk} - w_k) \lambda_{jk}$ , the second term instead allows cross-firm variation in occupational wages with the labor mix held at  $\lambda_{jk}$ , and is thus referred to as the *within-occupation component*.

The sign of the third term (called *the cross term*) is interesting. The cross term is positive for firms that allocate a bigger share of workers toward highly paid jobs compared with the national average ( $w_j^* - \bar{w} =$



$\sum_k w_k (\lambda_{jk} - \lambda_k) > 0$ ) if those firms also pay a higher wage across the board ( $w_j - w_j^* = \sum_k (w_{jk} - w_k) \lambda_{jk} > 0$ ).<sup>28</sup> In Section 4.B, we establish a strong pattern that MNEs and non-MNE exporters tend to have a labor mix more skewed toward skilled occupations compared to Local firms. The data also reveal that MNEs and non-MNE exporters pay slightly higher wages than Local firms within occupations. Thus, the cross-term expects to be positive. A positive sign of the cross term reflects some degree of assortative matching between firms and workers. That is, higher-wage firms employ a higher share of skilled workers than lower-wage firms.

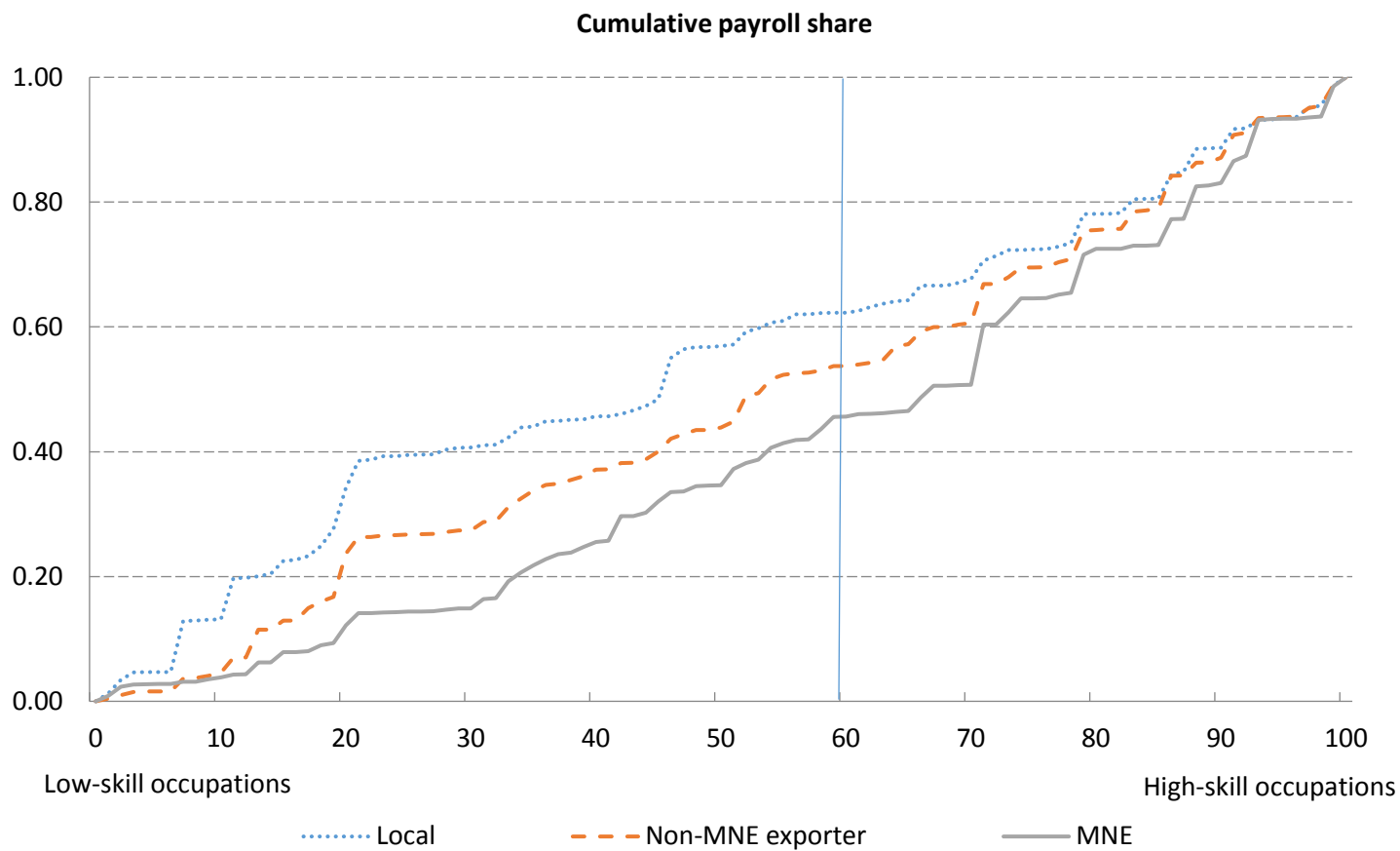
To assess the contribution of globalized firms to the overall wage dispersion, we can further decompose the overall wage dispersion as

