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Abstract

Previous literature generally predicts that individuals with higher skills work in industries with longer production chains. However, the opposite skill-sorting pattern, a “negative skill-sorting” phenomenon, is also observed in reality. This paper proposes a possible mechanism by which both cases can happen and shows that negative skill sorting is more likely to occur when the quality of intermediate inputs degrade rapidly (or improves slowly) along the production chain. We empirically confirm our theoretical prediction by using country-industry panel data. The results are robust regardless of estimation method, control variables, and industry coverage. This study has important implications for understanding countries’ comparative advantages and development patterns.

JEL Classification: J24, L23

Keywords: Skill sorting, Input quality, Production chains

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1. Introduction

Understanding why skill levels of workers are different across industries is important when considering countries' economic development patterns. In this paper, we focus on one mechanism, in which skill sorting across industries depends on the length of industry's production chains. As suggested by Grossman (2004), Asuyama (2012), and Sampson (2013), when high-skilled workers work in industries with shorter (resp., longer) production chains, the country is likely to have a comparative advantage in such sectors. Then, what should the government of a country do if it is to develop, for instance, manufacturing industries that are generally characterized by long production chains as well as high levels of employment creation? To answer this question, we need to understand the mechanism for countries' skill-sorting patterns across industries.

A production process is sequential if producing the final good requires several sequential production stages, whereas it is simultaneous if all inputs are combined simultaneously to produce the final good. In practice, however, most production processes are a mixture of sequential and simultaneous (Baldwin and Venables 2013).[1] For example, apparel production is sequential in a sense that it requires a "cotton to yarn to fabric to shirts" process (Baldwin and Venables 2013). At the same time, it also entails a simultaneous process of combining many parts, including fabric, thread, zippers, and buttons, to make a final product. Thus, when the production process requires either more sequential stages or a larger number of inputs, we say, in this paper, that the length of the production chain is longer.

Previous theoretical studies based on sequential production predict that higher-skilled individuals work at later production stages (Sobel 1992; Kremer 1993):[2] In other words, higher-skilled workers produce goods that have longer production chains. We call this

[1] Baldwin and Venables (2013) call sequential production processes "snakes" and simultaneous ones "spiders."

[2] Costinot, Vogel, and Wang (2013) present similar theoretical results. Instead of allocating workers with heterogeneous skills, their model uses countries with different productivity along the global supply chains. In their model, higher-productivity countries specialize in later production stages.

skill-sorting pattern *positive skill sorting* and the reverse one *negative skill sorting*.

In reality, however, positive skill sorting is not always observed. Consider the case where the length of production chains is measured at the industry level. If positive skill sorting is occurring, then the average skill level of workers must be higher in industries with longer production chains. Figure 1 shows that this is not always the case. In this figure, the average skill level (estimated average years of education) of each industry's workforce and the length of the industry's production chain in the latest available year are plotted for six countries. These data are analyzed empirically later. The length of production chains measures how much domestic intermediate input the industry requires, both direct and indirect, to produce one dollar worth of output (see Section 3). In all countries except Mexico, workers' skill levels are negatively associated with the length of production chains, which indicates that negative skill sorting is present.[3]

This paper aims to provide a possible mechanism that explains why both positive and negative skill-sorting patterns occur in reality. We assume that, as with the O-ring theory by Kremer (1993), the quality of intermediate inputs degrades more as the production chains become longer, due to more involvement of low-skilled workers, poor infrastructure such as unstable power supply and bumpy roads, and less-advanced production technology. When the degree of quality deterioration is substantial, higher-skilled individuals lose more wages as the production chains lengthen, resulting in negative skill sorting. Otherwise, positive skill sorting occurs. We empirically confirm this prediction by using country-industry panel data.

Our paper is most closely related to papers by Asuyama (2015), Kremer (1993), and Sampson (2013). Asuyama (2015) shares a similar hypothesis to ours, but her analysis is based on a simultaneous production model and on India's data only. We additionally propose a sequential production model and examine cross-country data to test whether the skill-sorting

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[3] Because Figure 1 illustrates a simple correlation based on one-year data, these skill-sorting patterns may be caused by industry characteristics other than the length of production chains. Thus, in this paper, we examine the association more rigorously by controlling for many other factors that might affect skill-sorting patterns.

patterns depend on the country's degree of quality changes in intermediate inputs along the production chains. Kremer (1993) analyzes, as we do, both simultaneous and sequential production. In his simultaneous production model, firms choose the optimal length of production chain and worker skill level, but the quality of intermediate inputs is not explicitly considered. In his sequential production model, the quality of the intermediate input produced at each stage is assumed to be either 0 or 1, and only the latter inputs are used at the next stage. Hence, again, the effect of quality deterioration of intermediate inputs on skill sorting is not studied. Similarly to our goal, Sampson (2013) aims to explain why skill-sorting patterns across industries are different across countries, doing so by examining the matching of high-skilled individuals with intermediate inputs in a simultaneous production model. We depart from his study by (i) additionally offering a sequential case; (ii) linking the sector-specific quality of intermediate inputs to its quantity (or production chain length), which is technologically fixed in each sector; and (iii) making his assumption of increasing return to skill unnecessary for skill sorting to emerge.

This paper is also related to several theoretical studies that analyze how higher-skilled workers are matched with other workers, rather than with intermediate inputs. Most studies predict that higher-skilled individuals work with (or manage) a higher number of workers (Lucas 1978; Murphy, Shleifer, and Vishny 1991; Rosen 1982).[4] In contrast, Grossman (2004) theoretically shows that high-skilled workers prefer to work alone in the so-called "software" sector and are reluctant to work in a team production sector (the "automobile" sector), in which wages are dragged down by lower-skilled team members because of imperfect labor contracts. Grossman (2004) is theoretical, based on a two-sector model with one production input (labor), and his assumption of imperfect labor contracts plays a key role in inducing skill sorting. In contrast, the key for skill sorting in our study is quality deterioration along the production

[4] Among these studies, Rosen (1982) analyzes skill allocation across within-firm *sequential* production activities from the lowest to the highest managerial ranks. He shows that higher-skilled individuals are assigned to higher ranks and manage a larger number of employees.

chains. We also present a multi-sector model, introduce intermediate inputs, and provide empirical analysis.

