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A Many-cone World?*

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Abstract

The breakdown of single-factor price equalization, or a single-cone world, is a central concern in various fields of economics. This paper examines the empirical validities of the following two claims: 1) the multiple-cone Heckscher–Ohlin (HO) model fits better than does the single-cone HO model; and 2) increases in the number of cones improve the fit of the model. One of the contributions of this paper is that it focuses *simultaneously* on factor endowments, production patterns, and wage disparities across economies. My empirical results support the first claim but not the second claim. The results suggest that although the multiple-cone model performs better than does the single-cone model, the increases in the number of cones do not necessarily result in better performance of the HO model.

Key words: multiple cones; Heckscher–Ohlin model; wages; sectoral production patterns; human capital
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"Complete equality of factor prices is ... almost unthinkable and certainly highly improbable" (Ohlin, 1933, p. 38).

1 Introduction

The breakdown of single-factor price equalization (FPE), or a single-cone world, is one of the central concerns in the field of development economics, economic geography, and international economics.[1] This is because a number of empirical studies that have examined the validity of the Heckscher–Ohlin (HO) model relied on the single-cone world assumption. For example, the Heckscher–Ohlin–Vanek (HOV) model is based upon common technology coefficients for the entire world, which comes from the assumption that factor prices are equalized for the world as a whole.[2] Although the single-cone world is a crucial assumption in many empirical studies on international trade, several studies such as those of Leamer and Levinsohn (1995) and Leamer and Schott (2005) confirmed the existence of large wage disparities across economies.

First, do we live in a single-cone world? Two strands of studies have attempted to answer this question.[3] One is the study of the paths of development: the relationship between factor endowments and sectoral production. For example, Schott (2003) estimated the relationship between the capital–labor ratio and sectoral production in order to test whether the multiple-cone HO model fits better than does the single-cone HO model. Using cross-country data in 1990, his results indicated that the two-cone model performed better

[1] The term "cone" refers to the cone of diversification that is defined as follows: "for given prices in the Heckscher–Ohlin model, a set of factor endowment combinations that are consistent with producing the same set of goods and having the same factor prices (Deardorff, 2006, p.72)." Thus, the number of cones is equivalent to the number of FPE sets. The HO model with a single diversification cone (single FPE set) is called a single-cone model, whereas a model with multiple diversification cones (multiple FPE sets) is called a multiple-cone model.

[2] For more detail, see Bhagwati, Panagariya, and Srinivasan (1998).

[3] A recent study by Bernhofen (2009) examined the theoretical prediction of the multiple-cone HO model. Because his model assumed that all countries were in different cones of diversification, whether we live in a single- or multiple-cone world is beyond the scope of his paper.

than did the single-cone model. Thus, the results do not imply that we live in a single-cone world.

The other strand of studies attempting to answer the above question is that examining the lens condition of Deardorff (1994): whether economies' capital–labor ratios (i.e., the endowment lens) are more diversified than sectoral capital–labor ratios (i.e., the goods lens). For example, Debaere and Demiroglu (2003) and Debaere (2004) asked whether the endowment lens lie inside the goods lens. Their results indicated that, although the lens condition held for OECD countries and for regions within countries, it was violated for the world as a whole.[4] Their results also suggest that we live in a multiple-cone world.

These studies have made significant contributions to the literature. However, previous studies have focused only on the relationship between factor endowments and production patterns. None of them has focused directly on the relationship with factor prices. In other words, factor prices have been ignored in the previous literature. Based on the fact that the FPE theorem has important policy implications and that the HO model builds on the general equilibrium framework, factor prices cannot be ignored. The relationship between factor endowments and factor prices should be explored in more detail.

This paper examines the empirical validities of the following two claims: 1) the multiple-cone HO model fits better than does the single-cone HO model; and 2) increases in the number of cones improve the fit of the model. One of the contributions of this paper is that it focuses *simultaneously* on factor endowments, production patterns, and wage disparities across economies. A concern is that, as the standard Ricardian model suggests, wage disparities among economies could reflect not only the differences in factor endowments but also those in technology. To address this concern, this paper utilizes Japanese regional data because identical technology across regions is plausible within a country as compared with

[4] On the other hand, Xiang (2007) found evidence of multiple cones in ten OECD countries. He examined whether the distribution functions of sectoral capital–labor ratios were different across the ten OECD countries. Thus his approach is different from that of the studies on the lens condition although it focused on the sectoral capital–labor ratios.

the situation across countries. Extending the methodology developed by Schott (2003), this paper then estimates the relationship between factor endowments, production patterns, and wage variations.[5]

One might be concerned that wage disparities across regions are negligibly small within a country. However, it is not necessarily true. Indeed, relatively large wage disparities are confirmed even among regions within a country. For example, Bernard, Redding, and Schott (2009) examined the relative wages between skilled and unskilled workers across 181 areas in the United States in 1972 and 1992, and found that there were significant disparities in relative wages across skill-scarce and skill-abundant areas. Similarly, Bernard, Redding, Schott, and Simpson (2008) confirmed the violation of FPE across 67 regions in the United Kingdom. Tomiura (2005) tested whether FPE holds across 47 regions in Japan. His test also rejected FPE, even when the analysis controlled for productivity differences among regions.

Figure 1 presents the disparities in average manufacturing wages across 47 regions in Japan in 2000,[6] based on the conventionally used format to explain wage disparities across economies (e.g., Leamer and Levinsohn, 1995; Leamer and Schott, 2005). Each region is represented by a horizontal line segment, the length of which indicates the regional share of the labor force. The average regional wage in manufacturing is indicated by the vertical position. The figure indicates clearly that wage disparities across regions in Japan are not negligibly small. For instance, the wage rate in Kanagawa is almost twice as high as the wage rate in Aomori.

=== Figure 1 ===

Bernard et al. (2008, 2009) and Tomiura (2005) found that some of the differences in

[5]Bernard, Robertson, and Schott (2005) argued that "empirical implementation of the lens condition is problematic if the 'true' number of either goods or regions is unknown" (p.1). This paper thus extends the work of Schott (2003) rather than that of Debaere and Demiroglu (2003) and Debaere (2004).

[6]A detailed description about the data is provided in Section 3.

factor prices across regions came from the differences in the regional industrial structure. However, these studies did not explicitly take into account the role of factor endowments. Building upon these studies, this study focuses directly on the relationship between regional wages and regional factor endowments. Thus, the analysis in this paper contributes to a deeper understanding of the differences in factor prices across regions within a country from the view of the HO trade theory.

In Section 2, I present the model used in this paper. The empirical framework is presented in Section 3. In Section 4, I present the estimation results. Section 5 provides a summary and concluding remarks.

2 Model

The model in this paper is based on Schott (2003), who extended the standard HO model to a multiple-cone model. To facilitate the discussion, this paper first focuses on a three-good, two-cone model and then extends the discussion to a model with many goods and many cones.

Suppose that there are three goods (labor-intensive good Y_1, intermediate capital-intensive good Y_2, and capital-intensive good Y_3) and two factors (labor L and capital K). The capital intensities of the goods are $k_1 < k_2 < k_3$, where $k_n = K_n/L_n$ $(n = 1, 2, 3)$. The capital–labor ratios that form the borders between cones are τ_j $(j = 0, 1, 2; \tau_0 = 0)$. The borders are referred to as "knots."[7] Let the per capita output and the capital–labor ratio in industry n be $y_n = Y_n/L_n$ and $k_n = K_n/L_n$, respectively ($K_1 + K_2 + K_3 = K$ and $L_1 + L_2 + L_3 = L$). Let p_n be the price of good n, w be the wage rate, and r be the capital rental rate. Assume that each economy is a small open economy such that the price p_n is given and fixed. Thus, $Z_n(= p_nY_n)$ is the output value of good n. Let the output value of

[7] The term "knot" comes from the spline regression analysis. For more detail, see Greene (2011, p. 159).

good n divided by *total* labor (i.e., the labor endowment) be denoted as $z_n(= p_n Y_n/L)$.

In extending the standard HO model, Schott (2003) introduced two assumptions. First, each sector has Leontief technology.[8] Second, each cone has an equal number of goods and factors. Figure 2 presents a three-good, two-cone Lerner diagram. The arrow illustrates a path of a small open economy accumulating capital (relative to labor). When the economy's capital–labor ratio lies between τ_0 and τ_1, it produces intermediate capital- and labor-intensive goods but does not produce the capital-intensive good. Similarly, when the economy's capital–labor ratio lies between τ_1 and τ_2, it produces capital- and intermediate capital-intensive goods but does not produce the labor-intensive good.[9] Capital accumulation moves countries into cones with higher wages ($w' \rightarrow w''$) and lower capital rental rates ($r' \rightarrow r''$).

=== Figure 2 ===

Figure 3 rewrites this relationship in terms of per capita output z and the capital–labor ratio k. The envelope $w'AB$ indicates per capita gross domestic output (GDP), which is defined as output divided by the labor endowment ($z = z_1 + z_2 + z_3$). The intervals between τ_0 and τ_1 and between τ_1 and τ_2 can be interpreted as diversification cones (and therefore FPE sets) because it is analogous to the Lerner diagram. As the economy accumulates capital (relative to labor), its production shifts from labor- to capital-intensive goods. The envelope $w'AB$ indicates that per capita GDP increases as the economy shifts production from one cone to the other cone.

[8] Ishikawa (1992) and Deardorff (2000) developed multiple-cone models with neoclassical production functions rather than Leontief production functions. While a neoclassical production function such as the Cobb–Douglas form is a more generalized functional form, there are two problems for the empirical implementation. First, economies specialize completely in the production of one type of good outside cones, which is not easy to interpret. Second, computational burdens increase because of the increases in the number of parameters. To reduce the possibility of complete specialization and computational burdens, this paper assumes Leontief technology. An alternative specification (a Cobb–Douglas functional form) is examined in a companion paper (Kiyota, 2008).

[9] The borders τ_1 and τ_2 will correspond to "knots" in the regression equation below.

=== Figure 3 ===

Figure 3 also shows the relationship between factor prices and the capital–labor ratio. Because of linear homogeneity and perfectly competitive markets, the return to capital r is the slope, whereas the wage w is the vertical intercept of the tangent to it. Both are constant within each cone at the values shown as w' and r' in the first cone and w'' and r'' in the second cone. Capital accumulation moves countries into the cone with higher wages ($w' \to w''$) and lower capital rental rates ($r' \to r''$). Accordingly, the slope of the envelope $w'A$ becomes steeper than that of the envelope AB.

