A Comparison of Human Capital and Productivity across Prefectures: Studies Based on Japan's Prefecture-level KLEMS Data[1]

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Japan's Prefecture-level KLEMS data (the R-JIP Database) is compiled in order to make productivity comparisons across 23 industrial sectors in Japan's 47 prefectures. It contains prefectural employment data cross-classified by gender, age, education, employment status, and industry of employment. Using these data, we construct a cross-prefectural index of human capital that captures the quality of the labor force available in each prefecture. Our index is based on the multilateral index proposed by Caves, Christensen, and Diewert (1982), which can be naturally applied to multi-regional comparisons of labor input. Although differences in the quality of the labor force across Japanese prefectures greatly converged in the more than four decades since 1970, there still remains a significant gap – to the extent that the level in the prefecture with the highest labor quality is 1.3 times that of the prefecture with the lowest. The main source of this gap in recent years has been differences in the composition of workers' educational attainment. Moreover, we find that one of the reasons for the cross-prefectural differences in the total amount of human capital is the migration of young workers to more prosperous prefectures.

[1] This is a revised chapter based on the work of Tokui, Makino, Kodama, and Fukao (2013b). Although our analytical approach is the same as in the previous paper before the revision, the previous paper used the data of the Regional-level Japan Industrial Productivity Database (R-JIP) 2012, and this chapter R-JIP 2017. Made-to-order data of the Japan's Population Census is used, because it is necessary to obtain numbers of workers in their place of work by industry and by characteristic. While R-JIP2012 utilized made-to-order data of the Population Census only for 1990 and 2000, R-JIP2017 took advantage of availability of such data including 1980 and 2010.

1. Introduction

In this paper, we construct a cross-prefectural index of human capital that captures the quality of the labor force available in each prefecture. Human capital is defined here as labor input reflecting overall differences in labor quality, which are determined not only by educational attainments of workers but also by other characteristics of labor force in each region such as age, gender, and industry of employment. This index of human capital is created from 1970 through 2010 and we can observe the changes in prefectural differences in labor quality in theses forty years. We also examine relationships between our constructed index of cross-regional differences in labor quality and regional productivities, and proceed to analyze which characteristic factors determine such differences. Furthermore, we discuss the degree of influence migration of young workers has on regional differences in human capital.

Various kinds of hypotheses have been proposed about the important role played by human capital in economic growth in the literature. One such hypothesis is an augmented Solow model that includes human capital, most notably proposed by Mankiw, Romer and Weil (1992). Their model indicates that economies that have high levels of human capital also promote accumulation of capital, and achieve higher per-capita income in the long run (steady state). On the other hand, the endogenous growth theory introduced by Lucas (1988) holds that, by allocating certain portion of human capital for more accumulation of the stock of human capital, the long-run (steady-state) growth rate itself will be shifted upward. Furthermore, Nelson and Phelps (1966) and Benhabib and Spiegel (1994), among others, focused on the phenomenon that economies with high levels of human capital are equipped with superior abilities to do research and development and to keep abreast of technological improvements. To apply such argument to regional development is a natural extension.

Based on these hypotheses, numerous empirical studies have been conducted, and one of the tricks of the research is how to measure the level of human capital in each region. There have been many studies in this area that used differences in the average educational levels of workers in their economy[2]. Such measurement of human capital that uses only schooling has a defect of neglecting human-capital formation through experience, such as on-the-job training.

In this paper, we construct index numbers of qualitative differences in human capital for the respective region that reflect more information besides educational attainments, such as age group, gender, and industry of employment. Our index is based on the multilateral index

[2] By the standard method of measuring the quantity of human capital, the equation of Mincer (1974) is estimated by regressing the logarithm of the wage on the number of schooling and on other characteristics. The result indicates the percentage of increase of the wage caused by additional year of schooling (the rate of return on schooling). The equation to obtain the quantity of human capital is $H = \exp(\phi S) L$, where H stands for the quantity of human capital, $\emptyset$ stands for the rate of return on schooling, S stands for the average years of schooling, and L stands for the number of workers. In this case, the quality of human capital is $H/L = \exp(\phi S)$. There is a survey article by Card (1999) on measurement of the rate of return on schooling.

