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The Impact of Production Fragmentation on Industry Skill Upgrading: New Evidence from Japanese Manufacturing*

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Abstract:
This paper examines the hypothesis that industries engaged in international fragmentation of production experience greater skill upgrading using a panel dataset of Japanese manufacturing over the period 1980-2000. The novelty of the study comes from the use of an index newly constructed using data on trade in parts and components to measure inter-industry variations in the degree of international vertical specialization (fragmentation intensity of trade). It also employs a methodology designed to embody peculiarities of Japan's fragmentation trade pattern. While the findings of existing studies are inconclusive, we find that the expansion of fragmentation trade with developing East Asian countries has had a significant impact on the skills composition of Japanese manufacturing employment. By contrast, trade with high income countries seems to have had a skill downgrading effect.

Key Words: International Fragmentation of Production; Skill Upgrading; Japanese Manufacturing
JEL Classification: F14, F16, J31

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1. Introduction

International fragmentation of production generally involves the relocation of unskilled labour-intensive production segments to developing countries where labour costs are relatively low, while retaining in developed countries the higher-end production activities that require high skills or sophisticated technologies. This process of international specialisation implies two forms of structural adjustment in the manufacturing industry in developed countries: First, it changes the composition of manufactured trade by the increase of cross-border trade in parts and components. Second, it brings about compositional shifts in the skill composition of demand for labour. The latter is the focus of this paper. In particular, the rise of the fragmentation process has the effect of shifting labour demand away from unskilled-labour toward skilled-labour *within* the manufacturing industry (or *within* firms), since domestic production increasingly specialises in the higher skilled and technology-intensive tasks. As a result, it pushes up demand for the relative wages of skilled workers while suppressing demand and wages for unskilled workers. This process is known as skill upgrading (Katz and Autor 1999).

Feenstra and Hanson (1996; 1999; 2003) have demonstrated that the fragmentation-based trade contributed 15% to 24% of the total increase in the wages of skilled workers in US manufacturing during the 1980s. Following these studies, similar analyses have been undertaken for a range of other developed countries: Strauss-Kahn (2004) for France, Hijzen, Görg, and Hine (2005) for the UK, Helg and Lucia (2005) for Germany, Hsieh and Woo (2005) for Hong Kong, Egger and Egger (2003) for Austria, and Hansson (2000) for Sweden. Broadly speaking, the findings of these studies are consistent with the Feenstra-Hanson results for US manufacturing. However, very little work has been done for Japanese manufacturing, and the findings of these studies remain inconclusive (Sakurai 2000; Ito and Fukao 2005). This is rather surprising, given the active role of Japanese firms (mainly, driven by the international production network of Japanese MNEs) in production sharing (Borrus 1997; Ng and Yeats 2001; Athukorala and Yamashita 2006). The present study is motivated by this inconclusiveness in the findings of existing studies. Our contention is that the failure to find a robust relationship between the increased fragmentation process and industry skill upgrading in Japanese manufacturing might be associated with methodological shortcomings.

The empirical analysis is based on a panel data set constructed for Japanese manufacturing industries from the newly updated Japanese Industrial Productivity Database (JIP 2006). The data set covers 52 industries over the period from 1980 to 2000. Thus, it has wider coverage in terms of the period and the number of industries compared to previous studies. The updated time coverage is particularly important because fragmentation activities in Japanese manufacturing began to grow rapidly from the late 1980s. In addition to the superiority of the database, there are three distinguishing features of the present study compared to previous Japanese manufacturing studies.

First, the analysis improves upon a main shortcoming of previous studies in associated with measurement of the fragmentation process for a given industry. Following Feenstra and Hanson (1996; 1999), the standard practice in the skill upgrading literature generally measures the fragmentation process by the imported intermediate inputs contents derived from Input-Output (I-O) table without making a distinction between the traditional raw materials and parts and components. However, this measure is fundamentally flawed in terms of capturing the true dynamics of the fragmentation process in Japanese manufacturing given its high dependency on imported raw materials. The fragmentation intensity measure based on the I-O table assigns very high rankings to industries with high dependency on imported intermediate inputs such as processed marine products, lumber and wood products and pulps and papers (Ito and Fukao 2005). However, they are not part of the rapidly growing production fragmentation process in Japanese manufacturing. Against this backdrop, the empirical analysis undertaken here proposes to use a measure constructed from trade data in parts and components based on careful disaggregation of trade data. This is the first time measure this has been implemented in relation to industry skill upgrading studies.

Second, the analysis explicitly takes into account the unique pattern of fragmentation in Japanese manufacturing. Japan's fragmentation pattern is not confined only to purchase of foreign intermediates inputs for processing. Rather, it has mainly evolved due to the outward orientation of the fragmentation process from exporting parts and components for the purpose of final processing in developing East Asian countries. Failing to capture the export orientation of the fragmentation process might result in underestimating the actual impact of fragmentation on skill upgrading.

Third, we examine whether the geographical orientation of the fragmentation process has a differential impact on skill upgrading. This is a useful extension because there might be some heterogeneity in the effect of the fragmentation activities on the skill structure of labour demand depending on specific geographic location. More specifically, imports of parts and components from developed countries may not have the same effect on skill upgrading as the imports from developing countries due to difference in skills contents.

The organization of this paper is as follows: The next section conceptually describes how an increase of the fragmentation process has implications for skill upgrading of domestic manufacturing, followed by a succinct survey of the relevant empirical studies. Section 3 discusses measurement issues central to the empirical analysis of a study. Section 4 discusses model specification, and econometrics methodology, followed by the interpretation of the results. The final section concludes by summarising the key findings and discussing the future trajectory of this research project.

2. Labour Market Consequences of Fragmentation

Fragmentation of production refers to the cross-border splitting of the production process within vertically integrated manufacturing industries. This either takes the form of importing parts and components or exporting the domestically produced components for further processing. This implies structural adjustment to the manufacturing process by reorganization of the entire production system into a new one. The former case is involved with the low-skill contents of the intermediate processing stage performed in the low-wage countries and imported back to home for further processing and assembly. This allows the domestic manufacturing process to specialise more on the high-tech and skill intensive segments of the production process. In the latter case, the relatively high-skills intensive components are *exported* for the purpose of further processing. This also facilitates specialization in skills intensive activity in domestic manufacturing. In both cases, the fragmentation process implies greater specialization in domestic manufacturing, by upgrading the skills intensity of the labour compositions.

A revealing example is given by Brown and Linden (2005) in relation to the semiconductor manufacturing process, which consists of three discrete steps: design, wafer fabrications, and test and assembly. Design requires higher skilled workers and levels of sophisticated technology. Wafer fabrication requires relatively less skills and testing and assembling is the process requiring the least average skills. Thus, workers skills contents go down along the value chain from design to testing and assembling. In the 1980s, the US computer chips industry began to move assembly activity to lower cost countries in Asia, while home production focussed more on design, fabrication, and managerial function: Chips were fabricated in the US, air freighted to Asia for assembly, and then returned to the US for final testing and packing. This had a direct impact on labour demand for more-skilled workers (technical workers, electronics engineers and sales workers), while placing downward pressure on unskilled labour in the US semiconductor industry during this period.