$$\sum_j \sum_h (w_{h(j),j} - \bar{w})^2 = \sum_{j \in G} \sum_h (w_{h(j),j} - w_j)^2 + \sum_{j \in G} l_j (w_j - \bar{w})^2 + \sum_{j \in L} \sum_h (w_{h(j),j} - w_j)^2 + \sum_{j \in L} l_j (w_j - \bar{w})^2,$$
where  $G$  indicates globalized firms, and  $L$  indicates local firms. The between-firm wage dispersion for globalized firms can be further decomposed as

$$\sum_{j \in G} l_j (w_j - \bar{w})^2 = \sum_{j \in G} l_j (w_j^* - \bar{w})^2 + \sum_{j \in G} l_j (w_j - w_j^*)^2 + 2 \sum_{j \in G} l_j [(w_j^* - \bar{w})(w_j - w_j^*)].$$

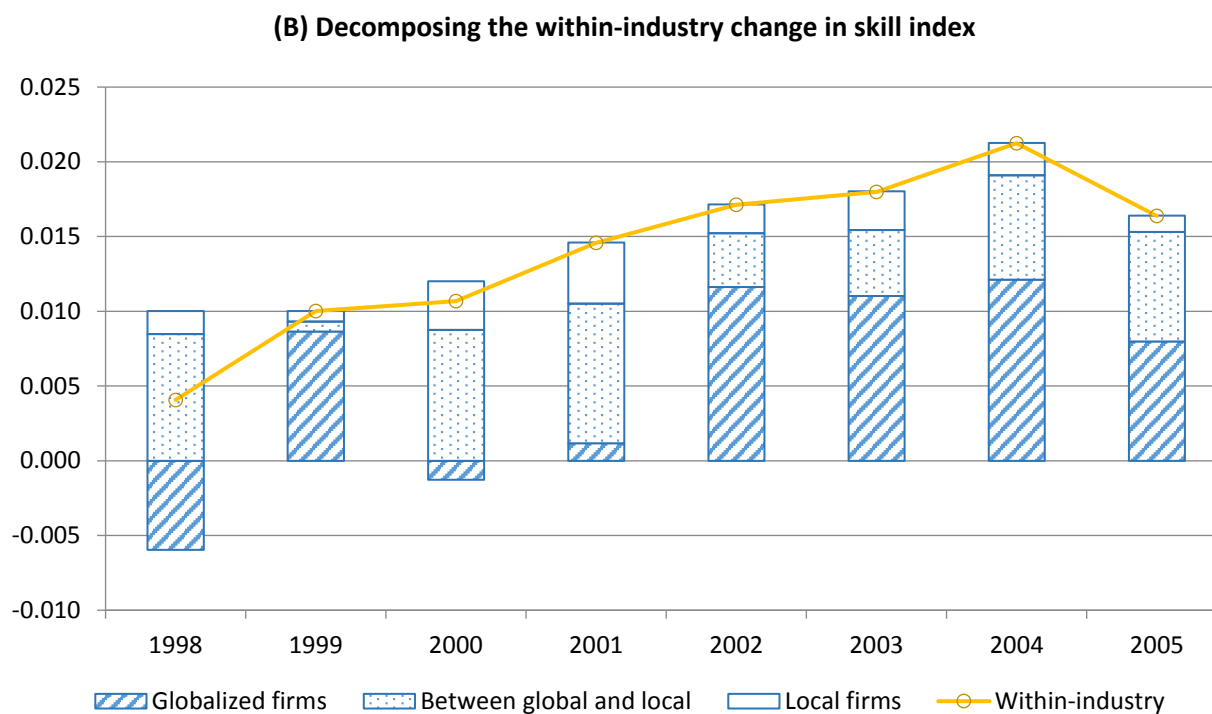
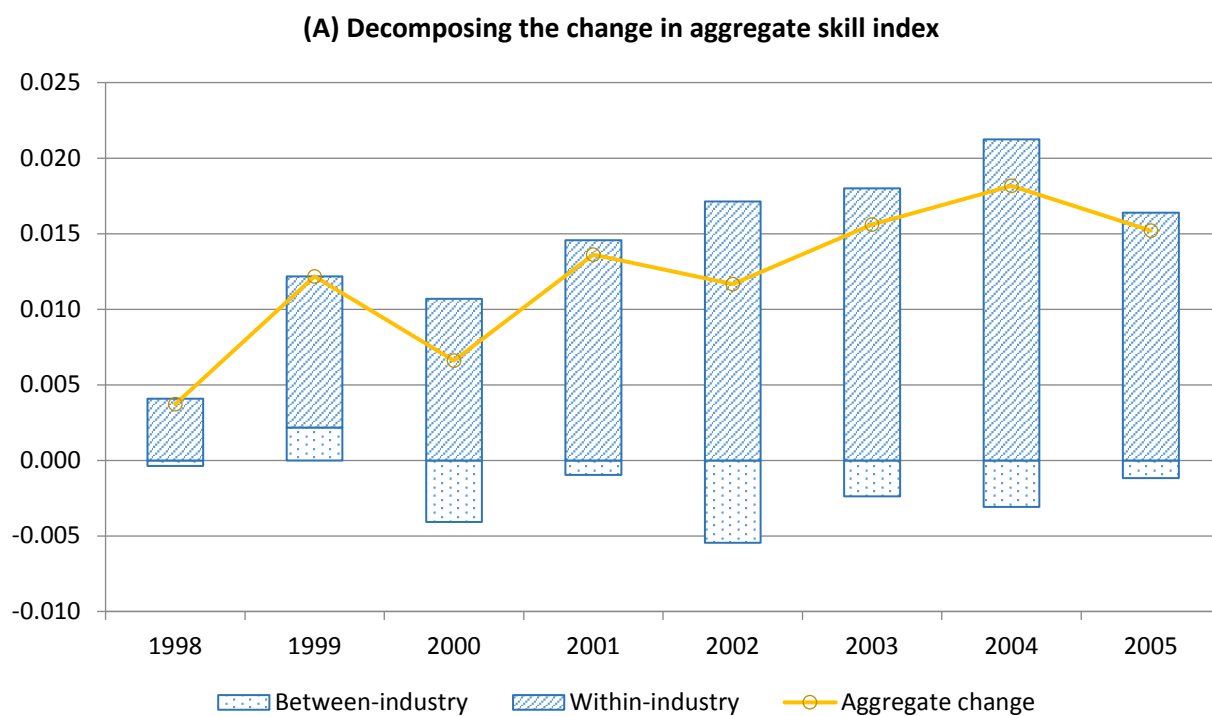
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<sup>28</sup> The cross term is also positive if firms tend to allocate a smaller share of workers toward highly paid jobs ( $w_j^* - \bar{w} < 0$ ) and pay a lower wage across the board ( $w_j - w_j^* < 0$ ).