The rest of the paper is organized as follows. Section 2 presents a possible mechanism by which both positive and negative skill sorting occurs. Section 3 explains the data and empirical strategy, and Section 4 presents the results of our empirical analysis. Section 5 concludes the paper.

2. A Simple Model

2.1 Sequential Production Model

First, we develop a sequential production model that explains how skill-sorting patterns are affected by the lengths of production chains. In the model, a final good is produced by a representative firm. Let $n \in [N_{\min}, N_{\max}]$ index the production stages, where larger values of n indicate later stages. As with Antràs and Chor (2013), the production of each intermediate good, which requires a worker and an intermediate input produced at the previous stage, is outsourced to a supplier. That is, the firm provides the necessary input to the supplier and collects the produced intermediate good, which in turn is provided to the supplier at the next stage as input.[5] The final good is produced at the final stage, $n = N_{\max}$, with the price given exogenously.

Let the revenue of the final good be given by[6]

$$y = \int_{N_{\min}}^{N_{\max}} x(n)dn\,.$$

By Leibniz's rule, we have

$$y'(n) = x(n)\,,$$

where $y(n) = \int_{N_{\min}}^{n} x(j)dj$. Thus, $x(n)$ is the marginal increase in revenue attributable to the

[5] We assume only a worker is required at the earliest stage, $n = N_{\min}$.

[6] This function corresponds to $\alpha = 1$ in a production function $y = (\int x(j)^{\alpha} dj)^{1/\alpha}$ with constant elasticity of substitution. Antràs and Chor (2013) consider the case in which $x(j)$ is imperfectly substitutable: $\alpha \in (0,1)$. Instead, we let $x(j)$ be perfectly substitutable ($\alpha = 1$), but each $x(j)$ is dependent on the quality of intermediate input used at each stage.

supplier at stage *n*.

To explicitly consider the effect of input quality on skill sorting, we decompose $x(n)$ into two components: quality (*Q*), and the value-added *(V)* attained when *Q*=1 at all production stages. This formulation is similar to the one used in the simultaneous production case in Kremer (1993). The quality component depends on the stage, *n*, and the total skill invested in intermediate-input production up to that stage, *H(n)*. The value component, *V*, depends on the stage and the worker's skill level. Thus, *x(n)* is expressed as

$$x(n) = Q(H(n), n)V(h(n), n),$$

where $h(n) \in [0,1]$ is the skill level of a stage-*n* worker, $H(n) \equiv \int_{N_{\min}}^{n} h(j)dj$, and *Q* and *V* are assumed to be twice continuously differentiable. We assume $Q_H > 0$ and $V_h > 0$.[7] The first inequality means that the quality component *Q* increases as the total skill invested in intermediate-input production increases. The second inequality means that the value component *V* increases as the worker's skill level increases. In addition, as in O-ring theory (Kremer 1993), we assume $Q_n < 0$; that is, quality deteriorates more as more stages are involved. Consider, again, production of a shirt. Even when the quality of cotton is perfect (100%), if the spinning, weaving, and sawing processes degrade the unfinished products by 1% each, the quality of a shirt falls to 97.0% ($= 100\% \times 0.99^3$).

As in Antràs and Chor (2013), the firm pays each supplier a fraction $\beta \in (0,1)$ of the marginal revenue raised by them. Assuming a competitive labor market, the wage for a stage-*n* worker of skill *h*, $w(n,h)$, equals the whole payment the firm makes to the stage-*n* supplier:

$$w(n,h) = \beta Q(H(n), n)V(h, n).$$

The optimal stage for a worker with skill *h*, $n^*(h)$—the stage where the worker receives the highest wage—is obtained by solving

$$\max_n w(n,h).$$

By the first-order condition, $n^*(h)$ satisfies[8]

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[7] Subscripts denote partial derivatives with respect to corresponding variables.

[8] The second-order condition is satisfied if *Q* and *V* are concave in *n* ($d^2Q/dn^2 < 0$ and

$$\frac{dQ}{dn}V + QV_n = 0,$$

where $dQ/dn = Q_H h(n) + Q_n$.

By the implicit function theorem, *negative skill sorting (* $dn^*/dh < 0$ *) occurs if and only if*

$$\frac{dQ}{dn}V_h + QV_{nh} < 0. \tag{1}$$

Let us focus on cases where (voluntary) skill sorting occurs: (i) $dQ/dn < 0$ and $V_n > 0$, and (ii) $dQ/dn > 0$ and $V_n < 0$. In case (i), (1) always holds when *V* is submodular (i.e., when $V_{nh} < 0$). When *V* is supermodular ($V_{nh} > 0$), high-skilled workers choose earlier stages only if *Q* decreases sufficiently rapidly with stage.[9] Otherwise, positive skill sorting occurs. In case (ii), *V* must be submodular for (1) to hold. In addition, (1) is more likely to hold when the positive value of dQ/dn is small. In sum, in either case (i) or (ii), the smaller dQ/dn is (whether positive or negative), the more likely that negative skill sorting occurs. In other words, *negative skill sorting occurs when intermediate goods degrade rapidly or their quality improves slowly with production stage.*

2.2 Simultaneous Production Model (Asuyama 2015)

Next, we briefly refer to the simultaneous production model developed by Asuyama (2015). In her model, industries differ in the amount of intermediate inputs required (*n*), that is, in the length of production chains. An individual with skill $h \in [0,1]$ chooses to work in the industry *n** (and utilize *n** units of intermediate inputs) that provides the highest wages (*w*). This is found by solving the following maximization problem:

$V_{nn} < 0$), which we assume.