Figure 4 presents sectoral output divided by *total* labor and wages. The relationship between sectoral per capita output and the capital–labor ratio is called the industry path of development (e.g., Leamer, 1987; Schott, 2003).[10] The paths of development are presented in Panel A for the labor-intensive good, in Panel B for the intermediate capital-intensive good, and in Panel C for the capital-intensive good. In Panel D, the wage rate is constant at w' when the economy's capital–labor ratio lies between 0 and τ_1 and w'' when the economy's capital–labor ratio lies between τ_1 and τ_2.

=== Figure 4 ===

An extension to many goods is straightforward from a theoretical point of view. Figure 5 presents the paths of development, allowing for many goods. The number of cones increases as the number of goods increases. Therefore, a model with a large number of goods can allow wages to take more values than can a model with a small number of goods. Capital-abundant economies are expected to pay higher wages than do capital-scarce economies.

=== Figure 5 ===

[10] Following Leamer (1987) and Schott (2003), this paper refers to the relationships between sectoral per capita output and the capital–labor ratio as the paths of development, although their studies utilize cross-sectional data, as does this study. Kiyota (2009) examined the paths of development, utilizing time-series data.

3 Empirical Framework

3.1 Data

The data cover 21 manufacturing industries in 47 regions in Japan for 2000.[11] An advantage in using Japanese regional data is that identical technology across regions is plausible within a country as compared with the situation across countries. For example, Harrigan (1997) found that technology differences as well as factor supplies were important determinants of the international specialization of production. Bernstein and Weinstein (2002) pointed out that the use of international data was sometimes subject to problems such as measurement error and government policy. The use of national data can overcome some of these problems.

On the other hand, there is a disadvantage in so far as factors are more mobile than in a cross-country analysis. Thus, the concern is that FPE is more likely to hold within Japan than across countries, implying that factor endowments are similar in the sense that they are located in the same diversification cone. Note, however, that the violation of FPE has been confirmed not only among countries but also among regions within a country as mentioned above. Moreover, labor mobility is relatively low in Japan. According to the Ministry of Internal Affairs and Communications (MIC) (2000), the migration rate of manufacturing workers among regions was 6.6 percent from 1995 to 2000.[12] This implies that the annual migration rate is about 1 percent, which is almost the same as the migration rates of some OECD countries such as Switzerland.[13]

The major source of data is the Japan Industrial Productivity database 2009 (JIP database 2009), which was compiled as a part of a research project of the Research Institute of Economy, Trade and Industry (RIETI) and Hitotsubashi University. The JIP database

[11] Strictly speaking, the 47 "regions" are called "prefectures" in Japan. To simplify the explanation, this paper uses the term "regions" rather than "prefectures".

[12] The migration rate refers to the inflows divided by the total labor force in manufacturing.

[13] For more details, see OECD (2006, p.32, Chart I.1.).

2009 runs annually from 1970 to 2006, covering 52 manufacturing and 56 nonmanufacturing industries. The major sources of the JIP database are government statistics and, therefore, its industrial classification is based on the Japan Standard Industry Classification (JSIC), which complies with the International Standard Industry Classification (ISIC) developed by the United Nations and JSIC. The database includes detailed information on sectoral output and inputs, including information on capital stocks.[14]

Although the JIP database 2009 contains the data for 1970–2006, I use cross-sectional data for 2000 because the JIP database is valued at 2000 prices. From the JIP database, I use value-added for outputs, and labor and capital for inputs. Value-added is defined as real gross output minus real intermediate inputs. Labor is defined as the number of workers. Capital is defined as real capital stocks. To obtain wages, I first divide the total regional wage payments by the number of workers, taken from *the Census of Manufactures* by the Ministry of Economy, Trade and Industry (METI) (2000). The average wage payments are further divided by the regional difference index of prices (country average = unity) in order to adjust for the differences in price levels across regions. The regional difference index of prices is obtained from the MIC (2004).[15]

The JIP database 2009 is not available at the regional level, whereas the *Census of Manufactures* is. However, the *Census of Manufactures* does not have detailed industry classification compared with the JIP database 2009. As a compromise, using the regional industry shares of output and inputs from the *Census of Manufactures* as weights, I calculate value-added, the number of workers, and capital for each region as follows:

$$Z_{nr} = s^Z_{nr} Z_n, \;\; K_{nr} = s^K_{nr} K_n, \;\text{ and } L_{nr} = s^L_{nr} L_n, \tag{1}$$

[14] For more details about the JIP database, see Fukao, Hamagata, Inui, Ito, Kwon, Makino, Miyagawa, Nakanishi, and Tokui (2007).

[15] The regional difference index of prices is available every five years after 1977, and, thus, is not available for 2000. This paper utilizes 2002 survey results to adjust for the difference in prices across regions.

where Z_{nr} is the value-added of industry n ($n = 1, ..., N$) in region r ($r = 1, ..., R$); K_r and L_r are the endowments of capital and labor in region r, respectively; and s^Z_{nr}, s^K_{nr}, and s^L_{nr} are the regional industry shares of nominal value-added, the value of tangible assets, and the number of workers, respectively.[16] The JIP database 2009 was aggregated into 21 sectors to match the industries available in the *Census of Manufactures*. Therefore, the data cover 21 manufacturing sectors in 47 regions in Japan in 2000.[17]

3.2 Intraindustry heterogeneity and the Heckscher–Ohlin aggregate

A concern arises in using "standard" industry classifications such as the ISIC and the JSIC. This relates to the point made by Schott (2003), who identified a potential problem in using the "standard" industry classification because the ISIC categories group output loosely, according to the similarity of end use (e.g., textiles, transportation machinery) rather than actual factor use (e.g., the capital-intensive good, the labor-intensive good). The actual industry capital intensity, therefore, may be different across regions.

Table 1 shows the sectoral capital intensities across regions. Let $k_{nr}(= K_{nr}/L_{nr})$ denote as the capital intensity of industry n in region r and let $k_r(= K_r/L_r)$ denote the capital–labor ratio in region r (i.e., the factor endowment in region r). The capital intensity of a given industry in a given region k_{nr} is represented by the color of each cell. White, light gray, gray, dark gray, and black indicate capital intensities for $k_{nr} = 0$ (i.e., no production),

[16] When the number of establishment is less than four, the *Census of Manufactures* does not report this information. I assume that the amount of output for the industry is also negligibly small enough to be regarded as zero production. In the *Census of Manufactures*, the capital stock data are sometimes not available at the industry-region level because of confidentiality. If the capital stock data are not available, I take the share of material input and use it as a proxy for the capital share of the region. The industry totals of value-added, labor, and capital correspond to those of the JIP database 2009.

[17] The average regional wage rate in manufacturing and regional capital–labor ratio are presented in Table A. The regions are sorted in order of the average wage rate. The correlation between average regional wage rate and regional capital–labor ratio is 0.786.

$0 < k_{nr} \leq 5$, $5 < k_{nr} \leq 15$, $15 < k_{nr} \leq 20$, and $k_{nr} > 20$, respectively.[18] The industries and the regions are sorted in order of capital intensity and relative capital abundance, respectively. When homogeneous goods are produced across regions, cells gradually become dark from left to right and from top to bottom in Table 1: like a map of ocean depth by gradient tints, the left cells in the upper rows will be lighter gray whereas the right cells in the lower rows will be darker gray or black.

=== Table 1 ===

Actual intensities depart from this pattern in two ways. First, within-region (across industries) capital intensity is not uniform. For example, general machinery is more capital intensive than transportation machinery in Okinawa whereas transportation machinery is more capital intensive than general machinery in Tokyo. Second, within-industry (across regions) capital-intensity rankings vary substantially. For example, Tokyo's transportation machinery is more capital intensive than is Okinawa's whereas Okinawa's general machinery is more capital intensive than Tokyo's. These results together imply the existence of intraindustry heterogeneity.[19] Table 1 also reports the average regional wage rate in manufacturing. The capital-abundant regions tend to pay higher wages than the capital-scarce regions. The correlation between the average regional wage rate and the regional capital–labor ratio is 0.786.

One may argue that the difference in capital intensity across regions is not a problem because capital intensity can be different if each region is operating with a different combination of labor and capital even though the production function is the same across regions. If industries in different regions have the same production function, the ranking of sectoral

[18]The unit of measurement is millions of yen per worker.

[19]Table 1 shows the uneven distribution of capital (relative to labor) among regions. It indicates that Yamaguchi is approximately 3.5 times more capital abundant than is Kochi. Such an uneven distribution of factors among regions suggests what Courant and Deardorff (1992) called the "lumpiness" of regions in Japan.

capital intensities will not change across different regions. Therefore, the rank correlation between two different regions will be unity.

=== Table 2 ===

Table 2 presents the correlation of rankings of capital intensities between two different regions. The number of region pairs is 1,081 (= 46+45+...+1). Table 2 indicates that only 6.9 percent of the region pairs have rank correlations greater than 0.9, and 57.2 percent of industries have rank correlations of less than 0.8. This result suggests cross-regional, intraindustry heterogeneity. For example, although all regions have electrical machinery industries, some regions manufacture capital-intensive semiconductors and satellites while other regions mainly manufacture lighting equipment and dry-cell batteries. Thus, the use of the "standard" industry classification poses problems because it does not reflect the similarities in capital intensities between industries. A more theoretically appropriate classification is needed.

To adjust industry output in a more theoretically appropriate way, I adapt the "HO aggregates" developed by Schott (2003). This procedure aggregates industries based on the region–industry capital intensities rather than the "standard" industry classification. That is, this procedure aggregates industries with similar capital intensities. Let h_i be i's boundaries of the HO aggregates: h_i and h_{i-1} are the maximum and minimum capital intensity for the i-th aggregates, respectively ($h_0 = 0$). For the three-good, two-cone model, the relationship between k_{nr} and h_i is written as follows:

$$i = \begin{cases} 1 \text{ (labor-intensive aggregate)} & \text{if } 0 < k_{nr} < h_1; \\ 2 \text{ (intermediate capital-intensive aggregate)} & \text{if } h_1 \leq k_{nr} < h_2; \\ 3 \text{ (capital-intensive aggregate)} & \text{if } k_{nr} \geq h_2. \end{cases} \quad (2)$$

Note that the aggregates for industries for which capital intensity is zero (i.e., $k_{nr} = 0$)

cannot be determined. When $k_{nr} = 0$, I use the industry average capital intensity k_n rather than k_{nr} to determine the aggregates.[20]

Let Z_{ir} denote the value-added of the HO aggregate i in region r, which is the sum of the value-added of all industries with capital intensities between h_{i-1} and h_i (irrespective of region):

$$Z_{ir} = \sum_{n \in \{n | k_{nr} \in [h_{i-1}, h_i)\}} Z_{nr}. \tag{3}$$

Using this classification, I aggregate 21 manufacturing industries into three aggregates (labor-, intermediate capital-, and capital-intensive aggregates) in estimating the three-good model.