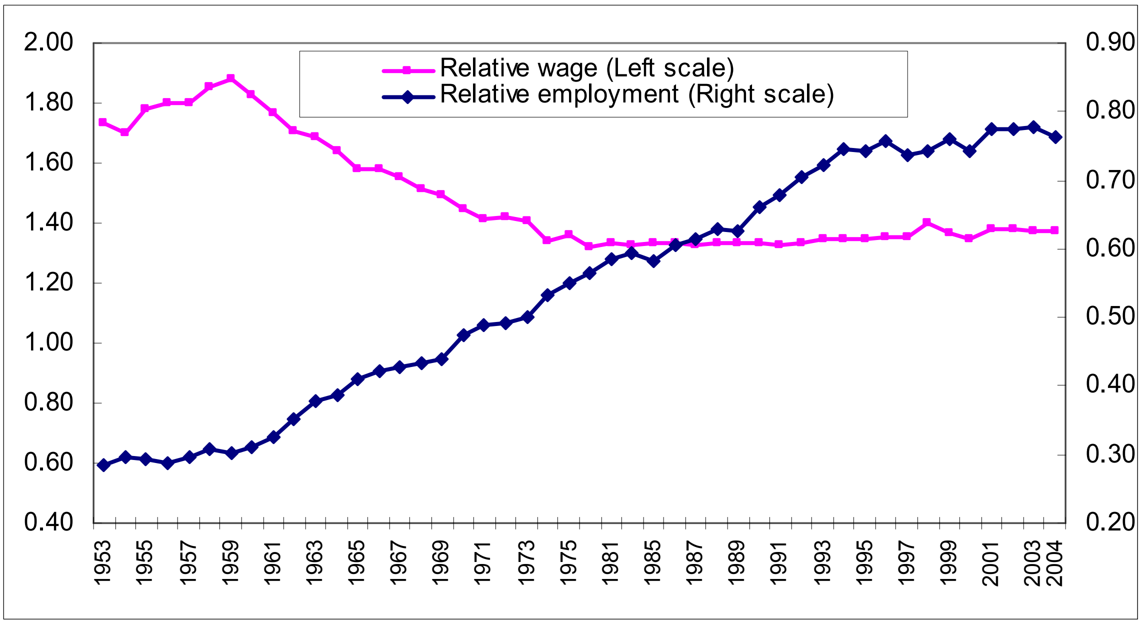
While the above example is useful for an illustration, the theory provides a less clear-cut guidance to the impact of production fragmentation on different types of workers (Jones and Kiezkowski 2002; Feenstra and Hanson 1996; Arndt 1997; Kohler 2004; Grossman and Rossi-Hansberg 2006). At this juncture, we take the general view that the fragmentation process might induce a shift in the skill composition of labour demand in favour of skilled-workers (ie, skill upgrading). This is the key hypothesis to be tested in this paper.

There is an extensive empirical literature on labour market implantations of increased trade orientation in developed countries (eg, Kruegman 1995; Sachs and Sharzs 1994; Lawrence and Slaughter 1993). Most of these works have been motivated by the observation of contraction of employment opportunities for unskilled workers and deterioration of relative wages in face of rapid penetration of manufacturing imports from developing countries.. Figure 1 illustrates this point for Japanese and US manufacturing for the period 1950s to 2004. Wages skilled workers (proxied by wages of non-production workers) relative to that of unskilled workers are measured on the left axis and relative employment of these two categories of workers is measured on the right axis. The Figure clearly shows that relative employment has moved in favour of skilled workers in both countries. However, patterns of relative wages are different between the two countries. For instance, in Japanese manufacturing there has been a sharp and persistent increase in relative employment of skilled workers since around the 1960s. In contrast, in US manufacturing there has been a massive increase in relative wages of skilled workers during the period from mid-1980s to early 2000s.[1] There is evidence that experiences of other industrial countries also in general similar to that of the USA in the past two decades (See Katz and Autor 1999 for a survey).

[1] This contrasting patterns of relative wages between Japanese and US manufacturing is an interesting subject for further research. In general, factor prices do not adjust perfectly when there is a strong presence of institutions and labour regulations (eg, minimum wages). This is mostly observed in Continual European countries such as France and Denmark. However, the Japanese labour market is generally thought to be relatively more oriented with the market flexibility and perfections (See the World Bank's doing business survey for a raking of labour marker flexibility). The failure to adjust relative wages in Japanese manufacturing might stem from the traditional labour market practices such as the lifetime employment and the seniority payments system.

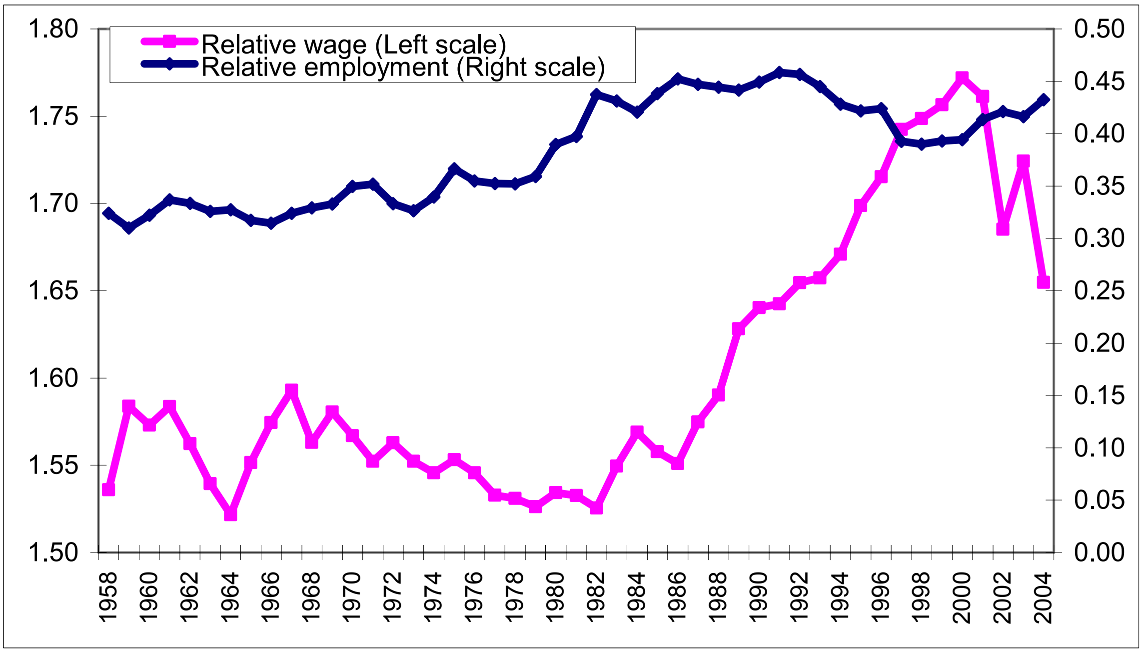
Figure 1:

Relative wage and employment of skilled workers to unskilled workers in Japanese Manufacturing, 1953-2004.



Source: Census of Manufactures (various years), Ministry of Economy, Trade and Industry. Government of Japan, Basic Survey on Wage Structure, Ministry of Health, Labour and Welfare.

Relative wage and employment of skilled to unskilled on workers in US manufacturing, 1958-2004.



Source: Annual Survey of Manufactures (ASM) (various years) The US Census Bureau.