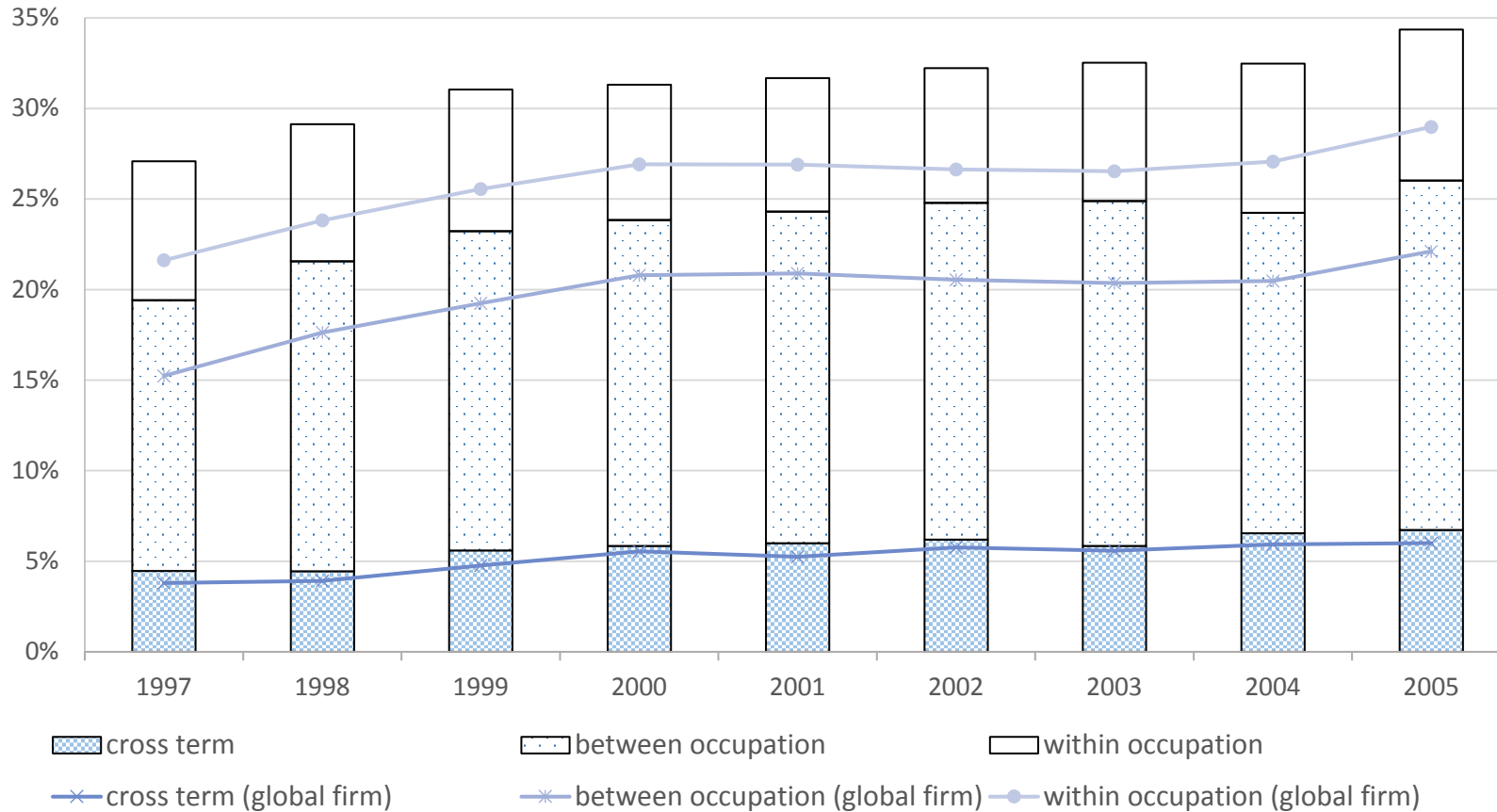
**Figure 1. Cumulative distribution of payroll by firm types**