3.3 Regression equations

In the three-good, two-cone model, the expected paths of development take the spline functional form shown in Figure 4: $w'\tau_1\tau_2$ for the labor-intensive aggregate, $0A\tau_2$ for the intermediate capital-intensive aggregate, and $0\tau_1 B$ for the capital-intensive aggregate. Let d_j be a dummy variable that takes a value of unity if k_r lies in the interval between τ_{j-1} and τ_j ($\tau_0 = 0$), and is otherwise equal to zero. The regression equations take the following forms:[21]

Labor-intensive aggregate

$$z_{1r} = \beta_1 (k_r - \tau_1) d_1 + \epsilon_{1r}. \tag{4}$$

Intermediate capital-intensive aggregate

$$z_{2r} = \beta_2 \left\{ k_r d_1 + \frac{\tau_1}{\tau_1 - \tau_2} (k_r - \tau_2) d_2 \right\} + \epsilon_{2r}. \tag{5}$$

[20]The industry average capital intensity is calculated based on the regions that have positive region–industry capital intensities.

[21]See the Appendix for the detailed manipulation.

Capital-intensive aggregate

$$z_{3r} = \beta_3(k_r - \tau_1)d_2 + \epsilon_{3r}. \tag{6}$$

Wages

$$w_r = -\beta_1\tau_1 d_1 - \frac{\tau_1}{\tau_2 - \tau_1}\left\{\beta_3(\tau_2 - \tau_1) - \beta_2\tau_2\right\} d_2 + \epsilon_{4t}. \tag{7}$$

where:

$$-\beta_1\tau_1 < -\frac{\tau_1}{\tau_2 - \tau_1}\left\{\beta_3(\tau_2 - \tau_1) - \beta_2\tau_2\right\}. \tag{8}$$

The parameters to be estimated are β_1, β_2, and β_3. Note that the wage equation includes all the parameters to be estimated. This means that the wage equation is an additional constraint for equations (4)–(6). Without this constraint, the estimated parameters β_1, β_2, and β_3 could be inconsistent with the observed wage patterns: capital-abundant regions tend to pay higher wages than do capital-scarce regions. This issue will be investigated in more detail in Section 4.

Note also that the error terms of the equations may be correlated with each other because factor endowment in year t is common across the equations. Therefore, the system of the paths of development is estimated using a seemingly unrelated regressions (SUR) model. The threshold of boundaries and the location of the knots are determined by gridding over all possible combinations of boundaries and knots for a given interval size, where the Akaike information criterion (AIC) takes the smallest value.[22]

[22] For the interval size, I use a grid interval of $\gamma = 0.1$ for boundaries ($10^{0.5} \leq 10^{\gamma} \leq 10^{1.8}$) and one million yen for knots ($9 \leq \tau_j \leq 28$). The interval 10^{γ} is used because capital intensity k_{nr} is log-normally distributed. The AIC is a log-likelihood criterion with a degree-of-freedom adjustment and is defined as $-2\ln L + 2p$, where $\ln L$ is the log-likelihood of the model and p is the number of parameters. The model with the smallest AIC is preferred. For more details, see Cameron and Trivedi (2005, pp.278–279).

4 Estimation Results

4.1 Baseline model

The extension to any number of goods is rather straightforward from a theoretical point of view. However, computational constraints prevent estimating the model with more than four cones. Thus, I estimate the HO model with up to four cones and examine how the fit of the model changes with the number of cones.

Table 3 presents the estimation results. Figures 6–8 show the corresponding patterns for the two-good, single-cone model; the three-good, two-cone model; and the four-good, three-cone model, respectively.[23] In each figure, the dashed lines represent the 95 percent confidence interval. The number indicates the region identification number. The fitted values are kinked and piecewise continuous because of the parameter restriction of the spline functions.

=== Table 3 & Figures 6–8 ===

The major findings are twofold. First, the multiple-cone model performs better than does the single-cone model in predicting the location of particular types of production activities in Japan. The AIC and Bayesian information criterion (BIC) in the three-good, two-cone model are smaller than those of the two-good, single-cone model. Figure 6 shows that the single-cone model explains the sectoral production but does not explain any wage disparities across economies. On the other hand, Figure 7 shows that the two-cone model can explain the sectoral production and some of the wage disparities. The result indicates that the data support the existence of multiple cones. A part of the wage disparities across regions can be explained by the differences in factor endowments.

[23]The figure for the five-good four-cone model is not presented for brevity. In addition, I test the null hypothesis that the error terms across equations are contemporaneously uncorrelated, using the Breusch–Pagan test. The test results indicate that the null hypothesis is rejected at the 1 percent level for all the baseline models.

In turn, this implies that the multiple-cone HO model fits better than does the single-cone HO model, which is consistent with the findings of previous studies. The results also imply that a high wage arises from an industry upgrading through capital accumulation, which is consistent with the theoretical prediction of Leamer (1995, p.8). One may be concerned that this finding contradicts that of Davis, Weinstein, Bradford, and Simpo (1997). They utilized Japanese regional data to examine the empirical validity of the HOV model and found that FPE was a good assumption for Japan (but not for the world). Note, however, that the analysis of this paper is different from that of Davis et al. (1997) in that this paper incorporated factor prices explicitly in the analysis.

Second, the increases in the number of cones do not necessarily improve the fit of the HO model. The AIC and BIC are larger for the four-good, three-cone model than in the case of the three-good, two-cone model. Similarly, the AIC and BIC of the five-good four-cone model are larger than those of the four-good, three-cone model. These results suggest that although the multiple-cone model performs better than does the single-cone model, the increases in the number of cones do not necessarily result in better performance of the HO model.

4.2 Robustness check I: Different year

The results may be sensitive to the choice of the year because the analysis is based on cross-sectional data. To address this concern, this paper reestimates the baseline models using data for 1995 and examines whether the findings of the baseline model are sensitive to the choice of the year.

Table 4 shows the estimated parameter values, the threshold of boundaries, and the location of knots.[24] The threshold of the HO aggregates and the location of the knots

[24]Because of data availability, the regional differences in prices are adjusted by a 1997 price index from the MIC (1999).

changed slightly. The results are quantitatively similar to those of the baseline results, even though the fit of the model becomes better than does that of the baseline model. The two-cone model fits better than the single-cone model. However, the increases in the number of cones do not necessarily improve the fit of the HO model. The results suggest that the major messages from the baseline model remain unchanged even when the analysis uses the data for a different year.

=== Table 4 ===

4.3 Robustness Check II: Beyond the two-factor model

Another concern might be that wage disparities come from another factor such as human-capital rather than the existence of multiple cones. However, as Schott (2003) argued, the estimation of the paths of development becomes extremely difficult in the case of more than two factors. As a shortcut, following Leamer (1987) and Schott (2003), this paper separates economies according to their human-capital abundance and then estimates the separate paths of development for each subsample. This procedure allows the location of the knots to vary with human-capital.

Human-capital is defined as the proportion of people who graduate from a university relative to the total population. The human-capital data are obtained from Statistics Bureau, Management and Coordination Agency (2009). The regions with values of human-capital greater than or equal to the median value (11.56) are regarded as human-capital-abundant regions, while others are classified as human-capital-scarce regions.[25] The threshold of boundaries and the location of the knots are determined by gridding over all possible combinations of boundaries and knots for a given interval size, where the Akaike information criterion (AIC) takes the smallest value.footnoteNote that human-capital-abundant

[25] Table A presents the proportion of people who graduate from a university relative to the total population, by region.

regions and human-capital-scarce regions takes the different knots. This further increases computational constraints, which prevent estimation of the model with more than three cones.

Table 5 presents the estimation results. Figures 9–10 show the corresponding patterns for the two-good, single-cone; and three-good, two-cone models, respectively.[26] There are three major findings. First, the AIC and BIC of the three-good, two-cone model are smaller than those of the two-cone single-cone model. This result suggests that the multiple-cone model fits better than the single-cone model.

=== Table 5 & Figures 9–10 ===

Second, however, the increases in the number of cones do not necessarily improve the fit of the HO model. The AIC and BIC of the four-good, three-cone model are larger than those of the three-good, two-cone model. The root mean squared error (RMSE) of the four-good, three-cone model with human-capital decreases for the wage equations. However, the RMSEs for the other equations do not necessarily decrease. As a result, the overall fit of the system of equations is not improved even though the number of cones increases. These results together imply that the major message of this paper holds even after human-capital is taken into account. Although the multiple-cone model fits better than does the single-cone model, the increases in the number of cones do not necessarily result in better performance of the HO model.

Finally, in the three-good, two-cone model, the locations of the knot (τ_1) for human-capital-abundant and -scarce regions are 12 and 10 million yen per worker, respectively. This result means that human-capital-abundant regions exit the labor-intensive aggregate at a slightly higher capital–labor ratio than human-capital-scarce regions. In the second cone, this slight shift of knot leads to larger differences in wages between human-capital-abundant and human-capital-scarce regions. The differences in the expected wage rate

[26]The figure for the four-good, three-cone model is not presented for brevity.

between human-capital-abundant and -scarce regions increase from 464,000 yen in the first cone to 563,000 yen in the second cone.

This result has an interesting implication. In the two-cone model, the labor-intensive goods are produced at the earlier stage of development whereas the capital-intensive goods are produced at the later stage of development. The results thus imply that the effect of human-capital on wages is marginal at the earlier stage of development but prominent at the later stage. In other words, the benefits of the human-capital accumulation stand out at the later stage of development.

4.4 Estimation Results Without Wage Equation

One may further concern that the results are not sensitive to the inclusion of the wage equation. In other words, it may be possible to obtain quantitatively and qualitatively similar results without including the wage equation. To address this concern, this paper reestimates all the baseline models, excluding the wage equation, and examines whether the findings of the baseline model are sensitive to the inclusion of the wage equation.

Table 6 shows the estimated parameter values, the threshold of boundaries, and the location of knots for the three-good, two-cone model.[27] Figure 11 shows the corresponding patterns. Not surprisingly, the fit of the model improves once the wage equation is excluded because of the lack of parameter constraints. The threshold of the HO aggregates changed slightly whereas the location of the knots is exactly the same as in the baseline model. The estimated paths of development in Figure 11 look qualitatively similar to those in Figure 7.