[9] Equation (1) can also be expressed as $\frac{V_{hn}}{V_h} < -\frac{dQ/dn}{Q}$, as in the case of simultaneous production (see footnote 10). Then, when $V_{hn} (= V_{nh}) > 0$, negative skill sorting occurs only when *Q* decreases with stage more rapidly than the increasing speed of V_h, or the marginal revenue of workers' skill.

$$max_n \ w(h,n,q) = Q(q,n)V(h,n) - nq,$$

where $q \in (0,1]$ is the quality of one unit of intermediate input, which is exogenously determined in the economy. Similarly to the sequential production case, *Q* is the quality component and *V* stands for the value of final output attained if intermediate input quality exerts no influence. $Q_q > 0$, $Q_n < 0$, $V_h > 0$, $V_n > 0$, $Q_{nn} < 0$, $V_{nn} < 0$ are assumed. Her analysis considers two cases: (a) When *V* is supermodular in *h* (worker's skill) and *n* (amounts of intermediate inputs used), that is $V_{hn} > 0$; and (b) when *V* is submodular ($V_{hn} < 0$). In case (a), *negative skill sorting ($dn^*/dh < 0$) occurs only when the quality of intermediate inputs (Q) deteriorates sufficiently rapidly along the production chains*.[10] In other words, the smaller Q_n is (i.e., the larger the absolute value of negative Q_n), the more likely that negative skill sorting will take place. In case (b), negative sorting always occurs, regardless of the speed of quality degradation.

3. Data and Empirical Strategy

We measure the length of production chains at the industry level.[11] We then test our theoretical prediction against country-industry panel data. More precisely, we extract the annual time-series input–output (IO) tables and the skill-distribution data of each industry for six countries from the World Input–Output Database (WIOD) (Timmer et al., 2015). In particular, we use the *National Input–Output Tables* (released in September 2012) and the *Socio Economic Accounts* (released in July 2014), which contain information on workers' skill levels and the

[10] In Asuyama's model, negative skill sorting occurs if and only if $V_{hn}/V_h < -Q_n/Q$. Thus, when *V* is supermodular ($V_{hn} > 0$), negative skill sorting occurs only when the speed of quality deterioration along the production chains exceeds the increasing speed of marginal revenue of worker's skill (V_h).

[11] The stage-*n* supplier in our sequential production model corresponds to a representative producer in a stage-*n* industry (i.e., an industry with production chain length *n*). If we assume a simultaneous production model, industries are distinguished by the different amounts of necessary intermediate inputs (i.e., lengths of production chains).

capital stock of each industry. The countries (and years) covered are Canada (1995–2009), China (1995–2008), India (1995–2004), Japan (1995–2005), Mexico (1995–2006), and the United States (U.S.; 1995–2009). Only for these six countries can we have sufficiently fine variations of skill-distribution data across industries. Each country has 33–35 industries.

Using the country-industry panel data, we estimate the following two types of skill-sorting equations.

Type 1: Sequential Production

$$Skill_{ict} = \alpha_{10} + \beta_{11} ChainL_{ict} + \beta_{12} ChainQ\_Import_{ict} + \beta_{13} ChainQ\_Skillcum_{ict},$$
$$+ \beta_{14} ChainL_{ict} * Qdiff\_h_{ct} + \beta_{15} ChainL_{ict} * Qdiff\_Qn_{ct} + \gamma Z_{ict} + F_t + \varepsilon_{ict}. \quad (2)$$

Type 2: Simultaneous Production

$$Skill_{ict} = \alpha_{20} + \beta_{21} ChainL_{ict} + \beta_{22} ChainQ\_Import_{ict} + \beta_{23} ChainQ\_Skill_{ict}$$
$$+ \beta_{25} ChainL_{ict} * Qdiff\_Qn_{ct} + \gamma Z_{ict} + F_t + \varepsilon_{ict}. \quad (3)$$

In these, subscripts *i*, *c*, and *t* indicate industry, country, and year, respectively. $Skill_{ict}$ is the average skill level of workers, which is measured by the estimated years of education of each industry's workforce (Table 1).[12]

$ChainL_{ict}$ stands for the length of *domestic* production chains. It is the column sum of the Leontief inverse coefficient of each industry, computed from each country's IO table (Table 1). We exclude imported inputs from our calculation, because we assume that substantial quality deterioration (or little quality improvement) of intermediate inputs along the production chains is caused by poor levels of worker skill, infrastructure, and technology of the *local* economy. This $ChainL_{ict}$ index measures how much of domestic intermediate inputs, both direct and indirect, industry *i* requires to produce one dollar's worth of industry *i* output. It measures the length of production chains generated from the mixture of both sequential and simultaneous production processes.[13] Table 2 lists industries with the five shortest and the five

[12] For the estimation method, see Appendix in addition to Table 1. Table 1 also displays the definitions and summary statistics for *Skill* and other variables.

[13] This index is used in Asuyama (2012, 2015) as a measure for the length of production chains. It is also equivalent to the *N* index in Fally (2012), which Fally claims measures "the number of production stages embodied in each product" (p. 2) or "the number of stages *before* obtaining"

longest production chains in the six countries. Although there are certain variations across countries, service industries such as real estate, education, retail, and wholesale trade tend to have shorter production chains, while manufacturing industries such as transport equipment, rubber and plastics, textiles, and leather tend to have longer production chains.

$ChainQ\_Import_{ict}$ (the degree of dependence on imported inputs), and $ChainQ\_Skillcum_{ict}$ or $ChainQ\_Skill_{ict}$ (skill level embodied in inputs from other industries) are the supplementary quality indicators of intermediate inputs not captured by $ChainL_{ict}$. $ChainQ\_Import_{ict}$, which is computed in a manner explained in Table 1, is controlled for because the quality of imported inputs is likely to differ from that of domestic inputs but is also likely to affect skill-sorting patterns.[14] $ChainQ\_Skillcum_{ict}$ is the cumulative skills embodied in the inputs from other industries, which approximates $H(n)$ in the sequential production model. In the case of simultaneous production, the average skill level embodied in the inputs from other industries ($ChainQ\_Skill_{ict}$) is used instead.[15]

$Qdiff\_h_{ct}$ and $Qdiff\_Qn_{ct}$ measure the country's degree of quality changes in intermediate inputs along the production chains. In the case of sequential production, they are proxies for $dQ/dn = Q_H h(n) + Q_n$. Assuming the same Q_H for all countries, dQ/dn can be approximated by $h(n)\,(= dH(n)/dn$, which is itself approximated by $dChainQ\_Skillcum/dChainL$) and Q_n (Table 1). The variables $Qdiff\_h_{ct}$ and $Qdiff\_Qn_{ct}$ measure *h(n)* and Q_n, respectively. We assume that Q_n becomes smaller as the economy's levels of worker skill, transportation and power supply infrastructure, and technology or, more roughly, income become lower. We thus use gross domestic product (GDP)

each product (p. 9). There is an alternative index that measures a position in production chains, that is, the *D* index in Fally (2012). That index is equivalent to the upstreamness version of *DownMeasure* in Antràs and Chor (2013). However, as Fally (2012) mentions, the *D* index measures the "distance to final demand." Since our focus is on the effect of quality deterioration embodied in inputs *before* producing good *i*, it is appropriate to use Fally's *N* index instead of the *D* index.