proposed by Caves, Christensen, and Diewert (1982), which can be naturally applied to multi-regional comparisons of labor input. Our basic data come from Japan's Population Census, in which we can decompose prefectural labor input by cross-classified worker characteristics[3]. Measuring regional differences in human capital by this method has the advantages that various worker characteristics can be considered at the same time, and that regional differences in human capital can be specifically expressed as multiplication of man-hour-based labor inputs by labor quality. The latter feature is convenient in case of applying results to growth accounting[4].

There are disadvantages as well. Index numbers are constructed on the assumption that the price of each factor of production should correspond to its marginal productivity. If, for any reason, the price in reality diverges from this assumption, that much error would be contained in measurements of regional differences in human capital[5]. Moreover, if human capital formed through formal school education and through experience, such as on-the-job training, are of different nature, letting a single indicator represent both of them may face limitations from the outset. The results introduced in this paper warrant attention to those points[6].

This paper is structured as follows: Section 2 reports on the calculated index numbers of qualitative differences in human capital among prefectures, and discusses their correlations with productivities across regions. Section 3 analyze which one of the factors of labor-input-characteristic under consideration (gender, educational attainment, age, and industry) primarily causes the measured qualitative differences in human capital among regions, and how that has changed over time periods (from 1970 through 2010). Section 4 discusses to what extent the uneven distribution of human capital across regions is caused by migration of young workers, by applying the method of constructing index numbers relative to hypothetical situation. The last section summarizes the obtained results and discusses their implications.

2. Changes in Regional Gaps in the Quality of Human Capital Over Time and Labor

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[3] The index numbers of human capital by prefecture in Japan have been constructed by Fukao and Yue (2000), who used the wage as the weight for the employment rates of the respective gender and schooling in each prefecture. Shioji (2001) also constructed index numbers of human capital by prefecture with a similar method, factoring in schooling and age. Our study considers more characteristics at the same time and adopts a more sophisticated method to construct index numbers based on the work of Caves, Christensen and Diewert (1982).

[4] This study is part of the project to build the R-JIP database. Measurement of relative total-factor productivities (TFP) by region requires adjustment of qualitative differences in labor inputs among regions, which also determines the direction of this study.

[5] Studies have been conducted on differences in labor productivity by worker characteristic based on estimation of production functions using microdata. These studies confirmed the divergence between the labor productivity gap and the wage gap, too. This has been studied overseas by Hellerstein and Neumark (1995 and 1999), and Hellerstein, Neumark, and Troske (1999), among others. In Japan, studies focused on comparisons with the seniority wage system have been conducted by Kawaguchi, et al. (2007). In addition, studies focused on the labor productivity of self-employed workers have been conducted by Tokui, Makino, and Takahashi (2009). See Kodama and Odaki (2010 and 2012), too.

[6] It should be noted that measurement of the quantity of human capital based on estimation of the equation of Mincer (1974) also uses wage differences by educational attainment as proxies of productivity differences, and hence has the same issue.

Productivities

The challenge of comparing regions in terms of production-factor input, output, productivity is that, because any two regions presumably have entirely different compositions of production-factor inputs, industry structures, and production technologies, it is unacceptable to just pick one element among them, say, differences in labor input, ignore other conditions and make comparisons. A convenient method was proposed by Caves, Christensen and Diewert (1982) to overcome such difficulty and compare relative productivities among regions. In this paper, we apply their approach for measuring quantity and quality of human capital by region as shown below[7]: We can calculate, H_r, which is the aggregate human capital in region r relative to a hypothetical representative region (average region), where ω_{rn} stands for cost shares of labor inputs in region r for the respective characteristic n relative to the total labor cost in region r, and L_{rn} stands for labor inputs (man-hour) in region r for characteristic n. Bars over $\overline{\omega_n}$ and $\overline{\log L_n}$ indicate taking average over all regions. Here, characteristic n has N categories (n = 1 … N) cross-classified by industries × genders × educational attainments × ages. The calculation is as follows:

(1) $$\log H_r = \sum_n^N \left\{ \frac{1}{2}\omega_{rn} + \frac{1}{2}\overline{\omega_n} \right\} \left[\log L_{rn} - \overline{\log L_n} \right]$$

This index satisfies the transitive requirement. Accordingly, if we let region s be Tokyo and use it as the basis of comparison, the aggregate human capital in region r relative to region s (in this paper, Tokyo) can be obtained from Equation (1) as follows:

(2) $$\log H_{rs} = \log H_r - \log H_s$$

Furthermore, the aggregate human capital, H, can be decomposed into man-hour input L, and labor quality (quality of human capital) Q, given $H = L \cdot Q$. Hence, we have

(3) $$\log Q_{rs} = \log H_{rs} - \log L_{rs}$$

Based on the above relationships, the first term of the right side of Equation (3) takes the value obtained from Equations (1) and (2) as the aggregate human capital for region r relative to region s (Tokyo), and the second term takes the value of input quantity measured in man-hours for region r relative to region s (Tokyo). This enables us to construct an index number of the qualitative difference in human capital for any of region r, using region s (Tokyo) as the base region.

We have used the data of numbers of workers by the characteristic categories of gender, age (5-year intervals), educational attainment[8], and industry of employment (23 industries) for 1970, 1980, 1990, 2000, and 2010 from the Japan's Population Census. Then,

[7] For more detailed descriptions about derivation of the index and its necessary assumptions, see Tokui et al. (2013).

[8] There are no categories of educational attainment for self-employed workers. Accordingly, we have five categories, consisting of four categories of educational attainment for employees plus "any educational attainment for self-employed workers."

with Equations (1), (2), and (3), we calculated qualitative differences in human capital by prefecture for each year. The results are shown in Figures 1 and 2. Here, we only show the results for 1970 (Figure 1) and 2010 (Figure 2), in which the left side of Equation (3) is expressed as a quotient after exponentiation to cancel the log (by definition, the value is one for Tokyo, which is treated as the base region for comparison).

(Figure1)
(Figure 2)

Figure 1 shows wide gaps in the quality of labor between Tokyo and the prefectures in the lower-ranking group as of 1970 that were more than twice as large (with Tokyo as the basis of comparison)[9]. This situation was gradually resolved over the years. As Figure 2 shows, as of 2010, divergences between the top-ranked Tokyo and the lower-ranked prefectures were somewhat above 30 percent at most ($1 \div 0.8 = 1.3$). On the other hand, in the four decades, there has been no major change in the rank order among the prefectures, with regions in the higher-ranking group and the lower-ranking group tending to remain within the same group. However, a closer look reveals some changes in the rank order – Aichi Prefecture, which was ranked the sixth in 1970, moved up to the second in 2010, just below Tokyo.

We now turn to Figure 3 (1970) and Figure 4 (2010) to see relationships between qualitative differences in human capital and labor productivities by prefecture. These are scatter plots to identify correlations, with the horizontal axis representing differences in labor quality, and the vertical axis labor productivities, by prefecture. These charts show positive correlations between the quality of labor and labor productivity across regions, both 40 years ago and the present. This result is consistent with the hypothesis of Mankiw, Romer, and Weil (1992), which extended the Solow model by including human capital[10]. These charts reveal another interesting point. While the gaps in the quality of labor have been gradually shrinking over the years, resulting in the narrower horizontal width of the plotted area, the gaps in labor productivity, or the vertical width, has not been shrinking that much. Consequently, the plotted data points show rising patterns at increasingly steeper angles. This means that about the same degree of qualitative differences in human capital have increasingly larger impacts on labor productivity, as the years go by. This could be a reflection of the progress in transition to

[9] Kanagawa Prefecture was at the top in 1970, exceeding the second-highest Tokyo by about 20 percent. This was due to the industry factor, which will be explained later; in our factor decompositions (Figure 2-5), there is evidence that Kanagawa Prefecture had a concentration of higher-paying industries in this era.