=== Table 6 & Figur 11 ===

Note that the wage rate can be calculated from the estimated parameters even without

[27]For brevity the results for other models are not reported.

the wage equation because the vertical intercept of the tangent indicates the wage rate. In the case of the three-good, two-cone model, from Figure 4 and equations (4)–(6), the relationships between wage rates and the estimated parameters for the first and second cone are:

$$w' = -\beta_1\tau_1 \quad \text{and} \quad w'' = -\frac{\tau_1}{\tau_2 - \tau_1}\left\{\beta_3(\tau_2 - \tau_1) - \beta_2\tau_2\right\}, \tag{9}$$

respectively.

Table 6 reports the wage rate calculated by the estimated parameters. The results indicate that the expected wage rates in the first and second cones are 4.7 million yen and 0.7 millions yen, respectively.[28] This result implies that the wage rate decreases as the economy accumulates capital relative to labor, which is inconsistent with the fact that capital-abundant regions tend to pay higher wages than do capital-scarce regions. Without the wage equation, therefore, some of the estimated parameters are under- or over-estimated. The inclusion of the wage equation enables us to estimate the paths of development more precisely.

5 Concluding Remarks

In this paper, I examined the empirical validity of the following two claims: 1) the multiple-cone HO model fits better than does the single-cone HO model; and 2) increases in the number of cones improve the fit of the model. One of the contributions of this paper is that it focuses *simultaneously* on factor endowments, production patterns, and wage disparities across economies.

The major findings are threefold. First, the multiple-cone model performs better than does the single-cone model in predicting the location of production activities and regional

[28]This is because the slopes of the estimated paths for the intermediate capital-intensive aggregate and the capital-intensive aggregate are shallower and steeper than those of the baseline model, respectively.

wage differences in Japan. Second, increases in the number of cones do not necessarily improve the fit of the model. The results suggest that although the multiple-cone model performs better than does the single-cone model, the increases in the number of cones do not necessarily result in better performance of the HO model.

Finally, the effect of human-capital on wages is marginal at the earlier stage of development but prominent at the later stage. Human-capital-scarce economies start the production of capital-intensive goods at a lower capital–labor ratio than do human-capital-abundant economies. This results in a large difference in wages when economies accumulate capital relative to labor. In other words, the benefits of human-capital accumulation stand out at the later stage of development.

In conclusion, there are several issues worth considering in future research. First, the application of the analysis to international data rather than national data would be an important extension. This paper finds that increases in the number of cones do not necessarily result in better performance of the HO model. However, it is important to ask whether the findings of this paper are robust for international data. To address this issue, one needs to control for the effects of technology differences across countries. The estimation of sectoral total factor productivity across countries may help to control for the effects of technology differences.

Second, further investigation of the multiple-cone model with more than two factors is also an important extension. Although this paper focuses on the binary differences between human-capital-abundant and -scarce regions (i.e., whether economies are human-capital abundant or not), the analysis gives more useful implications if one can control for the difference in a continuous way. Finally, a study utilizing data on different countries would add another national perspective to the literature on industrial development. It is important to examine the characteristics of different countries at various stages of industrial development. To conduct such analyses, it is essential that the quality and coverage of the industry-level data be improved and expanded.

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Appendix Derivation of the Regression Equations

This appendix explains the derivation of the regression equations. In the three-good, two-cone model, the expected paths of development take the spline functional form as in Figure 4: $w'\tau_1\tau_2$ for the labor-intensive aggregate, $0A\tau_2$ for the intermediate capital-intensive aggregate, and $0\tau_1 B$ for the capital-intensive aggregate. The regression equations thus take the following forms.

Labor-intensive aggregate

$$z_{1r} = \begin{cases} \alpha_1 + \beta_1 k_r + \epsilon_{1r} & \text{if } 0 \leq k_r \leq \tau_1; \\ 0 & \text{if } k_r \geq \tau_1. \end{cases} \tag{A-1}$$

Intermediate capital-intensive aggregate

$$z_{2r} = \begin{cases} \beta_2 k_r + \epsilon_{2r} & \text{if } 0 \leq k_r \leq \tau_1; \\ \alpha_2 + \gamma k_r + \epsilon_{2r} & \text{if } \tau_1 \leq k_r \leq \tau_2; \\ 0 & \text{if } k_r \geq \tau_2. \end{cases} \tag{A-2}$$

Capital-intensive aggregate

$$z_{3r} = \begin{cases} 0 & \text{if } 0 \leq k_r \leq \tau_1; \\ \alpha_3 + \beta_3 k_r + \epsilon_{3r} & \text{if } k_r \geq \tau_1. \end{cases} \tag{A-3}$$

Because the wage rate is provided by the vertical intercept of the lines $w'A$ and AB in Figure 3, the regression equation for the wages is written as follows:

Wages

$$w_r = \begin{cases} \alpha_1 + \epsilon_{4r} & \text{if } 0 \leq k \leq \tau_1; \\ \frac{\tau_1}{\tau_2 - \tau_1}\{\beta_3(\tau_1 - \tau_2) + \beta_2 \tau_2\} + \epsilon_{4r} & \text{if } k_r \geq \tau_1. \end{cases} \tag{A-4}$$

Because the paths of development are piecewise continuous, the following parameter restrictions are required to join the line segment of each pattern at the knots:

$$\underset{\textit{Labor-intensive aggregate}}{\alpha_1 + \beta_1 \tau_1 = 0} \qquad \overset{\textit{Intermediate capital-intensive aggregate}}{\begin{cases} \beta_2 \tau_1 = \alpha_2 + \gamma \tau_1 \\ \alpha_2 + \gamma \tau_2 = 0 \end{cases}} \qquad \underset{\textit{Capital-intensive aggregate}}{\alpha_3 + \beta_3 \tau_1 = 0} \tag{A-5}$$

Let d_j be a dummy variable that takes unity if k_r lies in the interval between τ_{j-1} and τ_j ($\tau_0 = 0$), and is otherwise equal to zero. The following regression equations are obtained by substituting (A-5) into (A-1)–(A-4).

Labor-intensive aggregate

$$z_{1r} = \beta_1 (k_r - \tau_1) d_1 + \epsilon_{1r}. \tag{A-6}$$

Intermediate capital-intensive aggregate

$$z_{2r} = \beta_2 \left\{ k_r d_1 + \frac{\tau_1}{\tau_1 - \tau_2}(k_r - \tau_2) d_2 \right\} + \epsilon_{2r}. \tag{A-7}$$

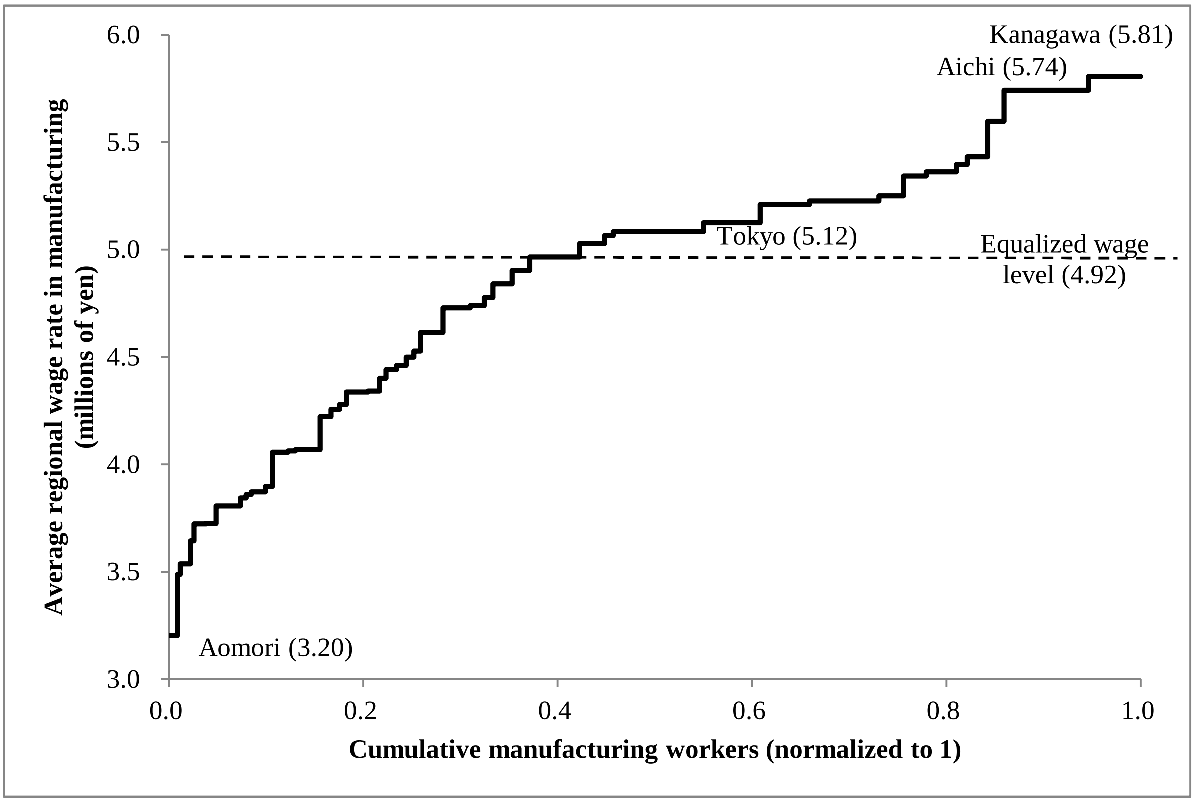
Capital-intensive aggregate

$$z_{3r} = \beta_3 (k_r - \tau_1) d_2 + \epsilon_{3r}. \tag{A-8}$$

Wages

$$w_r = -\beta_1 \tau_1 d_1 - \frac{\tau_1}{\tau_2 - \tau_1} \left\{ \beta_3 (\tau_2 - \tau_1) - \beta_2 \tau_2 \right\} d_2 + \epsilon_{4r}. \tag{A-9}$$

Figure 1. Average Regional Wages in Manufacturing for 2000



Sources: METI (2000) and MIC (2004).