14 We thank Satoshi Inomata for his advice on constructing this *ChainQ_Import*.

15 Controlling for *ChainQ_Skill* (instead of for *ChainQ_Skillcum*) in the sequential production case or controlling for *ChainQ_Skillcum* in the simultaneous production case does not change our main estimation results, except that it increases the number of significant results.

per capita as the measure of $Qdiff\_Qn_{ct}$.[16] In the case of simultaneous production, in which the degree of quality deterioration is captured by the magnitude of Q_n, we also use GDP per capita as the measure for $Qdiff\_Qn_{ct}$.

Finally, Z_{ict} is a vector of various industry characteristics, such as capital stock ($\ln K_{ict}$), employment ($\ln L_{ict}$), and the export- and import-ratio of the industries' final goods ($Export_{ict}$ and $Import_{ict}$, respectively) (Table 1). F_t are year dummies and ε_{ict} is an error term.

If negative (resp., positive) skill sorting occurs, that is, if higher-skilled individuals work in industries with shorter (longer) production chains, then the average skill level of workers should be higher in industries with shorter (longer) production chains. Additionally, as our model predicts, if negative skill sorting occurs only when the degree of quality deterioration (resp., quality improvement) along the production chains is sufficiently large (small), we should observe $\{\beta_{11} < 0, \beta_{14} > 0, \beta_{15} > 0\}$ in equation (2) and $\{\beta_{21} < 0, \beta_{25} > 0\}$ in equation (3). To see why we should observe such sign patterns, consider equation (3) as an example. If we correct terms with $ChainL_{ict}$, we get the equation in the following alternative form:

$$Skill_{ict} = \alpha_{20} + (\beta_{21} + \beta_{25} Qdiff\_Qn_{ct}) ChainL_{ict} + \beta_{22} ChainQ\_Import_{ict}$$
$$+ \beta_{23} ChainQ\_Skill_{ict} + \gamma Z_{ict} + F_t + \varepsilon_{ict}.$$

If the coefficient of $ChainL_{ict}$, [$\beta_{21} + \beta_{25} Qdiff\_Qn_{ct}$] is negative (resp., positive), then negative (positive) skill sorting is the predicted outcome in the economy. The sign of [$\beta_{21} + \beta_{25} Qdiff\_Qn_{ct}$] depends on the estimated coefficients $\{\beta_{21}, \beta_{25}\}$ and the actual value of $Qdiff\_Qn_{ct}$. If $\{\beta_{21} < 0, \beta_{25} > 0\}$, then the sign of [$\beta_{21} + \beta_{25} Qdiff\_Qn_{ct}$] becomes negative and indicates negative skill sorting when $Qdiff\_Qn_{ct}$ is very small (that is, when the degree of quality deterioration in the economy is substantial). It becomes positive (indicating positive skill sorting) as $Qdiff\_Qn_{ct}$ becomes larger. Thus, when $\{\beta_{21} < 0, \beta_{25} > 0\}$ (or $\{\beta_{11} < 0, \beta_{14} > 0, \beta_{15} > 0\}$ in equation (2)), it is consistent with our theoretical prediction.

[16] Data are extracted from the World Bank (2015).

According to our theoretical predictions, if *V* is submodular, then negative skill sorting occurs regardless of quality changes in intermediate inputs under certain conditions. However, if β_{14} and β_{15} in (2), or β_{25} in (3), is statistically significant, then this indicates that changes in input quality affect skill-sorting patterns.

If the unobservables in the error term ε_{ict} are correlated with the explanatory variables, then the obtained estimators will be biased and inconsistent. To deal with this issue, we estimate (2) and (3) using fixed-effects (FE) and first-differenced (FD) estimators. These methods control for or eliminate the unobserved country- and industry-specific time-invariant factors. The FE estimator is more efficient when the remaining time-invariant errors are serially uncorrelated, whereas the FD estimator is more efficient when the errors follow a random walk (Wooldridge 2010: p.321). Finally, it should be noted that our aim is not to identify causality but to measure association after controlling as much as possible for other possible factors that affect skill-sorting patterns.

4. Empirical Results

Table 3 reports the FE and FD estimates of the skill-sorting equation (2) for the sequential production case. We find $\{\beta_{11} < 0, \beta_{14} > 0, \beta_{15} > 0\}$, that is, a negative coefficient for *ChainL* and positive coefficients for *ChainL*Qdiff_h* and *ChainL*Qdiff_Qn*, in all specifications except column (18), regardless of the estimation method, control variables, and industry coverage. Thus, consistent with our theoretical prediction, negative skill sorting is more likely to occur in economies where intermediate goods degrade rapidly (or their quality improves slowly) with production stage. In some specifications, we restrict the sample to manufacturing and service industries by excluding primary resource industries such as agriculture and mining. This is because the quality of primary products is greatly affected by land, weather, and natural resources, which are not included as inputs in IO tables. We also examine only manufacturing industries to ensure that we are not capturing only the sectoral difference between services (which tend to have shorter production chains) and manufacturing (which tends to have longer production chains).

The FE and FD estimates of the skill-sorting equation (3) for the simultaneous production case are reported in Table 4. Although the results are less robust than those for the sequential production case, we find $\{\beta_{21} < 0, \beta_{25} > 0\}$, that is, a negative coefficient for *ChainL* and a positive coefficient for *ChainL*Qdiff_Qn*, in most specifications. In other words, negative skill sorting tends to occur in economies where quality deterioration along the production chains is more substantial.