[10] The Solow model is for one sector, however, where an abundance of human capital encourages investments and raises capital equipment ratios, which leads to higher labor productivity. In reality, the mechanism is not that simple because there are multiple industries with different intensities of factors. Although plotting qualitative differences in human capital and capital equipment ratios among regions reveals a weak positive correlation from 1970 to 1990, no such relation is observed after 2000.

knowledge-intensive industry structures[11].

(Figure 3)
(Figure 4)

3. Factor Decompositions of Index of Differences in Labor Quality among Regions

Our next question is, among characteristics of labor input that differ in composition among regions, which characteristic factor largely determines such regional gaps in the quality of labor. The factor decomposition of the Törnqvist index by characteristic, which we use to measure regional gaps in the quality of labor, was proposed by Jorgenson, Gollop and Fraumeni (1987). The method they applied to the Törnqvist index for time-series data can be applied to the index we created for cross-sectional data, because our index has the same form as the Törnqvist index. As our data contain four types of characteristics, by using this method, the index can be decomposed into four first-order effects, six second-order effects, four third-order effects, and one fourth-order effect.

The first-order effect can be obtained for each of the four types of characteristics. We now explain how to obtain the first-order effect, taking educational attainment as an example. The above mentioned Equation (1) calculates an index number that is a weighted sum of divergence rates from the geometric mean, the weight assigned to each rate being the share based on the categories of all types of characteristics. In order to extract from it only the first-order effect caused by compositional differences in educational attainment, we aggregate numbers of workers and cost shares by the category of educational attainment only, irrespective of other characteristics, and construct index numbers in the similar way. After converting into values relative to Tokyo and subtracting the rates of change in man-hour input quantity, the calculation process is the same. In this way, the first-order effect can be obtained for each of the four types of characteristics, i.e., gender, age, educational attainment, and industry of employment. It can be regarded as the primary effect of each characteristic.

It should be noted, however, that all of these first-order effects do not add up to the

[11] While we see these shrinking gaps in the quality of human capital among regions over the 40 years, what has gone in parallel was the tendency that small gaps in the quality of human capital now cause big gaps in labor productivity. There seems to be two mutually opposing forces at work. We computed values of the Theil index to measure gaps in economic sizes among regions in each year from 1970 to 2008, and decomposed them into labor productivity and labor input quantity. Our results show that the Theil index gradually declined from 1970 through the mid-1980s, showing shrinking regional gaps, which, however, gradually expanded again from the end of the 1980s until recent years, reverting in 2008 to the state of the early 1970s. During this time, the labor productivity factor was mostly on a declining trend, but the labor-input-quantity factor was on a rising trend. In the meantime, the former factor of equalizing labor productivity surpassed the latter factor of intensifying labor inputs by the mid-1980s, contributing to narrowing of regional gaps. In contrast, after the end of the 1980s, there was a stronger tendency of concentration in the quantity of labor inputs, while the tendency to equalize labor productivity petered out. (Rather, there has been an observed tendency of moderate expansion since the 2000s.) This resulted in larger gaps in economic sizes among regions. For details about the analysis of this phenomenon, see Tokui et al. (2013).

original value of the quality index. This is because these factors have relationships among themselves when affecting the quality index – for instance, between gender and educational attainment, or between educational attainment and industry of employment. Such relationships have the effects of higher order. With our data, they are the second-, third-, and fourth-order effects. For instance, the second-order effect of gender and educational attainment is calculated as follows. First of all, we produce index numbers by aggregating numbers of workers and cost shares by the category of gender and educational attainment, disregarding other characteristics. Next, we convert those into values relative to Tokyo and subtract the rates of change in man-hour input quantity, while also subtracting the first-order effects (log values) of gender and educational attainment. The process allows us to avoid double-counting, and obtain the second-order effect and then the third-order effect in sequence. The last residual will be the fourth-order effect. In this way, the quantity index can be completely decomposed.