*Note:* This figure shows the aggregate distribution of payroll across occupations by skill levels for three types of firms: multinationals (MNEs), non-MNE exporters, and Local firms (i.e., non-MNEs that do not export). The horizontal axis is the skill percentile ranking of occupations based on average wages for 1997. The vertical axis is cumulative payroll shares.



**Figure 2. Decomposing the change in aggregate skill index**

*Note:* Panel (A) displays the decomposition of the change in aggregate skill index (relative to 1997) into within- and between-industry changes. Panel (B) displays the decomposition of the within-industry change in skill index (relative to 1997) into (i) a change of skill index in globalized firms; (ii) a change of skill index in local firms; and (iii) a change due to the compositional shift from local to globalized firms and the difference in skill mix between local and globalized firms. See Section 4.C and Appendix B for more detail.



**Figure 3. Wage dispersion decomposition (1997-2005)**

*Note* : This figure displays the three components of between-firm wage dispersion as a share of overall wage dispersion. The between-occupation component captures the contribution of varying labor mix to wage dispersion given the same occupational wages. The within-occupation component allows cross-firm variation in occupational wages given the labor mix. The cross term is the covariance between the difference in labor mix and within-occupation wage differentials. It is positive if higher-wage firms employ a higher share of skilled workers than lower-wage firms. See Section 4.C and Appendix C for more detail.

**Table 1: Export shares and the skill mix for a sample of exporters**

	OLS	IV	OLS	IV	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export share	0.063*** (0.008)	0.209*** (0.035)	0.053*** (0.009)	0.275*** (0.036)	0.218*** (0.046)	0.045*** (0.009)	0.215*** (0.047)
Offshoring share					0.439*** (0.143)	-0.010 (0.020)	0.483*** (0.144)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.360	0.317	0.388	0.235	0.159	0.419	0.129
<i>First-stage regression of export share</i>							
Log WID <sub>97</sub>		0.032*** (0.002)			0.034*** (0.003)		0.034*** (0.003)
Log WID <sub>t-1</sub>				0.029*** (0.002)			
Log WES <sub>97</sub>					-0.004 (0.003)		-0.004 (0.003)
Swedish tariffs <sub>97</sub>							0.005 (0.004)
<i>First-stage regression of offshoring share</i>							
Log WES <sub>97</sub>					0.010*** (0.001)		0.010*** (0.001)
Swedish tariffs <sub>97</sub>							-0.004* (0.002)
Log WID <sub>97</sub>					-0.004*** (0.001)		-0.004*** (0.001)
F-statistic		186.1		228.8	26.34		17.69
Observations	16,018	9,290	9,290	11,643	7,696	7,696	7,696

*Note:* The dependent variable is skill index for firm  $j$  in year  $t$ :  $S_{jt} = \sum_k \lambda_{jkt} s_k$  where  $s_k$  is the skill percentile ranking of occupation  $k$  (based on the average occupational wages in 1997) and  $\lambda_{jkt}$  is the payroll share of occupation  $k$  at firm  $j$  in year  $t$ . The skill index is higher if payroll is allocated toward more skilled occupations. A value of 0.5 indicates that payroll is evenly distributed across all 100 different occupations. See Section 3.B for more details about the skill index. Export share is computed as the value of exports as a share of total sales. Offshoring share is computed as the value of intermediate imports as a share of total sales. Firm controls include the log of the number of employees, the capital-labor ratio, value added per employee and firm age. Industry and year fixed effects are included in all estimations. For the IV estimates in columns 2 and 4, we instrument for export shares using world import demand (WID). In column 5, we instrument for export shares and offshoring shares using WID and world export supply (WES). In column 7, we instrument for export shares and offshoring shares using WID, WES, and Swedish tariffs on imports. See Sections 3.C and 4.A for more detail about the instruments. The first-stage regressions include the instruments, firm controls, industry and year fixed effects. Standard errors are clustered by firm. \*\*\*, \*\*, \* show significance at the 1%, 5%, and 10% level, respectively.