Figure 2. Three-good Two-cone Lerner Diagram

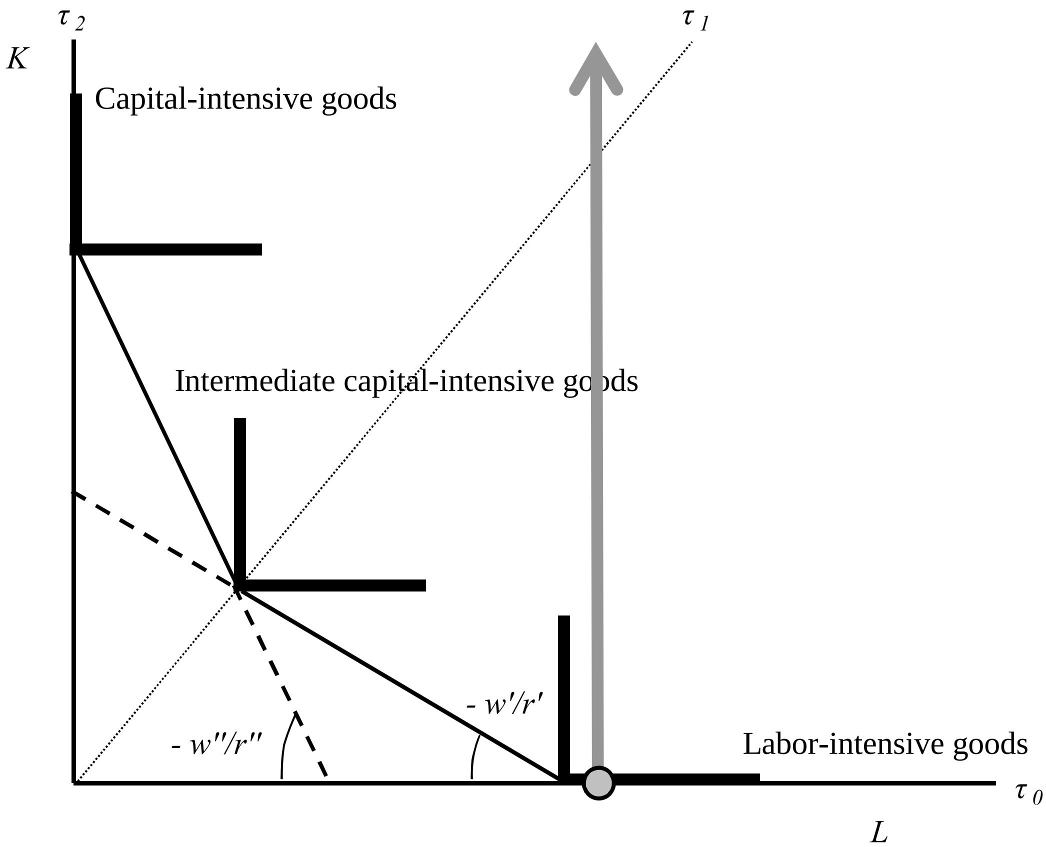


Figure 3. Relationship between Per-capita Output and Capital-labor Ratio: Three-good Two-cone Model

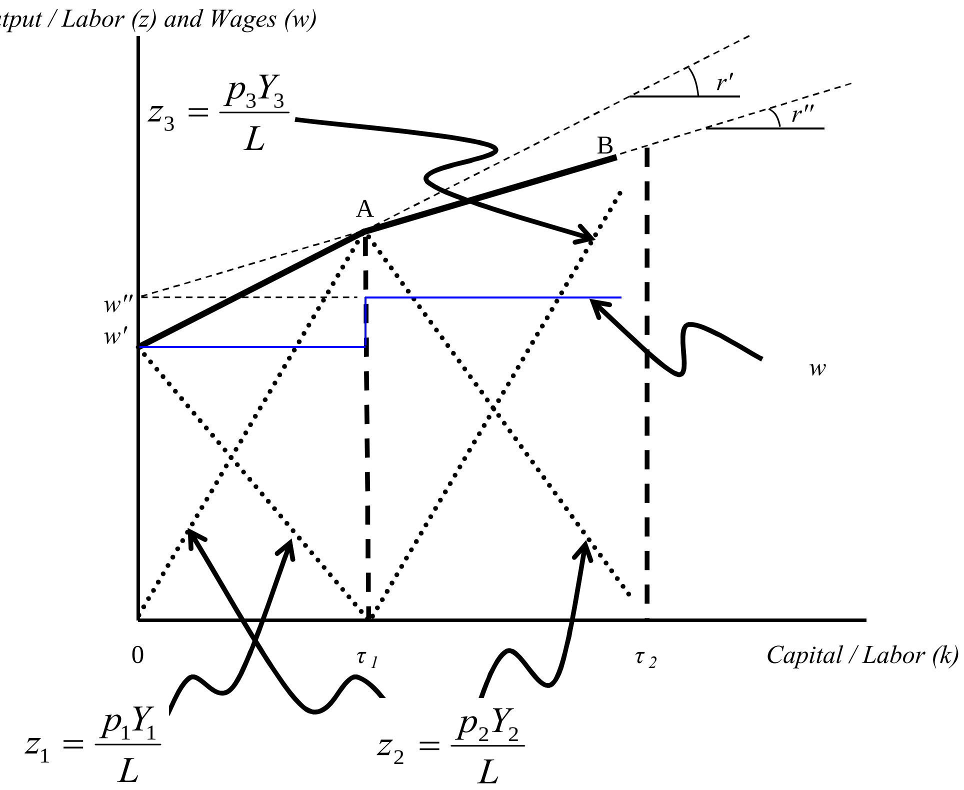
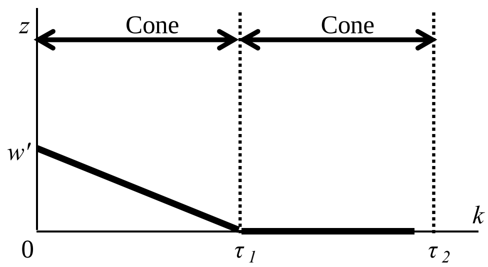
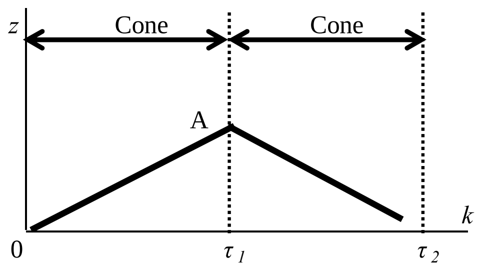


Figure 4. Paths of Development Implied by Figure 3

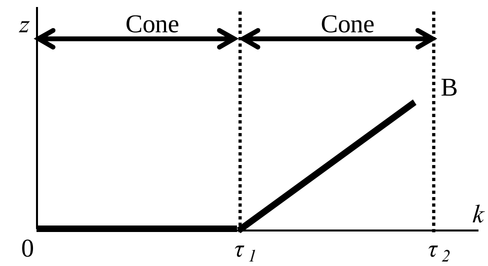
Panel A: Labor-intensive goods z_1



Panel B: Intermediate capital-intensive goods z_2



Panel C: Capital-intensive goods z_3



Panel D: Wages w

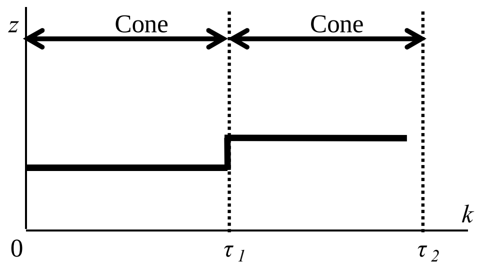


Figure 5. Many Goods and Many Cones

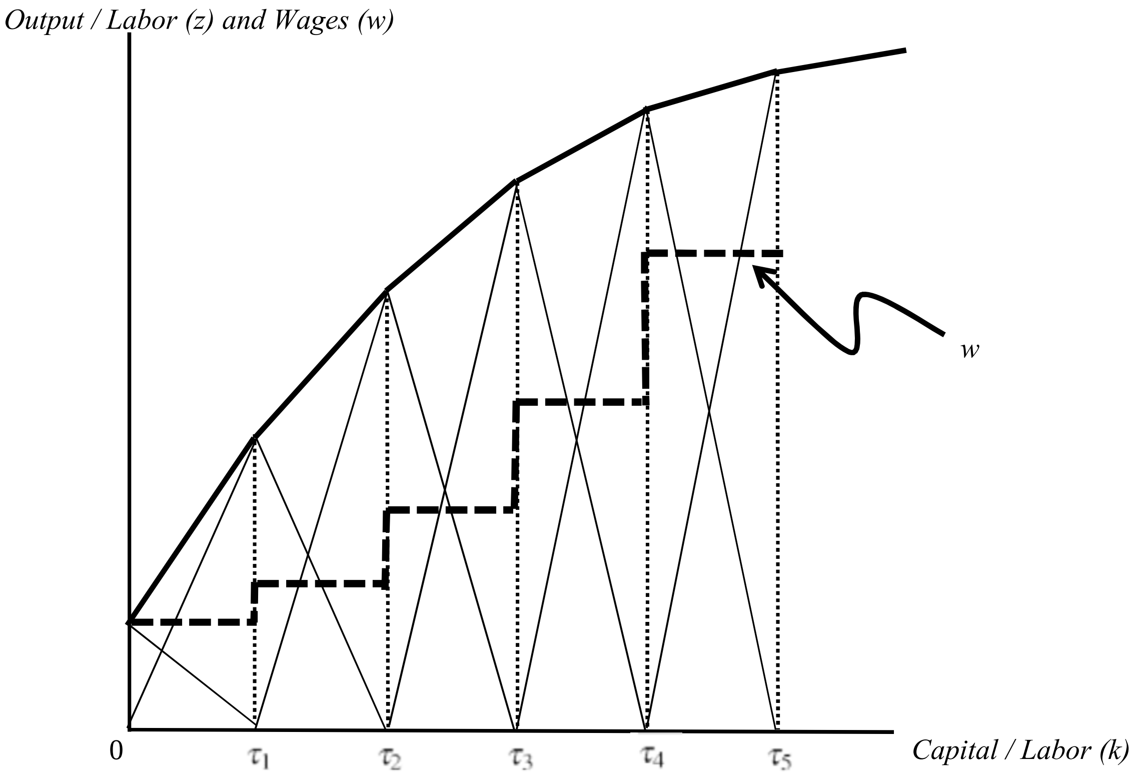
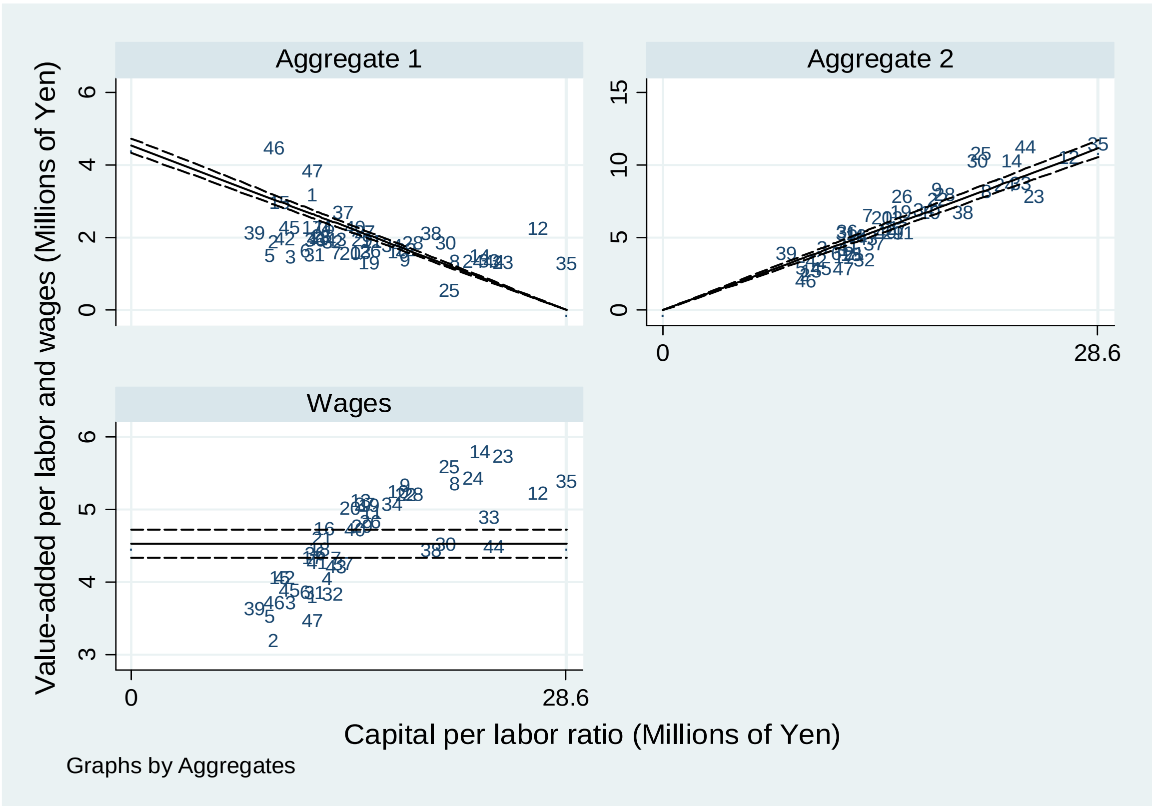