We carried out this factor-decomposition calculation for 1970 and 2010. The results of decompositions confirm that the first-order effects largely account for the labor-quality index when decomposed, while the effects of higher orders from second to fourth have only marginal influence on the quality index overall. Figure 5 and Figure 6 show the decompositions for the first-order effects by prefecture for 1970 and 2010. In these figures, the total first-order effect is represented by the thick solid line, and index numbers of differences in labor quality by bars. Gaps between the line and the bars are the cumulative totals of the second and higher-order effects, which are shown to be not so large[12].

(Figure 5)
(Figure 6)

The factor decomposition for 1970 in Figure 5 reveals that industrial location in a region is an important factor that causes regional gaps, following educational attainment. The result also shows that, because the totals of the first-order effects of the four types overestimate the actual regional differences, there are positive correlations among those first-order effects. Next, we turn to the factor decomposition for 40 years later, 2010, in Figure 6. It is evident that the regional industrial-location factor faded away, and the factor of the composition of worker's educational attainments generates almost all regional differences in labor quality. The reason why regional differences in industrial location seem to contribute to differences in labor quality is that, as wage levels differ among industries, in a region predominantly occupied by low-wage industries, where only low-wage employment opportunities are available, its human capital

[12] Tokui, Makino, Kodama, and Fukao (2013b) fully decomposed from the first- to the fourth-order effect for 1970, while using the data of R-JIP 2012.

appears inferior. Recent studies on the wage structures in Japan reported that these wage gaps among industries have been shrinking[13]. It is conjectured that such a transition may explain why the industrial-location factor faded away in Figure 6[14]. Consequently, regional differences in the composition of worker's educational attainments became prominent[15].

4. Does Migration of Young Workers Generate Regional Differences in Human Capital?

As the foregoing analysis reveals, qualitative differences in human capital among regions, although having gradually decreased over the 40 years, still remain in recent years. Moreover, according to our factor decompositions of the index , although the major factors causing qualitative differences in 1970 were differences in the composition of educational attainments of workers and differences in industrial location among regions, the latter factor has faded out over the subsequent 40 years, leaving the former educational factor as the cause of the remaining regional qualitative differences in human capital. Our next question is to what extent migration of young workers across prefectures causes these regional gaps in the composition of workers' educational attainments.

It may sounds strange to some people that free transfer of labor causes uneven distribution of the production-factor across regions, which is our hypothesis here, given that the standard theories of production-factor movement postulate that a factor moves from factor-abundant regions with low marginal productivities to factor-scarce regions with high marginal productivities, making the distribution of such factor even. Transfer of labor, however, does not simply change numbers of workers; instead it is accompanied by human capital in the form of the educational levels of workers who move. Furthermore, there is a tendency of concentration in knowledge-intensive industries. Accordingly, we consider transfer of labor rather makes the distribution of human capital uneven. Shioji (2001), based on the results of previous studies that did not support the postulate that transfer of labor across regions contributes to convergence of income gaps, made a hypothesis that such results were due to the effect of movement of many workers with higher human capital. He tested this hypothesis regarding the transfers of labor across regions in the Japanese economy from 1960 to 1990[16].

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[13] See Bognanno and Kambayashi (2006) and Kambayashi, Kawaguchi, and Yokoyama (2008).

[14] We also constructed index numbers of qualitative differences in human capital in a matrix of prefectures times industries, the results of which were expressed in three-dimensional graphs. They also confirmed that gaps in human capital among industries have been shrinking over the years. For more details, see Tokui et al. (2013).

[15] Tokui, Makino, Kodama, and Fukao (2013b) also refer to the outcome of factor decomposition of growth rates of time-series index values of human capital for each prefecture. Generally in Japan, among first-order effects, the most contributing factor to the growth of the index is the educational attainment as we expected. The age factor does not contribute much to growth rates of the index in many regions in Japan. The only exceptions are the greater metropolitan areas such as Tokyo, Kanagawa, and Osaka. This means that young workers (mostly baby boomers) who moved in masses from their home regions to large cities around 1970 (the starting point of the measurement) contributed to formation of human capital in cities in the subsequent 40 years as they grew older.