**Table 2: Export shares and the decomposition and skewness of skill mix for a sample of exporters**

	OLS				IV				OLS	IV
	$S_{jt}$	Within NP	Within P	Between	$S_{jt}$	Within NP	Within P	Between	Skewness	Skewness
				NP & P				NP & P		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
<i>Panel (A) Export shares and the skill mix</i>										
Export share	0.053*** (0.009)	0.023*** (0.005)	0.028*** (0.006)	0.002 (0.004)	0.209*** (0.035)	0.103*** (0.023)	0.084*** (0.018)	0.022 (0.015)	0.150*** (0.036)	0.654*** (0.145)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.388	0.205	0.409	0.561	0.317	0.145	0.384	0.557	0.203	0.150
Observations	9,290	9,290	9,290	9,290	9,290	9,290	9,290	9,290	9,207	9,207
<i>Panel (B) Controlling for offshoring shares</i>										
Export share	0.045*** (0.009)	0.019*** (0.005)	0.026*** (0.006)	0.000 (0.004)	0.218*** (0.046)	0.133*** (0.034)	0.032* (0.019)	0.053*** (0.019)	0.140*** (0.038)	0.455*** (0.165)
Offshoring share	-0.010 (0.020)	0.029** (0.012)	-0.025** (0.012)	-0.014* (0.008)	0.439*** (0.143)	0.434*** (0.104)	-0.192** (0.075)	0.197*** (0.063)	-0.174** (0.079)	-0.270 (0.519)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.419	0.222	0.454	0.586	0.159	-0.347	0.393	0.426	0.210	0.210
Observations	7,696	7,696	7,696	7,696	7,696	7,696	7,696	7,696	7,632	7,632

*Note*: In columns 1 and 5, the dependent variable is skill index for firm  $j$  in year  $t$ :  $S_{jt} = \sum_k \lambda_{jkt} s_k$  where  $s_k$  is the skill percentile ranking of occupation  $k$  (based on the average occupational wages in 1997) and  $\lambda_{jkt}$  is the payroll share of occupation  $k$  at firm  $j$  in year  $t$ . The skill index is higher if payroll is allocated toward more skilled occupations. A value of 0.5 indicates that payroll is evenly distributed across all 100 different occupations. We also decompose the skill index into a shift of payroll toward more skilled occupations within the non-production category (NP), a shift toward more skilled occupations within the production category (P), and a shift from production to non-production. These three components of the skill index are the dependent variable, respectively, in columns 2-4, and in columns 6-8. In columns 9-10, the dependent variable is a transformation of the Groeneveld-Meeden skewness measure. A larger positive value of the skewness measure indicates that the payroll distribution is more skewed toward higher skilled occupations. See Section 3.B for more details about the skill index and its decomposition, and the skewness measure of the payroll distribution. Export share is computed as the value of exports as a share of total sales. Offshoring share is computed as the value of intermediate imports as a share of total sales. Firm controls include the log of the number of employees, the capital-labor ratio, value added per employee and firm age. Industry and year fixed effects are included in all estimations. For the IV estimates in columns 5-8 and 10, we instrument for export shares and offshoring shares using world import demand shocks (WID<sub>97</sub>) and world export supply shocks (WES<sub>97</sub>). The first-stage regressions include the instruments, firm controls, industry and year fixed effects. To save space, the first-stage results are not reported in this table since they are identical to those reported in column 5 of Table 1. See Section 3.C for more detail about the instruments. Standard errors are clustered by firm. \*\*\*, \*\*, \* show significance at the 1%, 5%, and 10% level, respectively.