The coefficient of $ChainL_{ict}$ can be written as [$\beta_{11} + \beta_{14} Qdiff\_h_{ct} + \beta_{15} Qdiff\_Qn_{ct}$] in equation (2) and [$\beta_{21} + \beta_{25} Qdiff\_Qn_{ct}$] in equation (3). When this coefficient is negative, negative skill sorting is the predicted outcome for country *c* at time *t*. In contrast, when this coefficient is positive, positive skill sorting is the predicted outcome. Based on the estimates obtained with all the control variables under our consideration, which are the estimates in every third column of each sample in Tables 3 and 4, we list our sample economies where negative skill sorting is the predicted outcome (Table 5). In the remaining economies, positive skill sorting is predicted. Although the coverage of listed economies differs depending on which estimate we use, less-developed countries are more likely to experience negative skill sorting.

As for other variables, we expect positive coefficients for the degree of dependence on imported inputs ($ChainQ\_Import_{ict}$) and the skill level embodied in inputs from other industries ($ChainQ\_Skillcum_{ict}$ or $ChainQ\_Skill_{ict}$) in both Tables 3 and 4, assuming that higher values of these variables indicate higher quality of intermediate inputs. We expect this because, after controlling for the length of production chains, higher quality of intermediate inputs attracts higher-skilled workers by mitigating the effect of quality deterioration along the production chains. The results in Tables 3 and 4 show that the coefficient of $ChainQ\_Import_{ict}$ tends to be negative, contrary to our hypothesis. This may be because greater dependence on imported inputs does not necessarily indicate higher quality of intermediate inputs, particularly in developed countries that import natural resources and less-advanced intermediate goods. Consistent with our hypothesis, the coefficient on $ChainQ\_Skillcum_{ict}$ or $ChainQ\_Skill_{ict}$ tends to be positive.

5. Conclusion

We have proposed a possible mechanism that explains the negative skill sorting phenomenon, which is often observed in reality. Our model predicts that negative skill sorting is more likely to occur in economies where the quality of intermediate inputs degrades rapidly (or improves slowly) along the production chains. We empirically confirm this prediction by using country-industry panel data.

Untangling the relations among the length of production chains, input quality, and skill-sorting patterns is important when considering countries' economic development. For example, if a government wants to develop manufacturing industries, which are generally characterized by long production chains and high levels of employment creation, then policies that mitigate negative skill sorting or induce positive skill sorting are needed. The results of our study indicate that upgrading the quality of intermediate inputs through various policy instruments, such as skill development of workers, improvement of roads and power supply conditions, and the adoption of advanced technologies, will play a key role.

Finally, a more sophisticated empirical analysis—one that covers more countries, breaks down industries more narrowly, refines worker skill levels, considers employment-based skill-distribution data[17], and measures changes in the quality of intermediate inputs more precisely—is left for future research because such cross-country data are not currently available at a sufficiently fine resolution.[18]

[17] As Table 1 shows, skill-distribution data are based on working hours.
[18] As mentioned in Introduction, Asuyama (2015) conducts more sophisticated empirical analysis using Indian data.

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Appendix

A. Estimation of *Eduy* for 1995–2009 based on Barro and Lee (2013) data

$Eduy_{jct}$, that is, the average years of schooling for education level *j* (=*L*, *M*, *H*), is estimated on the basis of the world educational attainment data of Barro and Lee (2013). Barro and Lee (2013) have created country-level data on the average years of schooling for several education levels for the period 1950‐2010 at five-year intervals. Still, estimation of $Eduy_{jct}$ is necessary because WIOD and Barro and Lee (2013) use different education categories. In principle, low-skill (*L*) in WIOD denotes primary and lower-secondary education[19]. The medium-skill (*M*) contains upper-secondary and post-secondary non-tertiary education, and the high-skill (*H*) contains first- and second-stage tertiary education (Timmer ed., 2012: p. 58). In contrast, the four education categories of Barro and Lee (2013) are no schooling, primary, secondary, and tertiary education. Thus, $Eduy_{jct}$ is estimated by the following procedure[20]:

First, we assume that the standard years of schooling are 5 years for *L*, 12 years for *M*, and more than 12 years for *H* in India.[21] Then, we estimate $Eduy_{jct}$ for India for the years 1995, 2000, 2005, and 2010 as follows:

$$Eduy_{Lct} = Eduy_{Pct} * \{P_{ct} / (NoS_{ct} + P_{ct})\},$$

$$Eduy_{Mct} = 5 + Eduy_{Sct},$$

$$Eduy_{Hct} = 12 + Eduy_{Tct},$$

where $Eduy_{Pct}$, $Eduy_{Sct}$, and $Eduy_{Tct}$ are the average *completed* years of primary, secondary, and tertiary schooling, respectively, and NoS_{ct} and P_{ct} indicate the percentage of population (aged 15 and over) without schooling (*NoS*) and with some primary schooling (*P*), respectively. These right-hand-side variables are extracted from Barro and Lee (2013).

For the remaining five countries, we assume 9 years (= 6 for primary + 3 for

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[19] It also seems to implicitly include members of the population with less than primary education.

[20] As in the main text, *c* and *t* indicate country and year, respectively.

[21] The WIOD's skill definition of Timmer (2012: p.58) does not seem to apply to India. Thus we treat India differently. From the skill-distribution data of India (NSSO, various rounds), we consider that *L* includes workers with primary or less than primary education, *M* includes those with lower- and upper-secondary education, and *H* includes those with tertiary education.

lower-secondary schooling) for *L*, 12 years for *M*, and more than 12 years for *H*. Then, $Eduy_{jct}$ is estimated for the four periods (1995, 2000, 2005, and 2010) as follows:

$$Eduy_{Lct} = Eduy_{Pct} * \{P_{ct} / (NoS_{ct} + P_{ct} + LS_{ct})\} + (6 + Eduy_{LSct}) * \{LS_{ct} / (NoS_{ct} + P_{ct} + LS_{ct})\},$$

$$Eduy_{Mct} = 9 + Eduy_{USct},$$

$$Eduy_{Tct} = 12 + Eduy_{Tct},$$

where LS_{ct} is the percentage of population (aged 15 and over) with some lower-secondary education, estimated as half of the percentage with some secondary education. $Eduy_{LSct}$ and $Eduy_{USct}$ are the average *completed* years of lower-secondary (*LS*) and upper-secondary (*US*) education, respectively, which are estimated as follows:

$Eduy_{LSct}$ = (*standard* schooling years for *LS*)