[16] Shioji (2001) regressed changes in index numbers of regional human capital categorized by educational attainment and age on the net rates of inflow in each region and on other control variables. The results showed a positive effect

We tested whether migration of young workers causes regional differences in human capital by applying the method used in this paper for constructing relative index numbers of human capital, in a way different from the work of Shioji (2001). Our method is to focus on groups aged between 30 and 34 in 1990 and those in 2000, and consider a hypothetical situation in which all of them were employed in their prefecture of origin after completing school education. This is followed by comparisons between this hypothetical scenario and the actual composition of educational attainments of workers in each prefecture. Finally, we compute, had there been no transfers of labor across prefectures, how many times larger/smaller human capital would have been than the reality. The method allows us to calculate the impacts of inter-regional transfers of labor of these generations on aggregate human capital as well as on the quality of human capital, and to make inter-regional comparisons.

Our focus is on migration of young workers, as such transfers of labor are more likely to occur across prefectures at the time they enter the labor force right after completing school education. We also focus on groups aged between 30 and 34, because, by the time they reach these ages, most of them would have completed school education, and settled down in their place of work.

We begin by turning to groups who were aged between 30 and 34 as of 1990, 2000, and 2010. We go back 20 years (i.e., to 1970, 1980, and 1990) to obtain their populations by prefecture and gender when they were between 10 and 14 years old, still young and before graduating from junior high schools. We can count how many of them advanced to higher educational institutions after graduating from junior-high or high schools by applying the rates of education continuance by prefecture and gender for the respective year of graduation in the database of the Basic School Survey. In this way, we tracked how these age groups in these time periods formed their educational attainments by prefecture and gender. We also computed what proportion of them had died in 20 years before reaching 30 to 34 years of age, by applying the death rates for the respective age group and the time period recorded in the database of the Vital Statistics (we applied the nationwide figures of death rates). Their rates of employment by gender and educational attainment at ages from 30 to 34 were provided by the calculated rates of employment by prefecture, gender, and educational attainment based on the Population Census. By using those numbers, we obtained hypothetical numbers of workers (by prefecture, gender, and educational attainment) had they not migrated across prefectures.

Thus far, we have two sets of data: one is the factual numbers of workers aged 30 to 34 as of 1990, 2000, and 2010 in the respective prefecture who are categorized by gender and educational attainment; and another is the hypothetical numbers of their counterparts had there

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of net rates of inflow on changes in regional human capital, supporting the hypothesis that workers with higher human capital move. It was shown, however, that this effect is not large enough to solve the puzzle of income-gap convergence.

been no cross-regional transfers of labor. To compare those hypothetical values with the actual data, we applied an equation similar to Equation (1) in Section 2, which is Equation (4) below. Since we are comparing two sets of data of different kinds, we can apply Equation (1) as it is. The difference between Equations (1) and (4) is that while Equation (1) is an index for comparing two different regions (one of which is a hypothetical representative region), Equation (4) is an index for comparing a hypothetical case with the fact. In Equation (4), the superscript 'p' stands for the hypothetical case, and 'a,' the actual case, and 'p/a' on the left side of the equation means it is an index number of a hypothetical case when compared with the actual case. Moreover, the subscript, '30-34' is added to clearly indicate that the index number is constructed strictly for a 30-34 age group. In order to convert numbers of workers into their man-hour equivalents, we used the data of the average numbers of hours worked per employee by gender and educational attainment for groups aged between 30 and 34 for all industries combined throughout Japan that were extracted from the JIP Database. Likewise, in order to obtain hourly wage rates to calculate cost shares, we used the data of hourly labor costs from the same database for the same worker categories.

$$(4) \quad \log H^{p/a}_{30-34,r} = \sum_{n=1}^{6} \left\{ \frac{1}{2}\omega^{p}_{30-34,rn} + \frac{1}{2}\omega^{a}_{30-34,rn} \right\} \left[\log L^{p}_{30-34,rn} - \log L^{a}_{30-34,rn} \right]$$

The index numbers obtained from Equation (4) show that, had there been no transfers of labor across prefectures, how many times larger or smaller the aggregate human capital in each prefecture would be. Hence, if the index number is greater than one, the region experienced human-capital outflow, and if less than one, inflow. Figure 7 shows the results expressed in multiples by canceling log for all of 1990, 2000, and 2010 in the same graph with the prefectures ordered from the largest to the smallest in terms of their index value of human capital outflow as of 1990.