**Table 3: Export shares by destination characteristics**

	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Export to EU	0.017 (0.014)	0.120** (0.053)				
Export to non-EU	0.050*** (0.015)	0.170*** (0.053)				
Export to high-income markets			0.015 (0.012)	0.113** (0.047)		
Export to lower-income markets			0.094*** (0.028)	0.282*** (0.095)		
Export to top 10 export markets					-0.004 (0.013)	0.101** (0.047)
Export to smaller markets					0.097*** (0.017)	0.269*** (0.053)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.409	0.366	0.420	0.370	0.412	0.352
<i>First-stage regression of share of export to <math>R_1</math></i>		<i>EU</i>		<i>High-income markets</i>		<i>Top 10 markets</i>
Log WID <sub>97,R1</sub>		0.031*** (0.003)		0.042*** (0.003)		0.032*** (0.002)
Log WID <sub>97,R2</sub>		-0.007*** (0.002)		-0.003 (0.002)		-0.001 (0.002)
<i>First-stage regression of share of export to <math>R_2</math></i>		<i>non-EU</i>		<i>Lower-income markets</i>		<i>Smaller markets</i>
Log WID <sub>97,R2</sub>		0.026*** (0.002)		0.012*** (0.001)		0.019*** (0.001)
Log WID <sub>97,R1</sub>		-0.012*** (0.002)		-0.006*** (0.002)		-0.008*** (0.002)
<i>F</i> -statistic		38.75		44.41		73.19
Observations	6,143	6,143	4,887	4,887	6,367	6,367

*Note*: The dependent variable is skill index for firm  $j$  in year  $t$ :  $S_{jt} = \sum_k \lambda_{jkt} s_k$  where  $s_k$  is the skill percentile ranking of occupation  $k$  (based on the average occupational wages in 1997) and  $\lambda_{jkt}$  is the payroll share of occupation  $k$  at firm  $j$  in year  $t$ . The skill index is higher if payroll is allocated toward more skilled occupations. A value of 0.5 indicates that payroll is evenly distributed across all 100 different occupations. See Section 3.B for more details about the skill index. See Section 4.A for more details about the division of export destination markets and the component-specific instruments for export shares. Firm controls include the log of the number of employees, the capital-labor ratio, value added per employee and firm age. Industry and year fixed effects are included in all estimations. Standard errors are clustered by firm. \*\*\*, \*\*, \* show significance at the 1%, 5%, and 10% level, respectively.

**Table 4: Firms types and the skill mix for the full sample**

	$S_{jt}$	Within NP	Within P	Between NP & P	Skewness
	(1)	(2)	(3)	(4)	(5)
MNE	0.111*** (0.006)	0.062*** (0.005)	0.013*** (0.002)	0.036*** (0.003)	0.035* (0.018)
Non-MNE exporter	0.084*** (0.005)	0.050*** (0.004)	0.015*** (0.002)	0.019*** (0.002)	0.065*** (0.016)
Export share	0.043*** (0.008)	0.014*** (0.004)	0.031*** (0.005)	-0.002 (0.004)	0.179*** (0.031)
Offshoring	0.034*** (0.004)	0.020*** (0.003)	-0.004** (0.002)	0.017*** (0.002)	-0.001 (0.015)
Offshoring share	-0.016 (0.017)	0.040*** (0.011)	-0.040*** (0.010)	-0.016** (0.007)	-0.102 (0.065)
Firm controls	yes	yes	yes	yes	yes
Observations	25,790	25,790	25,790	25,790	25,151
R <sup>2</sup>	0.395	0.378	0.417	0.458	0.185