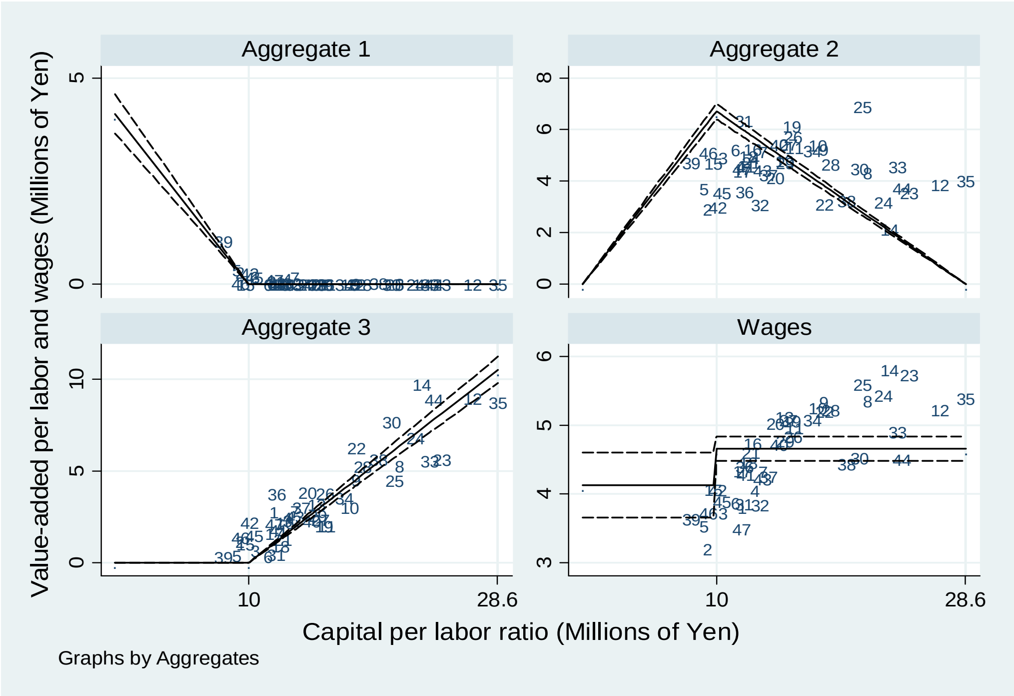
Figure 6. Estimated Paths of Development: Two-good Single-cone Model



Note: Figure 6 reports the estimated paths of development for two HO aggregates. The dashed lines represent the 95-percent confidence interval. Estimated parameter values are presented in Table 3. The number indicates region id. The fitted values are kinked and piecewise continuous because of the parameter restriction of spline functions.

Sources: The JIP database 2009, METI (2000), and MIC (2004).

Figure 7. Estimated Paths of Development: Three-good Two-cone Model



Note: Figure 7 reports the estimated paths of development for three HO aggregates. The dashed lines represent the 95-percent confidence interval. Estimated parameter values are presented in Table 3. The number indicates region id. The fitted values are kinked and piecewise continuous because of the parameter restriction of spline functions.

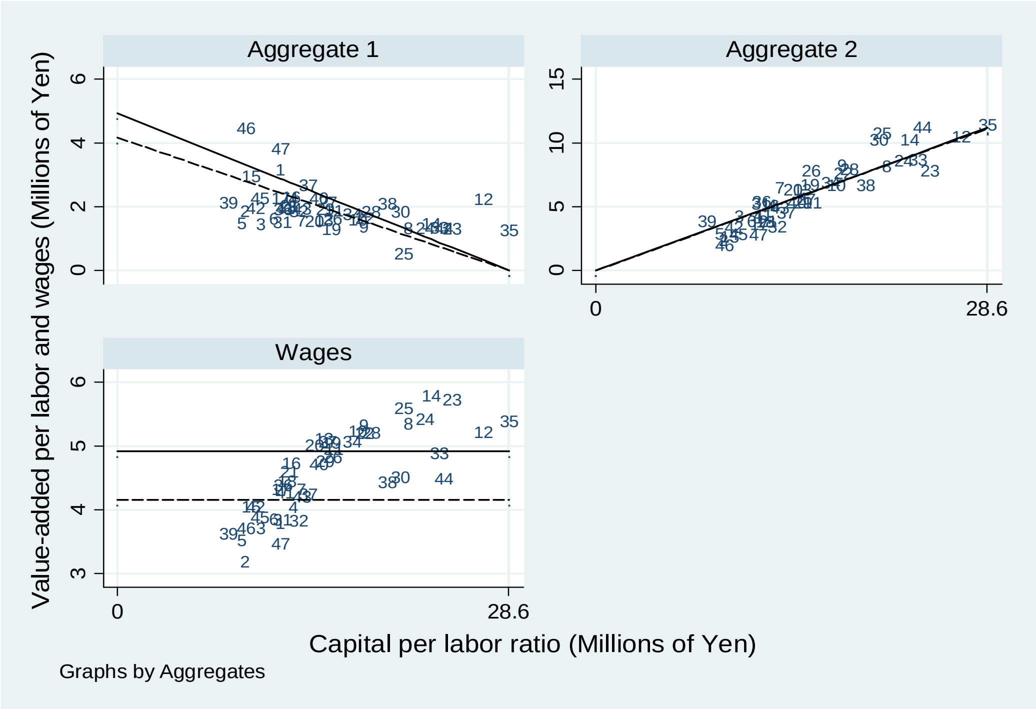
Sources: The JIP database 2009, METI (2000), and MIC (2004).

Figure 8. Estimated Paths of Development: Four-good Three-cone Model

Note: Figure 8 reports the estimated paths of development for four HO aggregates. The dashed lines represent the 95-percent confidence interval. Estimated parameter values are presented in Table 3. The number indicates region id. The fitted values are kinked and piecewise continuous because of the parameter restriction of spline functions.

Sources: The JIP database 2009, METI (2000), and MIC (2004).

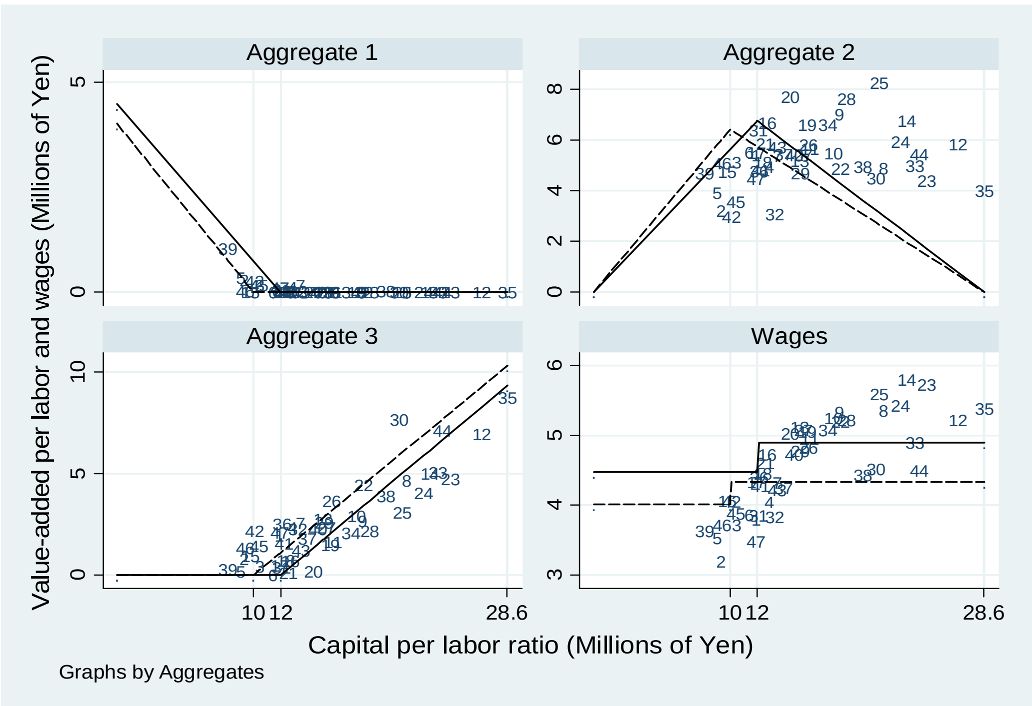
Figure 9. Difference between Human Capital Abundant and Scarce Prefectures: Two-good Single-cone Model



Note: Figure 9 reports the estimated paths of development for two HO aggregates. The dashed lines represent the paths for human capital scarce prefectures. Estimated parameter values are presented in Table 5. The number indicates region id. The fitted values are kinked and piecewise continuous because of the parameter restriction of spline functions.