The dominant view for the underlying cause of such skill upgrading is that skills-biased technological changes (eg, a large influx of computers and automation in the workplace) is the main culprit for shifting labour demand towards more-skilled workers in developed countries. Feenstra and Hanson (1996; 1999) have added a new dimension to the literature by highlighting that the processing trade (ie, trade in parts and components for further processing) is driven by an increase of the fragmentation activity as a source of skill upgrading. Their measurement of outsourcing intensity basically involves a calculation of imported intermediate inputs from the I-O tables and tests econometrically whether or not this indicator has any impact on industry skill upgrading. Their data sets cover 447 industries based on US Standard Industrial Classification (SIC) over 1979-1990. In these regressions, the dependent variable is the change of nonproduction (skilled) workers shares in total wage bills over the period. The estimation framework is based on a trans-log cost function, first employed by Berman et al. (1994) in the literature. The results support the hypothesis that foreign outsourcing has had a positive impact on the nonproduction share of total wage bills, alongside technological change indicators. The Feenstra and Hanson (1996; 1999) calculations suggest foreign outsourcing contributed a 15% to 24% of the total change in the nonproduction wage shares associated with a shift in total demand for labour towards more-skilled workers over the period 1979-1990.

Following Feenstra and Hanson (1996; 1999), a similar analysis has been undertaken for some other OECD countries. These studies include Anderton and Breton (1999) and Haizen et al. (2005) for the UK; Strauss-Kahn (2003) for France; Hansson (2000) for Sweden, Helg and Tajori (2005) for Germany; Hsieh and Woo (2005) for Hong Kong, and Yang (2006) for Canada. The findings of these studies are summarised in Table 1. Overall, the results suggest increased fragmentation of production has a sizable impact on shifting of labour demand towards more-skilled workers, albeit the estimated magnitude of the impact varies across countries.

Sakurai (2000), Ito and Fukao (2005), and Sasaki and Sakura (2004) examined the impact of production fragmentation for changes in the skill composition of manufacturing employment in Japanese manufacturing using the similar methodology.

However, unlike other country studies, the studies on Japanese manufacturing have not been able to come up with clear-cut results. Sakurai (2000) used employment and wage data for production and nonproduction workers for 39 manufacturing industries, cultivated from the Census of Manufacturing over the period 1987-1990. He constructed measures of outsourcing intensity following Feenstra and Hanson (1996) and tested for any statistical significance for change in nonproduction workers' share in total wage-bills in Japanese manufacturing. He found no statistical relationship between the intensity of imported intermediate inputs and skills upgrading.

Ito and Fukao (2005) extended the analysis to cover 35 manufacturing industries over a longer time period (1988-2002). In their various regression runs, foreign outsourcing variables exhibited the positive sign, but had no statistical significance. Sasaki and Sakura (2004) examined the possible impact on industry skill upgrading, based on education attainment levels (higher or lower educated) for a panel of 14 Japanese manufacturing industries during the period 1988-2003. This study was motivated by a concern that the inconclusive evidence of the previous studies was presumably due to failure to specifically allow for Japan's growing trade with countries in East Asia. They used the manufactured imports penetration ratio as an indicator of outsourcing intensity. They found increased imports penetration from developing East Asian countries contributed to around a 11-12% increase in high-educated worker's wage bills shares across industries. However, due to its poor measurement these results simply do not reflect the impact of the fragmentation process on skill upgrading of Japanese manufacturing.

There are perhaps two main shortcomings in the existing studies in the effects of increasing fragmentation activity on skill upgrading in Japanese manufacturing. First, as will be discussed below, a reliance on an I-O table to measure the intensity of the fragmentation activity is not appropriate. Second, these studies have failed to incorporate the peculiarities of the Japanese labour market setting and practices in their analysis. When labour markets deviate from the standard competitive labour market norms due to trade unions bargaining or rigid employment practices of firms (i.e. life-time employment) wages naturally do not adjust to clear labour markets in response to changes in international trade patterns or other external influences (Revenga 1992).[2] In this respect, the Feenstra and Hanson (1996) approach that was originally designed for analysing the competitive and flexible US labour market might not be suitable for examining the Japanese experience.

[2] Some studies took role of trade unions bargaining into account in the empirical framework (Skaksen and Søresen (2002) for Denmark and Egger and Egger (2003) for Austria).

Table 1: A Summary of Empirical Studies on the Skill Upgrading Effects of the Fragmentation Intensity

Study	Country	Data	Dependent variable	Measurement of Fragmentation Intensity	Statistical Relationship[1]
Feenstra and Hanson (1996; 1999)	the US	1979-1990, 447 SIC industry	Change in nonproduction workers' wage bills shares	I-O Table	+
Strauss-Kahn (2003)	France	1977-1993, 50 3-digit industries (INSEE)	Change in employment share of production workers	I-O Table	+
Helg and Tajori (2005)	Germany and Italy	20 mfg sector, 2-digit ISIC (Rev, 3)	Relative employment of skilled to unskilled workers (in log)	OAP (Offshore Assembly Programme) data	+
Hsieh and Woo (2005)	Hong Kong	19714-1996, 54 mfg industries	Change in nonproduction workers' wage bills shares	I-O Table	+
Haizen et al. (2005)	The UK	1982-1996, 50 mfg industries,	Change in nonproduction workers' wage bills shares	I-O Table	+
Anderton and Breton (1999)	The UK	1971-1986, 11 ISIC industries	Change in educated workers' wage bills shares	Trade Data – Import penetration in manufacturing	+
Skaksen and Søresen (2002)	Denmark	1981-1998, 50 mfg industries (ISIC Rev 3)	Change in high educated workers' wage bills shares	I-O Table	+
Egger and Egger (2003)	Austria	1990-1998, 20 mfg industries (NACE 2-digit)	Relative employment of nonproduction to production workers (in log)	I-O Table	+
Hansson (2000)	Sweden	1986-1995, 34 (19) mfg industries	Change in nonproduction workers' wage bills shares	I-O Table	+
Sakurai (2000)	**Japan**	39 mfg industries, 1987-1990 (Census of Manufacturers)	Change in high-educated workers' wage bills shares	I-O Table	NO
Ito and Fukao (2005)	**Japan**	35 mfg industries, 1988-2000(2002) (JIP 2003 Database)	Change in nonproduction workers' employment shares	I-O Table	NO

Notes: A positive sign (+) indicates the estimated coefficient of the fragmentation intensity of trade has the positive and statistically significant effect on explaining the variation of the dependent variable.

3. Measurement Issues

There is no unique way to measure the degree of the fragmentation process in manufacturing (Feenstra 1998; 2004). This section discusses the limitations of the widely-used measure of the fragmentation process in the literature, before proposing a more appropriate measure. This is followed by a discussion on issues involved in the measurement of the skill intensity of workers.

Measurement of Fragmentation Process in Manufacturing

Feenstra and Hanson (1996; 1999) measures the fragmentation intensity of trade for US manufacturing, using an Input-Output (I-O) Table. This has been a very popular method in this strand of literature ever since (Strauss-Kahn 2003; Ito and Fukao 2005; Haizen et al. 2005; Hsieh and Woo 2005; Ekholm and Hakkala 2006; Hansson 2000). The I-O table contains information about inter-industry flows of intermediate goods, final demand and value-added, generating the accounting framework for the circulation of the whole economy at industry level. The purpose is to measure the overall degree of dependence on imported intermediate inputs, as an indication of the fragmentation process for a given industry.