*Note* : In column 1 the dependent variable is skill index for firm  $j$  in year  $t$ :  $S_{jt} = \sum_k \lambda_{jkt} s_k$  where  $s_k$  is the skill level of occupation  $k$  (based on the average occupational wages in 1997) and  $\lambda_{jkt}$  is the payroll share of occupation  $k$  at firm  $j$  in year  $t$ . The skill index is higher if payroll is allocated toward more skilled occupations. A value of 0.5 indicates that payroll is evenly distributed across all 100 different occupations. We also decompose the skill index into a shift of payroll toward more skilled occupations within the non-production category (NP), a shift toward more skilled occupations within the production category (P), and a shift from production to non-production. These three components of the skill index are the dependent variable, respectively, in columns 2-4. In column 5 the dependent variable is a transformation of the Groeneveld-Meeden skewness measure. A larger positive value of the skewness measure indicates that the payroll distribution is more skewed toward higher skilled occupations. See Section 3.B for more details about the skill index and its decomposition, and the skewness measure of the payroll distribution. "MNE" is an indicator of multinational firms. "Non-MNE exporter" is an indicator of non-multinational firms that export. Offshoring is a dummy variable that equals one if a firm offshores. Export shares are computed as the value of exports as a share of total sales. Offshoring shares are computed as the value of intermediate imports as a share of total sales. Firm controls include the log of the number of employees, the capital-labor ratio, value added per employee and firm age. Industry and year fixed effects are included in all estimations. Standard errors are clustered by firm. \*\*\*, \*\*, \* show significance at the 1%, 5%, and 10% level, respectively.



**Table 5: Manufacturing vs. Non-manufacturing firms**

	Manufacturing				Non-manufacturing			
	$S_{jt}$	Within NP	Within P	Between NP & P	$S_{jt}$	Within NP	Within P	Between NP & P
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MNE	0.029*** (0.005)	0.009*** (0.002)	0.003 (0.003)	0.017*** (0.002)	0.149*** (0.007)	0.090*** (0.006)	0.011*** (0.002)	0.049*** (0.003)
Non-MNE exporter					0.124*** (0.006)	0.076*** (0.005)	0.017*** (0.002)	0.030*** (0.003)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,792	10,792	10,792	10,792	15,079	15,079	15,079	15,079
R <sup>2</sup>	0.419	0.205	0.395	0.316	0.399	0.366	0.373	0.386

*Note*: In columns 1 and 5, the dependent variable is skill index for firm  $j$  in year  $t$ :  $S_{jt} = \sum_k \lambda_{jkt} s_k$  where  $s_k$  is the skill percentile ranking of occupation  $k$  (based on the average occupational wages in 1997) and  $\lambda_{jkt}$  is the payroll share of occupation  $k$  at firm  $j$  in year  $t$ . The skill index is higher if payroll is allocated toward more skilled occupations. A value of 0.5 indicates that payroll is evenly distributed across all 100 different occupations. We also decompose the skill index into a shift of payroll toward more skilled occupations within the non-production category (NP), a shift toward more skilled occupations within the production category (P), and a shift from production to non-production. These three components of the skill index are the dependent variable, respectively, in columns 2-4, and in columns 6-8. See Section 3.B for more details about the skill index and its decomposition. "MNE" is an indicator of multinational firms. "Non-MNE exporter" is an indicator of non-multinational firms that export. Because the manufacturing sector has a small number of "Local firms" (i.e., non-MNEs that do not export), in columns 1-4 we compare MNEs with non-MNEs (most of which are exporters). In columns 5-8 the base group is non-MNEs that do not export. Firm controls include the log of the number of employees, the capital-labor ratio, value added per employee and firm age. Industry and year fixed effects are included in all estimations. Standard errors are clustered by firm. \*\*\*, \*\*, \* show significance at the 1%, 5%, and 10% level, respectively.