* (average *completed* years of schooling/*standard* years of schooling, up to *S*)

$$= 3 * (6 + Eduy_{sct}) / 12,$$

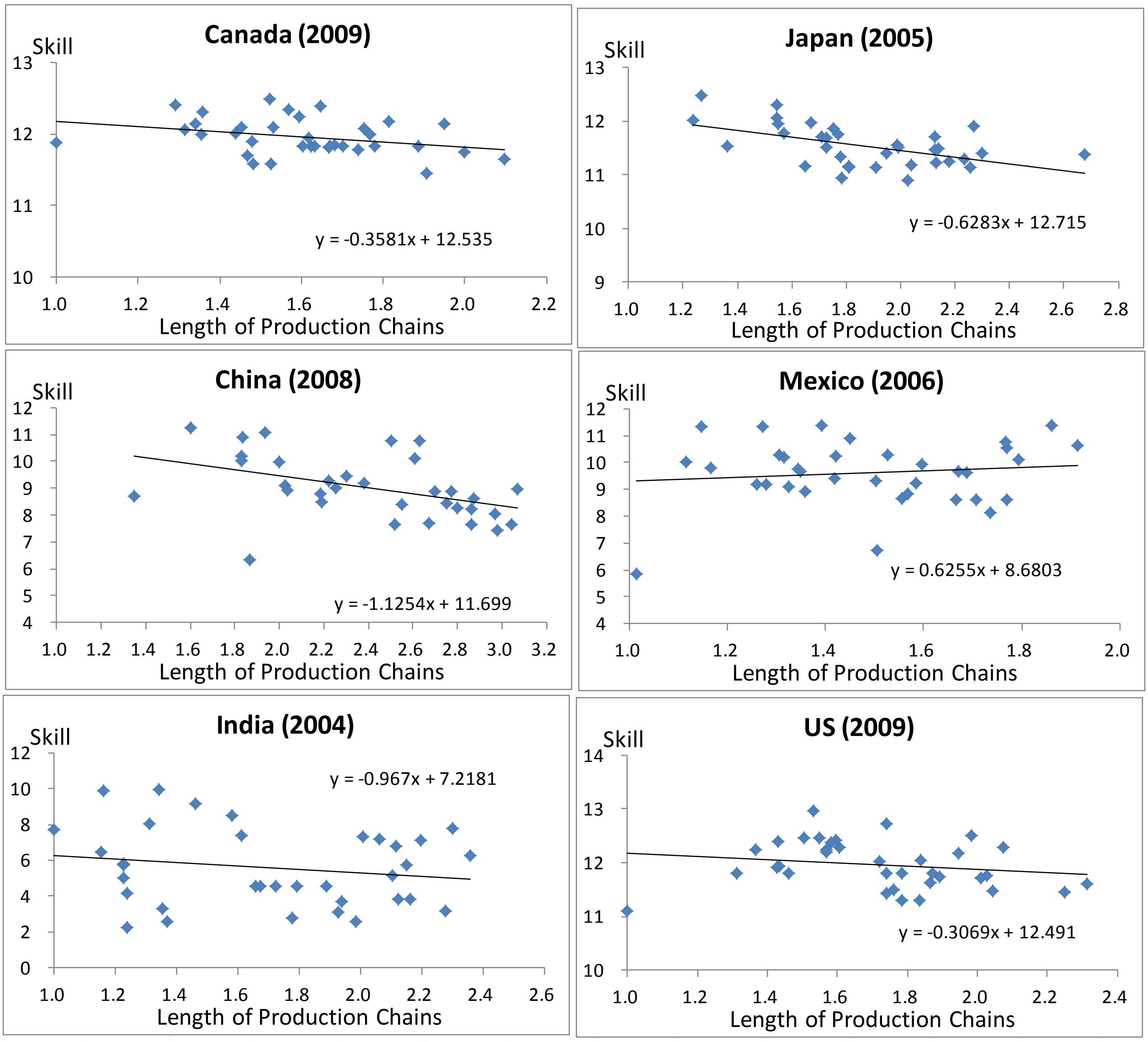
$Eduy_{USct}$ = (*standard* schooling years for *US*)

* (average *completed* years of schooling/*standard* years of schooling, up to *S*)

$$= 3 * (6 + Eduy_{sct}) / 12.$$

Data for the other years are interpolated under the assumption of a constant annual growth rate between points, with a five-year interval.

Figure 1. Industry-level simple correlation between workers' skill level and industry's production chain length



Notes: The unit of observation is industry. There are 33-35 industries in each country. *Skill* is the average skill level (estimated average years of education) of the industry's workforce. The length of production chains measures how much domestic intermediate input the industry requires, both direct and indirect, to produce one dollar's worth of output. For more details on these two variables, see Section 3 and Table 1.

Table 1. Construction of variables and summary statistics

Variable	Definition	Mean	Std. Dev.
$Skill_{ict}$	= $\sum_j h_{jict} * Eduy_{jct}$, where *j* (=*L*, *M*, *H*) indicates education level (low, middle, high) of workers; h_{jict} is *j*'s share of hours worked by persons engaged; and $Eduy_{jct}$ is *j*'s average completed years of schooling, estimated from Barro and Lee (2013). Estimation (see Appendix) is necessary because the education categories are different between WIOD and Barro and Lee (2013).	9.842	2.527
$ChainL_{ict}$	= $\sum_j leon_{jict}$, where $leon_{jict}$ is the (*j*, *i*)th entry of the Leontief inverse coefficient matrix *L*. $L = (I - A_d)^{-1}$, where *I* is the identity matrix and A_d is the input coefficient matrix for domestic input, with the (*j*, *i*)th entry a_{jict} representing the amount of domestic input from industry *j* directly used to produce one dollar's worth of output by industry *i*. As to why *L* is computed by the above formula, see Antràs and Chor (2013, pp. 2159-2160).	1.789	0.390
$ChainQ\_Import_{ict}$	= *ML*, where *M* is the row vector whose *i*th entry is *i*'s imported input to output ratio.	0.124	0.092
$ChainQ\_Skillcum_{ict}$	= $\sum_{j \neq i} Skill_{jct} * leon_{jict}$, which measures the cumulative skills embodied in the inputs from other industries.	6.709	3.101
$ChainQ\_Skill_{ict}$	= $(\sum_{j \neq i} Skill_{jct} * leon_{jict}) / \sum_{j \neq i} leon_{jict}$, which measures the average skill level embodied in inputs from other industries, weighted by *j* (input industry)'s share in the entire production chain length.	9.933	2.340
$Qdiff\_h_{ct}$	= Coefficient on *ChainL*, when regressing *ChainQ_Skillcum* on *ChainL* and 1, separately for each country and year.	7.178	2.292
$Qdiff\_Qn_{ct}$	Logarithm of GDP per capita (2005 USD prices)	9.122	1.653
$\ln K_{ict}$	Logarithm of industry's real fixed capital stock (1995 USD prices)	10.782	1.809
$\ln L_{ict}$	Logarithm of industry's number of persons engaged	7.110	1.798
$Export_{ict}$	Percentage of final goods export in industry output	13.617	18.117
$Import_{ict}$	Percentage of final goods import in industry output	19.902	55.418