Broadly speaking, there are two types of I-O tables, depending on the way import transactions are compiled in the accounting framework (Bulmer-Thomas, 1982). A competitive type I-O table does not distinguish the sources of inter-industry intermediate inputs coming from domestic or foreign countries. In a non-competitive (or complementary) I-O table, the independent import matrices table is prepared consisting of the inter-industry use of imported intermediate inputs. If an independent imported input matrix is not available, imported intermediate inputs for each industry i have to be estimated by the following formula (Feenstra and Hanson 1999);

$$(1) \quad \text{Imported Intermediate Inputs}_i = \underbrace{\sum_j [\text{inputs from industry } j \text{ to } i]}_{\text{Inter-industry intermediate inputs flows}} * \underbrace{[\frac{\text{imports}_j}{\text{domestic absorption}_j}]}_{\text{import penetration ratio}}$$

where subscript i is purchasing industry and j denotes supplying industry with intermediate inputs. Domestic absorption is usually defined as gross output, plus imports, and minus exports. This calculation essentially corresponds to summing up each column in import matrixes of a non-competitive type of I-O table. The fragmentation intensity is then defined as taking the ratio of imported intermediate inputs to the total expenditure on intermediate inputs.

There are many reasons why the use of either type of I-O table does not capture the true dynamics of the fragmentation process in a meaningful way. First, Equation (1) based on the competitive type of I-O table fails to make a distinction between imported intermediate inputs and imported final goods. If trade in intermediate inputs grows faster than trade in final goods (1st aggregation problem), this can induce a significantly biased measure. In fact, there is ample evidence to suggest trade in parts and components has been growing at a faster rate than trade in final goods in recent years (Yeats 2001; Athukorala 2006). Second, the use of import matrices does not permit separating the aggregate imported intermediate inputs used into ordinal intermediate inputs (raw materials), such as steel, metals, plastics, and chemical products and fragmentation-based intermediate inputs such as parts and components (2nd aggregation problem). This separation is particularly important to Japanese manufacturing due to its high dependency on imported raw materials. While raw material imports are mainly driven by resource endowments, the newly arising parts and components trade is influenced by totally different factors. Third, by its very nature, the I-O table only focuses on the import side. However, the fragmentation process can also be captured by the export side, when firms export domestically produced components to low-wage countries for further processing or assembling. In particular, Japanese and US MNEs are heavily involved in this export orientation of the fragmentation process for further processing offshore.

Mindful of these limitations, this study measures the intensity of fragmentation trade in a given industry, using detailed trade data in parts and components. (See the Appendix for a description of the method of data compilation identifying trade in parts and components). The formula is written as follows:

$$(2) \qquad FRG^{import} = \frac{\text{Imports of Parts and Components}}{\text{Intermediate Inputs Uses}}$$

$$FRG^{export} = \frac{\text{Exports of Parts and Components}}{\text{Gross Ourputs}}$$

There are three added advantages of this approach compared to the conventional I-O table approach. First, it avoids mixing traditional intermediate inputs into the estimates by making a distinction between trade in parts and components and ordinary intermediate inputs at the detailed 5-digit product level. Second, trade data captures both export and import orientation of the fragmentation process. Third, controlling for the direction of trade in parts and components makes it possible to differentiate the possible heterogeneity effects of the fragmentation activity on skill upgrading. For example, the possible impact on skill upgrading might be different, depending on whether an increase in parts and components imports is from developing countries or developed countries due to the difference in skills content. The former case might be expected to have skill *upgrading* effects in domestic manufacturing, whereas the latter case might be expected to have skill *downgrading* effects. In particular, this distinction is focal, because recent years have witnessed a rapid increase in components imports from developing East Asian countries (especially in the Japanese electronics industry). This division of labour with East Asian countries through the fragmentation process might be expected to result in a significant impact on skill upgrading.

Of course, this approach is not entirely free from shortcomings. The main one being the limited industry coverage, since a detailed separation of parts and components trade is mainly only possible for the electronics and transport equipment sector by the available trade commodity classification system. Therefore, this ignores fragmentation trade in other products. For instance, the textiles and garments and chemical industries have recently started to get involved with the fragmentation process. However, a single focus on the electronics and transport equipment sector is justified, because the available case-study based literature confirms that the bulk of fragmentation activity is concentrated in these industries (Brown and Linden 2005).

Measurement for Skills Intensity

A proper measurement of skill intensity must account for education levels, on-the-job training and work experience. The education attainment level of workers or occupation data according to the tasks performed by workers in particular jobs is usually used in order to proxy for the skill intensity of workers. This study uses the occupation-based proxy for the skill intensity of workers. This is because this measure seems conceptually more relevant to the actual manufacturing adjustments through the fragmentation activity. We are only interested in the extent to which activities and job tasks are relocated and which jobs are retained by the process of production fragmentation. Following the conventional occupational classification scheme used in the literature (Berman et al. 1994; Feenstra and Hanson 1999; Ito and Fukao 2005), 'nonproduction' (white-collar) workers, consisting of technical (system engineers and computer programmers), managers, administrative, advertising and sales workers are treated as more-skilled workers,. 'Production' (blue-collar) workers refer to manual, assemblers and operational workers defined as less-skilled workers.

Of course, this skill level categorization is not free from criticism. For instance, Leamer (1994) argues that this skill distinction is not entirely perfect due to skills misclassification of occupations. According to the standard classification (ILO), line supervisors and product development personnel are included among production workers, whereas delivery truck drivers and cafeteria workers are included in the non-production worker category. However, there is evidence to show that in practice the occupational classification as a measure of skill intensity of workers shows similar trends to using other skill categories such as the educational attainment level (Berman et al. 1994; Sachs and Shartz 1994; and Feenstra and Hanson 2003).

4 The Model

As observed in Section 2, the existing empirical studies have found no effect of the fragmentation intensity of trade on skill upgrading for the Japanese industry-level data. This section re-examines the hypothesis by conducting an econometric study on panel data of 52 Japanese manufacturing industries over the period 1980-2000. The estimation is based on a reduced form labour demand function, which is widely used in this strand of literature (Berman et al. 1994; Feestra and Hanson 1996 and 1999; Strauss-Kahn 2004; Ito and Fukao 2005). The innovative part of the analysis is the incorporation of a better measure of the fragmentation intensity for a given industry, namely trade in parts and components. Using this index allows examining the impacts of both the imports and exports side of fragmentation intensity on skills upgrading. It also investigates any differential impact on skill upgrading by disaggregating the geographical orientation of fragmentation intensity.

Industry minimizes a quasi-fixed (short-run) cost function, $C(\mathbf{w}, y)$ in which output (y) and $\mathbf{w}$ are a vector of factors of production such as capital (k) as a fixed factor (as exogenous) and more-skilled and less-skilled labour as variable factors. The cost function takes a translog form, which is the second order Taylor series approximation linearly homogenous function with concave in factor prices, *à la* Christensen, Jorgensen and Lau (1973). The translog short run cost function (c) with a subscript z denoting industry is then written as follows (a time subscription is dropped for convenience);

$$\begin{aligned}\ln c_z &= \alpha_0 + \sum_{i=1}^{M} \alpha_i \ln w_{z,i} + \sum_{k=1}^{K} \beta_k \ln x_{z,k} + \\ &\frac{1}{2}\left(\sum_{i=1}^{M}\sum_{j=1}^{M} \gamma_{i,j} \ln w_{z,i} \ln w_{z,j} + \sum_{k=1}^{K}\sum_{l=1}^{K} \delta_{k,l} \ln x_{z,k} \ln x_{z,l} \right) \\ &+ \sum_{i=1}^{M}\sum_{k=1}^{K} \phi_{i,k} \ln w_{z,i} \ln x_{z,k}\end{aligned} \tag{3}$$

where w_i refers to the optimally chosen variable factor prices with subscripts denoting $i, j = 1, \cdots M$ and x_k denotes either the quantities of fixed inputs (capital), outputs or other structural parameters with subscripts $k, l = 1, \cdots K$.