Sources: The JIP database 2009, METI (2000), and MIC (2000, 2004).

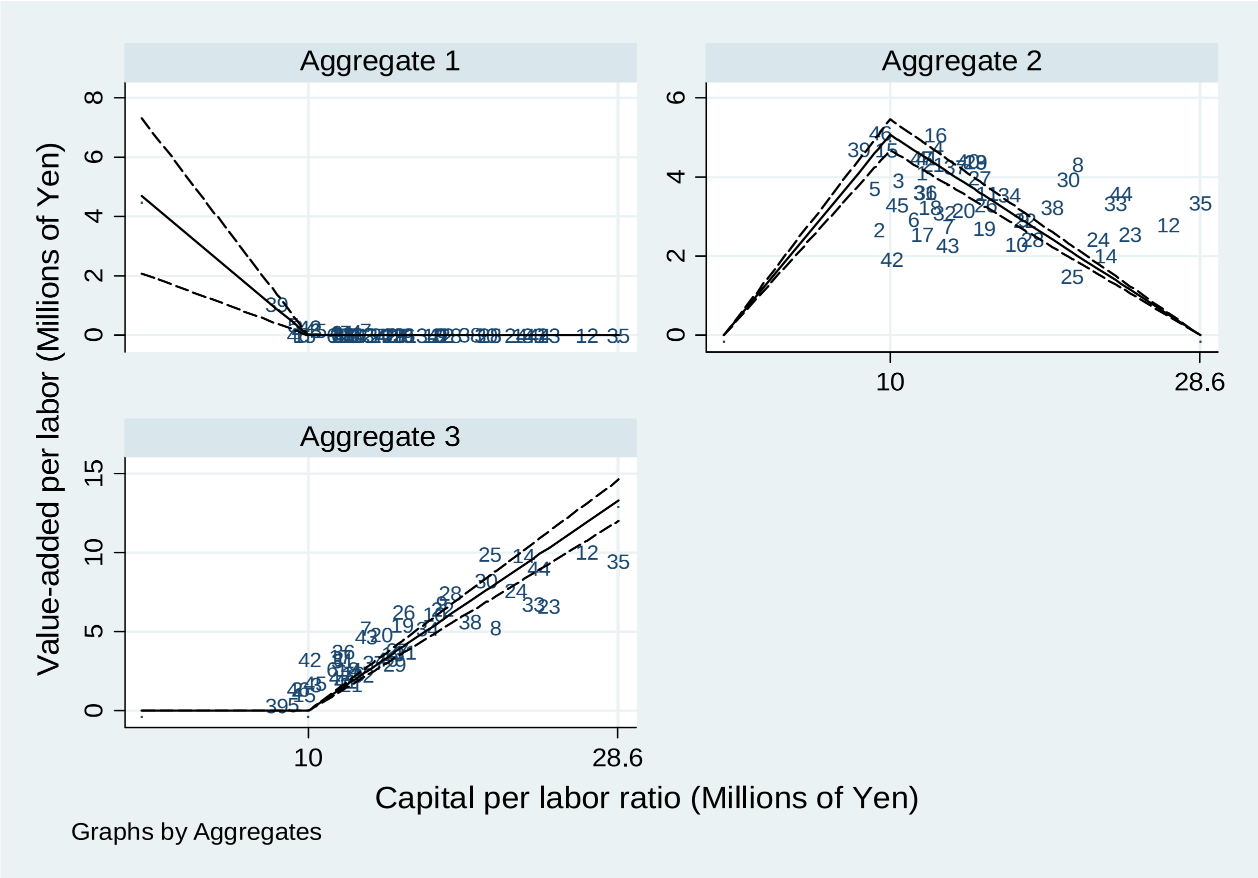
Figure 10. Difference between Human Capital Abundant and Scarce Prefectures: Three-good Two-cone Model



Note: Figure 10 reports the estimated paths of development for two HO aggregates. The dashed lines represent the paths for human capital scarce prefectures. Estimated parameter values are presented in Table 5. The number indicates region id. The fitted values are kinked and piecewise continuous because of the parameter restriction of spline functions.

Sources: The JIP database 2009, METI (2000), and MIC (2000, 2004).

Figure 11. Estimated Paths of Development: Three-good Two-cone Model without Wage Equation



Note: Figure 11 reports the estimated paths of development for three HO aggregates. The dashed lines represent the 95-percent confidence interval. Estimated parameter values are presented in Table 6. The number indicates prefecture id. The fitted values are kinked and piecewise continuous because of the parameter restriction of spline functions.

Sources: The JIP database 2009 and METI (2000).

Table 1. Prefecture-Industry Capital Intensity

Region id	Region	Prefecture capital-labor ratio (endowment)	Leather tanning and leather products	Furniture and fixtures	Food products	Publishing and printing	Textile products	Fabricated metal products	Timber and wooden products	Other manufacturing	Rubber products	Plastic products	Ceramic, stone and clay products	Precision machinery	General machinery	Electrical machinery	Transportation machinery	Pulp and paper	Beverages and Tobacco	Non-ferrous metals	Chemical products	Iron and steel	Petroleum and coal products
		Industry average capital labor ratio	3.7	5.1	5.8	6.4	6.9	7.0	7.2	8.9	9.0	11.9	12.9	13.6	16.4	17.9	20.2	21.3	22.4	32.5	38.0	58.4	93.0
39	Kochi	8.13																					
5	Akita	9.06																					
2	Aomori	9.31																					
46	Kagoshima	9.42																					
15	Niigata	9.78																					
42	Nagasaki	10.09																					
45	Miyazaki	10.43																					
3	Iwate	10.46																					
6	Yamagata	11.41																					
1	Hokkaido	11.88																					
47	Okinawa	11.90																					
17	Ishikawa	11.94																					
31	Tottori	12.06																					
36	Tokushima	12.10																					
41	Saga	12.23																					
18	Fukui	12.39																					
21	Gifu	12.58																					
16	Toyama	12.71																					
4	Miyagi	12.83																					
32	Shimane	13.27																					
7	Fukushima	13.44																					
43	Kumamoto	13.47																					
37	Kagawa	13.93																					
20	Nagano	14.41																					
40	Fukuoka	14.70																					
13	Tokyo	15.10																					
29	Nara	15.17																					
27	Osaka	15.38																					
19	Yamanashi	15.65																					
26	Kyoto	15.74																					
11	Saitama	15.82																					
34	Hiroshima	17.17																					
10	Gumma	17.56																					
9	Tochigi	17.98																					
22	Shizuoka	18.08																					
28	Hyogo	18.55																					
38	Ehime	19.74																					
30	Wakayama	20.70																					
25	Shiga	20.93																					
8	Ibaraki	21.25																					
24	Mie	22.47																					
14	Kanagawa	22.93																					
33	Okayama	23.53																					
44	Oita	23.87																					
23	Aichi	24.43																					
12	Chiba	26.73																					
35	Yamaguchi	28.65																					

Notes:
: no production
: capital intensity is between 0 and 5.
: capital intensity is between 5 and 10.
: capital intensity is between 10 and 15.
: capital intensity is between 15 and 20.
: capital intensity is greater than 20.

Sources: The JIP database 2009 and METI (2000).

Table 2. Rank Correlation of Industry Capital Intensities for Different Region Pairs, 2000

Spearman's rank correlation (ρ)	Number of region pairs for 21 industries	Share (%)
$\rho = 1.0$	0	0.0
$0.9 \leq \rho < 1.0$	75	6.9
$0.8 \leq \rho < 0.9$	388	35.9
$0.7 \leq \rho < 0.8$	346	32.0
$0.6 \leq \rho < 0.7$	182	16.8
$0.5 \leq \rho < 0.6$	70	6.5
$0.4 \leq \rho < 0.5$	14	1.3
$0.3 \leq \rho < 0.4$	5	0.5
$0.2 \leq \rho < 0.3$	1	0.1
$0.1 \leq \rho < 0.2$	0	0.0
$0 \leq \rho < 0.1$	0	0.0
$\rho < 0$	0	0.0
Total	1081	100.0

Note: Rank correlation of capital intensities is calculated for different region pairs in 2000. The number of correlations is 1081 (= the number of region pairs (46 + 45 + … + 1)).

Sources: The JIP database 2009 and METI (2000).

Table 3. Estimation Results of the Single- and Multiple-cone Model: Baseline Model, 2000

	Coefficient	S.E.	p-value	N	RMSE
Two-good, single-cone model					
Threshold of the HO aggregates: h_1 = 10.0					AIC = 324.5
Location of knots: τ_1 = 28.6					BIC = 328.2
	Coefficient	S.E.	p-value	N	RMSE
Aggregate 1	-0.158	0.003	0.000	47	0.772
Aggregate 2	0.389	0.010	0.000	47	1.053
Wages	4.530	0.099	0.000	47	0.665
Three-good, two-cone model					
Threshold of the HO aggregates: h_1 = 3.2, h_2 = 20.0					AIC = 256.5
Location of knots: τ_1 = 10, τ_2 = 28.6					BIC = 262.1
	Coefficient	S.E.	p-value	N	RMSE
Aggregate 1	-0.413	0.024	0.000	47	0.085
Aggregate 2	0.670	0.015	0.000	47	1.812
Aggregate 3	0.564	0.020	0.000	47	1.187
Wages	4.131	0.241	0.000	47	0.607
	4.663	0.090	0.000		
Four-good, three-cone model					
Threshold of the HO aggregates: h_1 = 3.2, h_2 = 15.8, h_3 = 39.8					AIC = 431.5
Location of knots: τ_1 = 10, τ_2 = 17, τ_3 = 28.6					BIC = 438.9
	Coefficient	S.E.	p-value	N	RMSE
Aggregate 1	-0.390	0.022	0.000	47	0.087
Aggregate 2	0.551	0.014	0.000	47	2.263
Aggregate 3	0.892	0.030	0.000	47	1.604
Aggregate 4	0.613	0.028	0.000	47	0.939
	3.896	0.223	0.000		
Wages	4.448	0.098	0.000	47	0.483
	4.940	0.146	0.000		
Five-good, four-cone model					
Threshold of the HO aggregates: h_1 = 3.2, h_2 = 15.8, h_3 = 39.8, h_4 = 50.1					AIC = 566.0
Location of knots: τ_1 = 10, τ_2 = 23, τ_3 = 26, τ_4 = 28.6					BIC = 575.2
	Coefficient	S.E.	p-value	N	RMSE
Aggregate 1	-0.386	0.032	0.000	47	0.087
Aggregate 2	0.508	0.059	0.000	47	1.671
Aggregate 3	0.456	0.126	0.000	47	1.824
Aggregate 4	2.028	0.648	0.002	47	0.854
Aggregate 5	2.345	0.756	0.002	47	1.694
	3.861	0.323	0.000		
	4.433	0.261	0.000		
Wages	4.705	1.280	0.000	47	0.616
	4.912	1.532	0.001		

Note: Standard errors are bootstrapped using 1,000 replications to obtain heteroskedasticity robust standard errors.