Notes: Number of observations is 2616 for $ChainQ\_Skillcum_{ict}$ and $ChainQ\_Skill_{ict}$, and 2656 for other variables.

Table 2. Industries with the five shortest and the five longest production chains

	Industries with the five shortest production chains				***Industries with the five longest production chains***			
	ChainL rank	Industry	*ChainL*	*Skill*	*ChainL* rank	Industry	*ChainL*	*Skill*
Canada (35 industries, 95-09)	1	PHEP (S)	1.000	11.610	31	Air Transport (S)	1.772	11.600
	2	Education (S)	1.278	12.155	32	Agriculture & HFF (P)	1.849	11.191
	3	Real Estate (S)	1.280	11.688	33	Coke & Refined Petroleum (M)	1.850	11.884
	4	Electricity, Gas & Water Supply (S)	1.290	11.920	34	Food, Beverages & Tobacco (M)	1.997	11.524
	5	Health & Social Work (S)	1.315	12.066	35	Wood, Wood Products, & Cork (M)	2.009	11.434
China (33 industries, 95-08)	1	Real Estate (S)	1.469	8.855	29	Rubber & Plastics (M)	2.646	7.580
	2	Financial Intermediation (S)	1.680	11.045	30	Construction (S)	2.674	7.756
	3	Agriculture & HFF (P)	1.812	5.668	31	Metals (M)	2.696	7.994
	4	Post & Telecommunications (S)	1.837	10.576	32	Leather & Footwear (M)	2.715	6.912
	5	Education (S)	1.881	10.909	33	Transport Equipment (M)	2.764	8.567
India (35 industries, 95-04)	1	Public Admin & Defense (S)	1.000	7.271	31	Leather & Footwear (M)	2.215	3.352
	2	Real Estate (S)	1.139	6.357	32	Paper , Printing & Publishing (M)	2.219	6.116
	3	Education (S)	1.183	9.260	33	Food, Beverages & Tobacco (M)	2.232	2.779
	4	Retail Trade (S)	1.268	4.472	34	Rubber & Plastics (M)	2.346	6.150
	5	Sale & Maintenance of Motor Vehicles (S)	1.268	4.991	35	Transport Equipment (M)	2.400	6.627
Japan (34 industries, 95-05)	1	Real Estate (S)	1.248	11.759	30	Textiles & Textile Products (M)	2.194	10.710
	2	Education (S)	1.269	12.234	31	Chemicals & Chemical Products (M)	2.204	11.667
	3	Coke & Refined Petroleum (M)	1.436	11.492	32	Metals (M)	2.228	10.954
	4	Retail Trade (S)	1.541	11.615	33	Rubber & Plastics (M)	2.278	11.084
	5	Financial Intermediation (S)	1.551	12.078	34	Transport Equipment (M)	2.701	11.083
Mexico (35 industries, 95-06)	1	PHEP (S)	1.024	5.319	31	Leather & Footwear (M)	1.786	7.479
	2	Real Estate (S)	1.112	9.603	32	Chemicals & Chemical Products (M)	1.793	10.489
	3	Education (S)	1.153	11.089	33	Food, Beverages & Tobacco (M)	1.796	8.185
	4	Mining & Quarrying (P)	1.210	8.827	34	Air Transport (S)	1.842	11.185
	5	Retail Trade (S)	1.271	8.593	35	Coke & Refined Petroleum (M)	1.983	10.267
US (35 industries, 95-09)	1	PHEP (S)	1.000	10.816	31	Water Transport (S)	2.089	11.726
	2	Wholesale Trade (S)	1.420	11.698	32	Textiles & Textile Products (M)	2.122	11.049
	3	Retail Trade (S)	1.437	11.743	33	Transport Equipment (M)	2.132	11.948
	4	Real Estate (S)	1.451	12.173	34	Wood, Wood Products, & Cork (M)	2.230	11.247
	5	Other Transport (S)	1.489	11.726	35	Food, Beverages & Tobacco (M)	2.339	11.437

Notes: P, M, and S in parentheses indicate primary, manufacturing, and service sector, respectively. Both *ChainL* and *Skill* are average figures over the sample period. The meanings of abbreviations are as follows: PHEP = private households with employed persons; Agriculture & HFF = agriculture, hunting, forestry, and fishing; Retail Trade = retail trade except of motor vehicles and motorcycles, and repair of household goods; Wholesale Trade = wholesale trade and commission trade except of motor vehicles and motorcycles; Sale & Maintenance of Motor Vehicles = sale, maintenance, and repair of motor vehicles and motorcycles as well as retail sale of fuel; Other Transport = other supporting and auxiliary transport activities as well as activities of travel agencies; Coke & Refined Petroleum = coke, refined petroleum, and nuclear fuel.