Equation (3) requires the following linear parameter restrictions to satisfy the property of linearly homogenous with respect to variable factor costs (w_i);

$$\gamma_{i,j} = \gamma_{j,i}\,,\ \delta_{k,l} = \delta_{l,k}\,,\ \sum_{i=1}^{M} \alpha_i = 1\,,\text{ and }\ \sum_{i=1}^{M} \gamma_{i,j} = \sum_{i=1}^{M} \varphi_{i,k} = 0\,.$$

Differentiating Equation (3) with respect to $\ln w_i$ yields the cost share of variable factor i : $\dfrac{\partial \ln C_z}{\partial \ln w_i} = \left(\dfrac{\partial C}{\partial w}\right)\left(\dfrac{w_i}{C_z}\right)$ where $\left(\dfrac{\partial C}{\partial w}\right)$ refers to factor demand for input i by Shephard's lemma. It follows that $\dfrac{\partial \ln C_z}{\partial \ln w_i} = \dfrac{E_i w_i}{C_z} = S_{z,i}$ is equal to the share of factor i in total costs, denoted by $S_{z,i}$ (where E is a factor i employment). In the end, it yields a cost share equation of variable factor of input *i*;

(4) $$S_{z,i} = \alpha_i + \sum_{j=1}^{M} \ln w_{z,j} + \sum_{k=1}^{K} \varphi_{i,k} \ln x_{z,k} \quad \text{and} \quad \sum_{i=1}^{M} S_{z,i} = 1$$

Equation (4) relates to the cost share of variable factor i to factor prices and the output level and fixed input capital. A cost share for variable factor *j* can be derived similarly. By assuming the coefficients of independent variables equal across all industries, Equation (4) can be pooled a cross-industry and time.

While Equation (4) implies the relevant dependant variable is the labour costs share, we focus on the employment share of skilled workers. This is justified over the several decades the only relative employment adjustment in Japanese manufacturing has been evident, as shown in Figure 1. In contrast, the relative earnings dispersion between skilled and unskilled workers has not been changing much during the periods.

The most important explanatory variable is the measure of the production fragmentation intensity (*FRG*) across industries. This is based on parts and components in trade data (See Equation 2 for the formulation). In general, positive signs are expected for *FRG*, since it is postulated that the fragmentation activity has skills upgrading effects. An increasing component trade with developing East Asian countries is hypothesised to be positively related with change for employment of skilled workers (See the Appendix Table 4 for the definitions of country groups). On the other hand, a skill downgrading effect with a negative sign is expected with higher intensity of the fragmentation activity with OECD countries.

Two potential candidates to represent the industry scale of production (*Y*) are value-added and gross output.[3] Over this choice, value-added is used to represent the industry output measure, rather than gross output. This is because gross output might be too inclusive to serve as a clear indicator of industry output scale (Maskus 1991).[4] The sign of this variable depends, *ceteris paribus*, on whether expansion of the industry output scale would require more skilled workers. If the estimates coefficients are zero, the hypothesis that the underlying production function is homothetic cannot be rejected. Otherwise, it implies non-homothetic, suggesting the ratio of the optical inputs demands depend on the level of outputs.

The ratio of capital stock to value-added (K/Y) is used to measure capital intensity of production. The sign of this variable can be either positive or negative depending on whether skilled workers are complementary (the positive sign) or substitutes (the negative sign) to physical capital stock in the production process.

R&D intensity (the R&D expenditure ratio to value-added) is included in the model to capture any effect of skills-biased technological change introduced into working practices in association with change in production technologies, new capital investment, and the use of the computers. The expected sign of the coefficient on this variable is positive. Alternatively, the stock of patents data can alternatively be used, but they are not considered here due to the data constraint.[5]

[3] Berman et al. (1994) and Feenstra and Hanson (1999) both prefer the use of value-added, but in the empirical application, they instead alternate with the value of industry shipment (ie, gross outputs) due to the absence of the reliable price deflators.
[4] The estimation results are however less sensitive to the use of gross output.
[5] Feeestra and Hanson (1996 and 1999) alternated more specific high-tech capital variables such as computer investment, whereas other studies have used the employee computer usage (Autor et al. 1998). Improvement of this variable will be considered in the future.

Lastly, both the industry fixed effect and time-specific effect are incorporated in order to guard against omitted variables for explaining the variation in the employment share of skilled workers in the respective dimensions: the former is needed to control for any unmeasurable (or unobserved) time-invariant heterogeneity, such as industry-specific persistent technological differences or difference in the average management quality. Time-specific effects are also introduced to control for a homogenous form of technological change across industries, but varying across time as well as capturing other macroeconomics shocks.

Based on the above discussion, the stochastic form of Equation (4) can be written as:

(5) $$\mathrm{Sh}_{z,t} = \phi_0 + \phi_1 \mathrm{Y}_{z,t} + \phi_2 \mathrm{K}_{z,t} + \phi_3 \mathrm{R\&D}_{z,t} + \phi_4 FRG_{z,t}^{\mathrm{m,\,x}} + \alpha_Z + \gamma_t + \varepsilon_{z,t}$$

where Sh is nonproduction (skilled) workers share in total employment, and subscripts z and t denote industry and time, respectively. Superscripts m and x represent imports and exports, respectively. The explanatory variables are listed below with the expected sign of the regression coefficient of each variable given in the bracket.

Y	Gross output (+ or -),
K	Capital intensity (+ or -),
R&D	Research and development intensity (+),
FRG	Fragmentation intensity of trade (+),
α_Z	Industry-specific fixed effect,
γ_t	Time-specific fixed effect,
ε	Random error term, representing other omitted influences.

Data and Econometric Methodology

The regression analysis is performed using a panel dataset for 52 Japanese manufacturing industries at 5 year intervals over the period from 1980 to 2000 (namely, 1980, 1985, 1990, 1995, and 2000) (See the Appendix Table 3 for a list of industries). The main data source is the latest version of the Japan Industrial Productivity (JIP 2006) developed as a part of the research project "Study on

Industry-Level and Firm-Level Productivity in Japan” at the REITI (Research Institute of Economy, Trade and Industry)(See the Appendix for further details on JIP 2006). Real gross outputs and real intermediate inputs use are extracted from this database to construct real value added of industry as well as nominal values of these series. Also, capital stocks and R&D expenditures are extracted from this database. The most desirable feature of this dataset is that it gives the employment proportion of nonproduction and production workers in each industry. The original employment data across industries in JIP 2006 is based on the survey data of the Population Census, conducted every 5 years.[6] The data series on intensity of fragmentation trade (FRG) was compiled from the United Nations (UN) Comtrade database. This is based on a commodity list of 5-digit product level of parts and components. Product-level trade data is then mapped into around 13 manufacturing industries of the JIP 2006 Database by referring to a concordance.

As for the estimation procedure, both fixed effects and random effect estimators are used in order to exploit the panel feature of the dataset. The choice between fixed- and random-effect model depends on whether the time-invariant industry heterogeneity are fixed or random (Wooldridge 2000). If they are random, then an ordinary least square (OLS) estimator will understate the standard error. Therefore, it calls for the use of General Least Square (GLS) estimator (ie, the random-effects). If they are fixed and correlated with any of explanatory variables, then it is subjected to the omitted variable bias. In this case, the fixed effect models need to be employed to remove such biases. We follow the standard approach over the choice between the two estimators: We estimate both a random- and fixed-effects model, and then use a Hausman test to determine which one applies.