Sources: The JIP database 2009, METI (2000), and MIC (2004).

Table 4. Estimation Results of the Single- and Multiple-cone Model: Baseline Model, 1995

	Coefficient	S.E.	p-value	N	RMSE
Two-good, single-cone model					
Threshold of the HO aggregates: $h_1 = 7.9$					AIC = 284.3
Location of knots: $\tau_1 = 23.9$					BIC = 288.0
Aggregate 1	-0.179	0.005	0.000	47	0.698
Aggregate 2	0.392	0.010	0.000	47	0.842
Wages	4.285	0.109	0.000	47	0.665
Three-good, two-cone model					
Threshold of the HO aggregates: $h_1 = 2.5$, $h_2 = 15.8$					AIC = 198.7
Location of knots: $\tau_1 = 7$, $\tau_2 = 23.9$					BIC = 204.3
Aggregate 1	-0.553	0.035	0.000	47	0.087
Aggregate 2	0.794	0.014	0.000	47	1.527
Aggregate 3	0.505	0.014	0.000	47	0.909
Wages	3.868	0.245	0.000	47	0.646
	4.321	0.076	0.000		
Four-good, three-cone model					
Threshold of the HO aggregates: $h_1 = 2.5$, $h_2 = 12.6$, $h_3 = 31.6$					AIC = 321.8
Location of knots: $\tau_1 = 7$, $\tau_2 = 15$, $\tau_3 = 23.9$					BIC = 329.2
Aggregate 1	-0.521	0.027	0.000	47	0.087
Aggregate 2	0.657	0.015	0.000	47	1.908
Aggregate 3	0.649	0.025	0.000	47	1.346
Aggregate 4	0.618	0.034	0.000	47	0.978
	3.650	0.189	0.000		
Wages	4.083	0.075	0.000	47	0.510
	4.624	0.110	0.000		
Five-good, four-cone model					
Threshold of the HO aggregates: $h_1 = 2.5$, $h_2 = 12.6$, $h_3 = 31.6$, $h_4 = 39.8$					AIC = 456.9
Location of knots: $\tau_1 = 7$, $\tau_2 = 20$, $\tau_3 = 21$, $\tau_4 = 23.9$					BIC = 466.1
Aggregate 1	-0.522	0.044	0.000	47	0.087
Aggregate 2	0.632	0.083	0.000	47	1.357
Aggregate 3	0.381	0.151	0.012	47	1.340
Aggregate 4	4.973	2.041	0.015	47	0.660
Aggregate 5	1.714	0.754	0.023	47	1.538
	3.652	0.311	0.000		
Wages	4.143	0.214	0.000	47	0.662
	4.438	2.320	0.056		
	4.446	1.236	0.000		

Note: Standard errors are bootstrapped using 1,000 replications to obtain heteroskedasticity robust standard errors.

Sources: The JIP database 2009, METI (2000), and MIC (2004).

Table 5. Estimation Results of the Single- and Multiple-cone Model

Two-good, single-cone model

Threshold of the HO aggregates: h_1 = 10.0 AIC = 305.3

Location of knots: τ_1 = 28.6 BIC = 312.7

	Prefectures	Coefficient	S.E.	*p*-value	*N*	RMSE
Aggregate 1	HC scarce	-0.145	0.004	0.000	47	0.739
	HC abundant	-0.172	0.004	0.000		
Aggregate 2	HC scarce	0.388	0.014	0.000	47	1.040
	HC abundant	0.391	0.011	0.000		
Wages	HC scarce	4.160	0.109	0.000	47	0.528
	HC abundant	4.921	0.109	0.000		

Three-good, two-cone model

Threshold of the HO aggregates: h_1 = 3.2, h_2 = 25.1 AIC = 246.3

Location of knots: τ_1 = 10 (HC scarce), τ_1 = 12 (HC abundant), τ_2 = 28.6 BIC = 257.4

	Prefectures	Coefficient	S.E.	*p*-value	*N*	RMSE
Aggregate 1	HC scarce	-0.401	0.024	0.000	47	0.087
	HC abundant	-0.373	0.005	0.000		
Aggregate 2	HC scarce	0.643	0.021	0.000	47	2.275
	HC abundant	0.563	0.013	0.000		
Aggregate 3	HC scarce	0.554	0.031	0.000	47	1.223
	HC abundant	0.561	0.024	0.000		
Wages	HC scarce	4.014	0.242	0.000	47	0.522
	HC scarce	4.334	0.130	0.000		
	HC abundant	4.478	0.059	0.000		
	HC abundant	4.897	0.100	0.000		

Four-good, three-cone model

Threshold of the HO aggregates: h_1 = 3.2, h_2 = 15.8, h_3 = 39.8

Location of knots (HC scarce): τ_1 = 10, τ_1 = 16, τ_2 = 28.6 AIC = 429.7

Location of knots (HC abundant): τ_1 = 12, τ_1 = 18, τ_2 = 28.6 BIC = 444.5

	Prefectures	Coefficient	S.E.	*p*-value	*N*	RMSE
Aggregate 1	HC scarce	-0.382	0.022	0.000	47	0.089
	HC abundant	-0.366	0.011	0.000		
Aggregate 2	HC scarce	0.542	0.028	0.000	47	2.115
	HC abundant	0.488	0.017	0.000		
Aggregate 3	HC scarce	1.034	0.072	0.000	47	1.616
	HC abundant	1.073	0.048	0.000		
Aggregate 4	HC scarce	0.581	0.057	0.000	47	0.927
	HC abundant	0.680	0.039	0.000		
Wages	HC scarce	3.820	0.217	0.000	47	0.411
	HC scarce	4.105	0.149	0.000		
	HC scarce	4.753	0.302	0.000		
	HC abundant	4.398	0.137	0.000		
	HC abundant	4.710	0.110	0.000		
	HC abundant	5.086	0.176	0.000		

Note: Standard errors are bootstrapped using 1,000 replications to obtain heteroskedasticity robust standard errors. Regions with greater (smaller) than median human capital ratio are defined as human capital abundant (scarce) regions.

Sources: The JIP database 2009, METI (2000), and MIC (2000, 2004).

Table 6. Estimation Results of the Single- and Multiple-cone Model: Without Wage Equation

Three-good, two-cone model					
Threshold of the HO aggregates: h_1 = 3.2, h_2 = 15.8					AIC = 186.2
Location of knots: τ_1 = 10, τ_2 = 28.6					BIC = 191.8
	Coefficient	S.E.	p-value	N	RMSE
Aggregate 1	-0.470	0.128	0.000	47	0.082
Aggregate 2	0.507	0.020	0.000	47	1.301
Aggregate 3	0.713	0.036	0.000	47	1.643
Wages	4.696				
	0.652				

Note: Standard errors are bootstrapped using 1,000 replications to obtain heteroskedasticity robust standard errors. Wages are calculated from the estimated parameters, based on equation (9).

Sources: The JIP database 2009 and METI (2000).

Table A. Summary Statistics

Region id	Region	Average regional wage rate in manufacturing (millions of yen)	Regional capital-labor ratio (endowment)	Human capital (share of people who graduates from a university to total population)	Region id	Region	Average regional wage rate in manufacturing (millions of yen)	Regional capital-labor ratio (endowment)	Human capital (share of people who graduates from a university to total population)
2	Aomori	3.203	9.31	7.30	21	Gifu	4.614	12.58	11.63
47	Okinawa	3.487	11.90	11.23	40	Fukuoka	4.728	14.70	14.48
5	Akita	3.537	9.06	7.37	16	Toyama	4.739	12.71	12.16
39	Kochi	3.644	8.13	9.19	29	Nara	4.777	15.17	20.16
3	Iwate	3.723	10.46	8.11	26	Kyoto	4.840	15.74	18.10
46	Kagoshima	3.725	9.42	8.92	33	Okayama	4.903	23.53	12.97
1	Hokkaido	3.806	11.88	9.95	11	Saitama	4.966	15.82	17.94
32	Shimane	3.844	13.27	9.53	20	Nagano	5.028	14.41	11.11
31	Tottori	3.860	12.06	10.83	19	Yamanashi	5.065	15.65	12.56
6	Yamagata	3.871	11.41	8.45	34	Hiroshima	5.083	17.17	15.67
45	Miyazaki	3.897	10.43	8.91	27	Osaka	5.084	15.38	16.54
4	Miyagi	4.057	12.83	12.29	13	Tokyo	5.125	15.10	26.59
42	Nagasaki	4.062	10.09	8.94	22	Shizuoka	5.210	18.08	12.29
15	Niigata	4.069	9.78	8.52	28	Hyogo	5.226	18.55	18.16
43	Kumamoto	4.222	13.47	10.32	12	Chiba	5.227	26.73	19.74
37	Kagawa	4.257	13.93	13.54	10	Gumma	5.251	17.56	10.86
41	Saga	4.278	12.23	9.91	9	Tochigi	5.342	17.98	11.09
7	Fukushima	4.336	13.44	8.61	8	Ibaraki	5.362	21.25	12.12
17	Ishikawa	4.341	11.94	12.77	35	Yamaguchi	5.396	28.65	11.28
36	Tokushima	4.401	12.10	11.93	24	Mie	5.432	22.47	11.56
38	Ehime	4.442	19.74	11.86	25	Shiga	5.597	20.93	14.94
18	Fukui	4.461	12.39	11.38	23	Aichi	5.742	24.43	15.81
44	Oita	4.500	23.87	10.53	14	Kanagawa	5.806	22.93	23.89
30	Wakayama	4.527	20.70	10.75		MEDIAN	4.527	14.41	11.56

Note: Regions are sorted in order of average prefecture wage rate. Shaded regions are classified as human capital-abundant regions (whose human capital is greater than median value). Wages and human capital are weighted by the number of workers.

Sources: The JIP database 2009 and METI (2000).