Table 3. FE and FD skill-sorting equation estimates: sequential production case

	(A) FE estimates								
	All-industry Sample			Manufacturing & Service Sample			Manufacturing Sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ChainL	-2.782***	-2.796***	-2.774***	-2.785***	-2.803***	-2.736***	-2.747***	-3.147***	-2.930***
	(0.259)	(0.288)	(0.289)	(0.260)	(0.290)	(0.291)	(0.334)	(0.345)	(0.292)
ChainQ_Import		-0.080	-0.162		-0.092	-0.141		-0.665*	-0.674*
		(0.321)	(0.317)		(0.325)	(0.321)		(0.362)	(0.389)
ChainQ_Skillcum		0.012	0.008		0.014	0.013		0.075**	0.076*
		(0.023)	(0.023)		(0.023)	(0.023)		(0.035)	(0.042)
*ChainL*Qdiff_h*	0.114***	0.109***	0.113***	0.113***	0.107***	0.111***	0.105***	0.079***	0.085***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)	(0.021)	(0.024)
*ChainL*Qdiff_Qn*	0.235***	0.232***	0.234***	0.235***	0.231***	0.226***	0.234***	0.231***	0.211***
	(0.024)	(0.031)	(0.032)	(0.024)	(0.032)	(0.033)	(0.027)	(0.035)	(0.035)
R-squared	0.704	0.704	0.706	0.703	0.702	0.704	0.780	0.787	0.790
Number of obs.	2656	2616	2616	2502	2462	2462	1078	1078	1078
	(B) FD estimates								
	All-industry Sample			Manufacturing & Service Sample			Manufacturing Sample		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ChainL	-1.068***	-1.206***	-1.151***	-1.072***	-1.188***	-1.100***	-1.072***	-1.290***	-1.111***
	(0.163)	(0.178)	(0.182)	(0.165)	(0.179)	(0.180)	(0.199)	(0.215)	(0.196)
ChainQ_Import		-0.436***	-0.423***		-0.377**	-0.365**		-0.500**	-0.473**
		(0.161)	(0.163)		(0.167)	(0.172)		(0.203)	(0.214)
ChainQ_Skillcum		0.023	0.025		0.023	0.028		0.043*	0.048*
		(0.017)	(0.018)		(0.017)	(0.018)		(0.024)	(0.027)
*ChainL*Qdiff_h*	0.037***	0.032***	0.034***	0.036***	0.031***	0.033***	0.053***	0.041***	0.044***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.015)	(0.015)	(0.015)
*ChainL*Qdiff_Qn*	0.092***	0.089***	0.078***	0.095***	0.088***	0.072***	0.083***	0.073**	0.044
	(0.018)	(0.022)	(0.026)	(0.018)	(0.023)	(0.026)	(0.022)	(0.028)	(0.033)
R-squared	0.039	0.043	0.046	0.040	0.043	0.048	0.081	0.090	0.101
Number of obs.	2449	2412	2412	2307	2270	2270	994	994	994

Notes: The dependent variable is *Skill*. Year dummies and a constant are also included in all specifications. In addition, *lnK*, *lnL*, *Export*, and *Import* are controlled for in the third column of each sample (i.e., in columns (3), (6), (9), (12), (15), and (18)). The unit of panel is country-industry. Standard errors clustered by country-industry are in parentheses.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4. FE and FD skill-sorting equation estimates: simultaneous production case

	(A) FE estimates								
	All-industry Sample			Manufacturing & Service Sample			Manufacturing Sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ChainL	-2.068***	-0.430	-0.507	-2.087***	-0.491	-0.549	-2.163***	-1.082***	-0.994***
	(0.247)	(0.326)	(0.327)	(0.247)	(0.331)	(0.333)	(0.281)	(0.360)	(0.361)
ChainQ_Import		0.002	-0.129		-0.041	-0.162		-0.818**	-0.936***
		(0.318)	(0.320)		(0.325)	(0.326)		(0.348)	(0.327)
ChainQ_Skill		0.609***	0.629***		0.604***	0.622***		0.650***	0.673***
		(0.048)	(0.046)		(0.049)	(0.047)		(0.071)	(0.066)
*ChainL*Qdiff_Qn*	0.227***	0.056*	0.071**	0.227***	0.062**	0.074**	0.233***	0.104***	0.103***
	(0.025)	(0.031)	(0.031)	(0.025)	(0.031)	(0.031)	(0.027)	(0.033)	(0.034)
R-squared	0.679	0.775	0.778	0.677	0.775	0.777	0.755	0.845	0.848
Number of obs.	2656	2616	2616	2502	2462	2462	1078	1078	1078
	(B) FD estimates								
	All-industry Sample			Manufacturing & Service Sample			Manufacturing Sample		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ChainL	-1.040***	-0.609***	-0.613***	-1.047***	-0.589***	-0.575***	-1.071***	-0.794***	-0.743***
	(0.157)	(0.179)	(0.180)	(0.160)	(0.181)	(0.177)	(0.190)	(0.152)	(0.149)
ChainQ_Import		-0.191	-0.195		-0.131	-0.142		-0.323**	-0.324**
		(0.142)	(0.142)		(0.144)	(0.147)		(0.155)	(0.162)
ChainQ_Skill		0.428***	0.426***		0.435***	0.431***		0.537***	0.527***
		(0.054)	(0.054)		(0.055)	(0.056)		(0.061)	(0.059)
*ChainL*Qdiff_Qn*	0.116***	0.069***	0.070***	0.117***	0.068***	0.067***	0.119***	0.085***	0.080***
	(0.016)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.020)	(0.016)	(0.017)
R-squared	0.031	0.095	0.096	0.032	0.100	0.101	0.060	0.159	0.162
Number of obs.	2449	2412	2412	2307	2270	2270	994	994	994

Notes: Same as for Table 3.

Table 5. Economies where negative skill sorting is the predicted outcome

Estimates used			Economies where negative skill sorting
Table	Estimator	Column	is the predicted outcome
Table 3 (sequential production case)	FE	(3)	China, India
		(6)	China, India, Mexico (1995-96)
		(9)	China, India, Japan, Mexico
	FD	(12)	Canada (1995-2003), China, India, Japan, Mexico, U.S.
		(15)	Canada, China, India, Japan, Mexico, U.S.
		(18)	Canada, China, India, Japan, Mexico, U.S.
Table 4 (simultaneous production case)	FE	(3)	China (1995-2001), India
		(6)	China (1995-2004), India
		(9)	China, India, Mexico
	FD	(12)	China, India
		(15)	China, India
		(18)	China, India, Mexico

Notes: Years in parentheses indicate periods for which negative skill sorting is predicted. Negative skill sorting is predicted in all sample periods when no period is given. The sample economies not listed in this table have positive skill sorting as the predicted outcome.