In the case of the fixed effect model, there are three alternative estimation techniques available to purge the industry-specific effects; the time-demeaning (ie, within transformation), Least Square Dummy Variables (LSDV), and the first differencing. While the last one is frequently used in the literature (Berman et al. 1994; Feenstra and Hansen 1996 and 1999; Ito and Fukao 2005), it might not be

[6] See the RIETI website for the data compilation method - http://www.rieti.go.jp/jp/database/d04.html.

suitable for the current context due to the nature of dataset. When the number of time-period exceeds two as in our case, other two estimators become more efficient under the assumption of no serial correlation in the error term (Wooldridge 2000). Otherwise, the first-differencing method is preferred. However, the data is less likely to prone to the problem of serial correlation for a panel of every 5 years intervals of records. Moreover, the first-differencing data approach can exacerbate any potential problem from measurement errors in the data (Griliches and Hausman 1986; Hijzen et al. 2005).

Over the choice between within-transformation and LSDV is more subtle, since both estimators should give identical estimated coefficients and test-statistics under the normal circumstance. However, the former is preferred, because the alternative method is not appropriate due to the degree of freedom problem by the inclusion of the slope dummy for all 52 industries. Following the standard practice in the literature, the model is then estimated by the weighted least squares (WLS) method, in which weights are the manufacturing employment share. In doing so, more 'weight' is placed on relatively large industry.

Results

The Hausman specification test turns out to be mixed, depending on the specification of the model (5). However, the results based on fixed effect and random effect estimators turned out to be closely comparable. Therefore, the following inferences focus solely on the fixed effects estimation results in presented in Table 2.[7] Alternative random-effect estimates are given in the Appendix Table 1 for the purpose of comparison. Summary statistics and the correlation matrix for the variables used in the estimation are presented in Tables 3 and 4 to facilitate interpretation of the key results. In order to guard against possible heteroscsdascity, White's robust standard errors have been used in calculating t-ratio. All variables, other than time-dummy variables, were used in natural logarithms, and hence the estimated coefficients can be interpreted as elasticises.

[7] This is the standard approach in the literature (Feenstra and Hanson 1996 and 1999; Strauss-Kahn 2003; Ito and Fukao 2005).

Regressions 1 and 2 in Table 2 present the benchmark estimation results. The estimated coefficients of both components imports and exports ratios are hardly statistically significant. They suggest there are no statistical relationships between fragmentation intensity and skill upgrading. This is an unexpected result, although it is consistent with the existing evidence (Sakurai 2000; Ito and Fukao 2005). However, perhaps this might not be surprising, given the fact that component imports in trade data are a subset of imported intermediate inputs based on the I-O Table. Or, total components trade might be masking some heterogeneity skill upgrading effects of the fragmentation activity. The baseline specification is then re-estimated by disaggregating components trade into source and destination countries groups: developing East Asia countries, OECD countries, and the rest of the world. The coefficient on components imports and exports ratios from developing East Asian countries turned out to be positive and statistically significant at the 1 percent level, suggesting significant skill upgrading effects on overall change in the employment of nonproduction workers (Regressions 3 and 4). In particular, it suggests on average a 1 percent increase of components imports ratios from developing East Asian countries would lead to over a 7 percent increase in skilled workers' employment share. In other words, increasing part components trade in parts and components with developing East Asian countries would involve a substantial increase of the employment share of skilled workers in Japanese manufacturing. This is consistent with the well-known practice of Japanese companies in undertaking simple assembly activities in developing East Asia for exporting largely to third country markets, while retaining capital- and technology-intensive component production in Japan (Belderbos 1997). Perhaps, this practice has led to a greater vertical specialization between Japan and developing East Asian countries over years and Regression 3 and 4 are capturing such effects. This finding adds a new dimension to the literature on industry upgrading through international production fragmentation in Japanese manufacturing.

As expected, an increase in component imports intensity from OECD countries seems to have skill downgrading effects (Regression 3). This suggests increased components imports from OECD countries require more unskilled workers for further processing. This is indeed consistent with the argument put forward that component imports from high-income countries, presumably highly capital and technology-intensive contents, might substitute for the domestic skilled worker.

All regressions in Table 2 show a negative industry output scale effect (*Y*) on the demand for skilled workers. The negative scale effect suggests Japanese manufacturing industries would require, *ceteris paribus*, less skilled workers as output expands. The estimated coefficient on capital-intensity (*K*) suggests capital utilisation has a positive relationship to skilled workers (ie, the complementarily relationship between skilled workers and capital investments), but is found to be statistically insignificant. In fact, capital-output ratio on average accounts for very little of the variation in the employment change of skilled workers. This finding is markedly different from the commonly found robust complementarily relationship between capital utilization and skilled workers in US manufacturing (eg, Berman et al. 1994). But, this is quite consistent with a previous study in Japanese manufacturing (eg, Sakurai 2000). The result for the R&D intensity variable suggests a positive and statistically significant effect on skill upgrading on average. This finding is consistent with the general findings (Berman et al. 1994; Feenstra and Hanson 1999; Sakurai 2001; Ito and Fukao 2005) and supports the hypothesis that skills-biased technological change is strongly associated with the skill upgrading of Japanese manufacturing. It should be noted that the size of the estimated coefficient for the *R&D* variable is somewhat smaller than the *FRG* variable. The fixed-effects model estimations without weights are performed for a sensitivity check (Appendix Table 2). The key results do not change appreciably when large industries are no longer given greater weights. But, the sign for output scale has changed to a positive sign with no statistical significance.

To sum up, the results indeed suggest a significant effect of increasing fragmentation trade on skill upgrading across industries in Japanese manufacturing over the period 1980-2000. In particular, the main skill upgrading effects come from the increased fragmentation process in developing East Asian countries. On the other hand, the evidence points to skill downgrading effects from increasing components imports from OECD countries. These findings are in contrast to that of Sakurai (2000) and Ito and Fukao (2005) who failed to find any evidence that increasing practices of production fragmentation contribute to skill upgrading in Japanese manufacturing.

Table 2:
Evidences of Skill Upgrading Effects in Japanese Manufacturing, 1980-2000: Weighted Fixed-Effect (Within Transformation) Estimates

		Regression 1	Regression 2	Regression 3	Regression 4
Dependant variable: Nonproduction (skilled) workers employment share					
Estimator:		Weighted Fixed Effects (FE)			
Explanatory Variables:					
ϕ_0	Constant term	0.02 (0.02)	0.02 (0.01)	0.02 (0.01)	0.03 (0.01)*
Y	Output scale	-0.10 (0.01)***	-0.10 (0.01)***	-0.11 (0.01)***	-0.11 (0.01)***
K	Capital Intensity	0.02 (0.05)	0.03 (0.05)	0.04 (0.06)	0.00 (0.05)
R&D	R&D expenditure intensity	1.42 (0.24)***	1.38 (0.24)***	1.36 (0.21)***	1.25 (0.22)***
FRG^{import}:	Intensity of Fragmentation Trade (total imports);	0.01 (0.67)			
East Asia countries	Imports from East Asia countries			7.14 (1.91)***	
OECD countries	Imports from OECD countries			-2.49 (0.95)***	
Other countries	Imports from Others countries			-27.41 (70.77)	
$FRG^{exports}$:	Intensity of Fragmentation Trade (total exports);		-0.36 (0.31)		
East Asia countries	Export to East Asia countries				2.89 (0.88)***
OECD countries	Export to OECD countries				0.24 (0.76)
Other countries	Export to Others countries				-9.47 (1.94)
Diagnostic Test Statistics	$\overline{R}^2$: Within	0.73	0.73	0.75	0.77
	Between	0.88	0.88	0.88	0.88
	Overall	0.87	0.87	0.87	0.87
	F-Statistic	42.29***	43.78***	42.40***	39.87***
	Number of observation	260	260	260	260

Notes:
All variable are in natural logarithms. Time-dummy variables are included for all estimations, but the results are suppressed here. Weighted least-square (WLS), weights equal to the industries' employment share in total manufacturing. Standard errors based on White's heteroscadasticity correction are given in brackets, with statistical significance (two-tailed test) denoted as: *** 1per cent, ** 5 per cent, and * 10 per cent. East Asian countries and OECD countries are defined in Appendix Table 3.

Variable Definitions:
Y: Real value added,
K: Ratio of capital stock to value added,
R&D: Ratio of R&D expenditure to value-added,
FRG^{import} : Ratio of parts and components imports to total intermediate inputs,
FRG^{export} : Ratio of parts and components exports to gross output.

Table 3: A Statistical Summary of the Key Variables

	Minimum	Maximum	Mean	Std. Deviation	Coefficient of Variation
Sh	-0.674	-0.190	-0.156	0.098	0.628
Y	0.276	5.871	1.928	1.004	0.521
K	0.009	0.311	0.117	0.061	0.521
R&D	0.000	0.061	0.008	0.009	1.125
FRG^{import}	0.000	0.024	0.001	0.003	3.182
FRG^{export}	0.000	0.059	0.002	0.006	3.224

Table 4: Correlation Matrix of the Key Variables

	Sh	*Y*	*K*	*R&D*	FRG^{import}	FRG^{export}
Sh	1.00					
Y	-0.92	1.00				
K	-0.71	0.76	1.00			
R&D	-0.05	0.19	0.24	1.00		
FRG^{import}	-0.04	0.11	0.20	0.28	1.00	
FRG^{export}	-0.04	0.10	0.19	0.27	0.86	1.00

Variable Definitions:
Sh: Nonproduction (skilled) workers employment share,
Y: Real value added,
K: Ratio of capital stock to value added,
R&D: Ratio of R&D expenditure to value-added,
FRG^{import} : Ratio of parts and components imports to total intermediate inputs,
FRG^{export} : Ratio of parts and components exports to gross output.

Notes: All variables are weighted by the industry employment share of total manufacturing and are converted into the natural logarithms. Variables for *R&D,* FRG^{import} and FRG^{export} are converted into logarithmic form by log(1+x) where x is the variable.

5 Conclusion

This paper examined the hypothesis that industries engaged in international fragmentation of production experience greater skill upgrading using a panel dataset of 52 Japanese manufacturing industries over the period 1980-2000. Previous studies have failed to find a significant effect of the fragmentation trade intensity on skill upgrading for the Japanese industry-level data (Sakurai 2000; Ito and Fukao 2005). In particular, these studies have not been able to replicate the commonly found results for the US and other OECD countries (See Table 1). However, there are ample reasons to doubt their findings, since both skill upgrading and the fragmentation activity have been key features in Japanese manufacturing transformation over the last two decades. The present paper improved upon the existing empirical framework by incorporating a better measure of the fragmentation trade intensity. It also explicitly allows for the possible differential impact of fragmentation trade intensity with developing East Asian countries and high income countries. It is found that increased fragmentation with developing East Asian countries has significantly contributed to change in skilled worker employment in Japanese manufacturing over the period 1980-2000. At the same time, components imports from OECD countries have had the effect of skills downgrading effects.

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Appendix:

Trade Data

This paper takes a systematic approach in identifying parts and components in trade data as detailed below. First, we refer to the classification system of the United Nations, Broad Economic Category (BEC) and pick the relevant parts and components items. The BEC classification system is originally constructed in order to categorize SITC-based trade statistics by approximate class of goods in the Social National Accounts framework (See the further details on development of the BEC system and the industry classification).[8] Among seven major categories, industrial supplies, capital goods, and transport equipment category has sub-category for 'parts and accessories'. The corresponding sub-categories are namely BEC22, BEC42 and BEC53. Second, a judgment has to be made, since all the items under BEC22, 42, and 53 do not correspond to parts and components. We only pick all the items, which are under BEC sub-category and also correspond to Standard International Trade Classification, SITC 7 (machinery and transport equipment) and SITC8 (miscellaneous manufacturing). By limiting to SITC 7 and 8 prevents the inclusions of some components which are traded as 'products in their own rights' under specific trade names (eg, Michellen tyres). The final list prepared though this procedures contains a total of 264 items.[9]

The trade data compiled is then mapped in Japan Industrial Productivity 2006 (JIP 2006) industries. However, there are no formal concordance tables developed between JIP 2006 industry classification and SITC system. Only the *reference* table between the standard trade commodity and JIP industry classification.[10] We use it as a benchmark and mapped it to JIP 2006 industries. This mapping identifies 13 JIP 2006 industries corresponding to SITC 7 and 8.

[8] <http://unstats.un.org/unsd/cr/family2.asp?Cl=10>

[9] All the commodity classification systems used are stored in the UN Statistical Division: Classification Registry Website: <http://unstats.un.org/unsd/cr/registry/regdnld.asp?Lg=1>

[10] The type of trade commodity classification used for this reference table in JPI Database is unknown: <http://www.esri.go.jp/en/archive/bun/abstract/bun170index-e.html>

Japan Industrial Productivity 2006 Database (JIP 2006)

The original version of the JIP database (JIP 2003) was compiled in a collaboration project between Economics and Social Research Institutes, the Cabinet office of Japan (ESRI) and Hitotsubashi University (Fukao et al. 2003). The database was updated on July 2006, by covering more industries and expanding the time coverage (JIP 2006). See the further details on the website in REITI (Research Institute of Economy, Trade and Industry)[11] or refer to Fukao et al (2006). A brief description of the variables used in the regression analysis is given below.

Value added is derived from gross output (100millions in Japanese Yen) and intermediate inputs use (100millions in Japanese Yen). Gross output is measured as the sum of industry shipment, revenues from repairing and fixing services, and revenues from performing subcontracting works. Intermediate inputs are defined as the sum of raw materials, fuels, electricity, and subcontracting expenditure. The notable feature of JIP database is that price index of intermediates inputs use is constructed, making possible to convert the nominal values into the real series. We therefore approximate real value added for a given industry by subtracting real intermediate input from real gross output.

Capital stock (100 millions in Japanese yen) refers to the nominal book value of tangible fixed assets including buildings, machinery, tools, and transport equipment. Nominal R&D expenditures (100millions of Japanese Yen) are not available in JIP2006, but are available in JIP2003. We use R&D expenditure reported in JIP2003 industry classification as the benchmark and update the series into JIP 2006. A close inspection of the concordance table between JIP2003 and JIP2006 industry classification reveals that some JIP2003 industry is further disaggregated and others are aggregated up in JIP2006. In the case of disaggregation of industry from JIP2003, we assume that R&D expenditure does not vary across the corresponding JIP2006 industries. On the other hand, in the case of aggregation, the average value of R&D expenditure in JIP2003 is used for the corresponding JIP2006 industry. Data on the employment share of nonproduction and production workers in JIP2006 are originally

[11] http://www.rieti.go.jp/jp/database/d04.html

from *the Population Census of Japan,* published by the Statistics Bureau, Ministry of Public Management, Home Affairs, Posts and Telecommunications. This is conducted every five years, covering detailed occupational categories (3 digit, close to 300 different occupations) and industries. Nonproduction workers are defined as those with the occupation of professional and technical, managers and administrators, clerical and secretarial, sales, and services. Production workers are plant and machine operators and also engage in craft and related occupations.

Table A-1: Evidences of Skill Upgrading Effects in Japanese Manufacturing, 1980-2000: Weighted Random-Effect Estimates

	Dependant variable: Nonproduction (skilled) workers employment share				
		Regression 1	Regression 2	Regression 3	Regression 4
	Estimator:	Weighted Random Effects (RE)			
	Explanatory Variables:				
ϕ_0	Constant term	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.009)
Y	Output scale	-0.09 (0.06)***	-0.09 (0.06)***	-0.10 (0.01)***	-0.09 (0.01)***
K	Capital Intensity	0.02 (0.05)	0.02 (0.05)	0.03 (0.05)	0.00 (0.05)
R&D	R&D expenditure intensity	1.33 (0.22)***	1.31 (0.22)***	1.27 (0.20)***	1.15 (0.21)***
FRG^{import}:	Intensity of Fragmentation Trade (total imports);	0.18 (0.62)			
East Asia countries	Imports from East Asia Countries			6.38 (1.79)***	
OECD countries	Imports from OECD Countries			-2.09 (0.79)***	
Other countries	Imports from Others Countries			-9.36 (61.78)	
$FRG^{exports}$:	Intensity of Fragmentation Trade (total exports);		-0.27 (0.23)		
East Asia countries	Export to East Asia Countries				2.72 (0.73)***
OECD countries	Export to OECD Countries				0.06 (0.59)
Other countries	Export to Others Countries				-8.09 (1.99)
Diagnostic Test Statistics	$\overline{R}^2$: Within	0.73	0.73	0.754	0.76
	Between	0.87	0.88	0.882	0.88
	Overall	0.88	0.87	0.876	0.87
	F-Statistic	1251.6***	1312.9***	1279.8***	1454.2***
	Number of observation	260	260	260	260

Notes:
All variable are in natural logarithms. Time-dummy variables are included for all estimations, but the results are suppressed here. Weighted least-square (WLS), weights equal to the industries' employment share in total manufacturing. Standard errors based on White's heteroscadasticity correction are given in brackets, with statistical significance (two-tailed test) denoted as: *** 1per cent, ** 5 per cent, and * 10 per cent. East Asian countries and OECD countries are defined in Appendix Table 3.

Variable Definitions:
Y: Real value added,
K: Ratio of capital stock to value added,
R&D: Ratio of R&D expenditure to value-added,
FRG^{import}: Ratio of parts and components imports to total intermediate inputs,
FRG^{export}: Ratio of parts and components exports to gross output.

Table A-2:
Evidences of Skill Upgrading Effects in Japanese Manufacturing, 1980-2000: Unweighted Fixed-Effect Estimates

Dependant variable: Nonproduction (skilled) workers employment share					
		Regression 5	Regression 6	Regression 7	Regression 8
Estimator:		Unweighted Fixed-Effect (FE)			
Explanatory Variables:					
ϕ_0	Constant term	-1.76 (0.27)***	-1.69 (0.26)***	-1.55 (0.29)***	-1.48 (0.29)***
Y	Output scale	0.02 (0.01)	0.02 (0.01)	0.01 (0.02)	0.01 (0.02)
K	Capital Intensity	0.06 (0.04)*	0.06 (0.04)*	0.06 (0.03)*	0.05 (0.03)
R&D	R&D expenditure intensity	0.65 (0.16)***	0.64 (0.15)***	0.65 (0.15)***	0.65 (0.16)***
FRG^{import}:	Intensity of Fragmentation Trade (total imports);	0.00 (0.16)			
East Asia countries	Imports from East Asia Countries			4.07 (1.24)***	
OECD countries	Imports from OECD Countries			-1.56 (0.51)***	
Other countries	Imports from Others Countries			-0.76 (19.22)	
$FRG^{exports}$:	Intensity of Fragmentation Trade (total exports);		-0.15 (0.07)		
East Asia countries	Export to East Asia Countries				1.96 (0.49)***
OECD countries	Export to OECD countries				-0.62 (0.37)*
Other countries	Export to Others countries				-3.56 (1.23)
Diagnostic Test Statistics	$\overline{R}^2$: Within	0.32	0.33	0.34	0.34
	Between	0.10	0.12	0.10	0.09
	Overall	0.12	0.12	0.12	0.12
	F-Statistic	1333.23***	1495.44***	1339.07***	1676.92***
Number of observation		260	260	260	260

Notes:
All variable are in natural logarithms. Time-dummy variables are included for all estimations, but the results are suppressed here. Standard errors based on White's heteroscadasticity correction are given in brackets, with statistical significance (two-tailed test) denoted as: *** 1per cent, ** 5 per cent, and * 10 per cent. East Asian countries and OECD countries are defined in Appendix Table 3.

Variable Definitions:
Y: Real value added,
K: Ratio of capital stock to value added,
R&D: Ratio of R&D expenditure to value-added,
FRG^{import}: Ratio of parts and components imports to total intermediate inputs,
FRG^{export}: Ratio of parts and components exports to gross output.

Table A-3:
A List of 52 Industries in JIP 2006

JIP code	Industry
8	Livestock products
9	Processed marine products
10	Rice polishing, flour milling
11	Other foods
12	Fertilizers
13	Beverages
14	Tobacco
15	textiles (silk, spinning, fabrics and other textiles, apparel and accessories)
16	Lumber and wood products
17	Furniture
18	Pulp, paper,
19	paper products
20	Publishing and printing
21	Leather and leather products
22	Rubber products
23	Chemical fertilizers
24	Organic chemical basic products
25	Non-organic chemical basic products
26	Organic chemical products
27	Chemical fibres
28	Chemical Final products
29	Other chemicals
30	Petroleum products
31	Coal products
32	Glass products
33	Clay products
34	Stone products
35	Other stone, clay & glass products
36	Steel manufacturing
37	Other steel
38	Non-ferrous metals
39	Non-ferrous metals processed products
40	Metal products
41	Other metal products
42	General machinery equipment
43	Special machinery equipment
44	Other general machinery products
45	Office and services
46	Electrical machinery
47	Equipment and supplies for household use
48	Electric computing equipment (main parts, accessory equipment)
49	Wired communication equipment, radio communication equipment, other communication
50	Electric measuring instruments
51	Semiconductor devices, integrated circuits
52	Electron parts
53	Other electrical machinery
54	Motor vehicles
55	Motor vehicles, components
56	Other transportation equipment (Ships)
57	Precision machinery & equipment
58	Plastic products
59	Other manufacturing

Table A-4
Definition of country groups

Developing East Asian Countries (10 countries)	OECD Countries (21 countries)	Other countries
Hong Kong	Austria	The rest of world
Korea, Republic of	Belgium	
Singapore	Denmark	
Taiwan	Finland	
China	France	
Indonesia	Germany	
Malaysia	Greece	
Philippines	Ireland	
Thailand	Italy	
Vietnam	Netherlands	
	Norway	
	Portugal	
	Spain	
	Sweden	
	Switzerland	
	United Kingdom	
	United States	
	Mexico	
	Canada	
	Australia	
	New Zealand	