(Figure 7)

There are obvious differences in the heights between the left and right sides of the bar graph that shows movement from 1970, indicating large gaps between the outflowing and inflowing regions in terms of human capital, and massive movements of young people across regions in this period. Such trend gradually decreased over the subsequent 20 years. As for the period from 1990, there were regions, such as Niigata and Hokkaido that even changed from outflowing to inflowing regions. The greater metropolitan areas (Tokyo, Kanagawa, Saitama, and Chiba, however, continue to receive inflows of human resources, albeit in smaller scales.

The effect on the quality of human capital can be obtained by dividing an index number of the quantity of human capital by the ratio of the hypothetical value to the actual value in terms of the simple sum of labor inputs in man-hours for the 30-34 age group ($L_{30-34,s}^{p/a}$), which is Equation (5) below.

(5) $\log Q_{30-34,r}^{p/a} = \log H_{30-34,r}^{p/a} - \log L_{30-34,r}^{p/a}$

The results are illustrated in Figure 8 similarly as in Figure 7. With regard to effects on the quality of human capital, as expected, the greater metropolitan areas such as Tokyo, Kanagawa, Chiba, and Saitama received inflows of human resources that worked in favor of enhancing the quality of human capital. Figure 8, which looks at impacts on the quality of human resources is somewhat different from the previous cases of aggregate human resources, however, in that the impacts reflect various regional characteristics. For instance, Okinawa Prefecture, which is regarded as a prefecture that experienced outflows in terms of aggregate human capital, there were transfers of labor that worked in favor of raising the quality of human capital there; unlike many other outflowing prefectures, less educated workers in Okinawa were more inclined to move to other regions in search of jobs. Another example is Osaka in the period starting from 1970; although there were inflows in terms of aggregate human capital, the quality of human capital declined as a result, where workers with relatively low levels of education flowed in during this period.

(Figure 8)

When comparing those three time periods, the bars for the period starting from 1980 are outstandingly high in many regions from which human resources flowed out, indicating the occurrence of outflows of highly-educated young people from regional areas in this period. This could be because the 1980s was the period in Japan when there was a rapid increase in the percentage of people who went to college, and such young people moved from regional areas to urban areas after graduating from college.

Figure 9 and Figure 10 were created to examine whether such migration of young workers causes more uneven distributions of human capital across regions in terms of its impact on aggregate human capital and the quality of human capital, respectively. The prefectural data are plotted in the graph, where the horizontal axis represents the index numbers of gaps in the quality of human capital 20 years ago (Tokyo = 1), and the vertical axis the index numbers of the impacts made by migration of young workers. We drew the graphs for the period starting from 1970, when there were massive movements of young human resources.

In Figure 9, the vertical axis represents the index numbers of the impacts on aggregate human capital. The graph clearly shows a negative correlation, indicating that regions with low-quality human capital tend to have outflows of human capital, and regions with high-quality human capital tend to have inflows of human capital. As we initially predicted, this result confirmed that, in terms of aggregate human capital, migration of young workers causes more uneven distributions of human capital across regions.

(Figure 9)

But when we drew Figure 10, letting the vertical axis represent the index numbers of the impacts on the quality of human capital, this time, a negative correlation like the one seen in the preceding graph is no longer there. Both of the regions where migration of young workers enhanced and lowered the quality of human capital (where the index numbers of the impacts are less than one, and greater than one, respectively) have the index numbers of gaps in the quality of human capital as of 20 years ago that are dispersed from high to low. Based on the above, although there is surely a tendency that the effect of migration of young workers on aggregate human capital is concentrated in regions with human capital of higher quality, this is not necessarily so when it comes to its effect on the quality of regional human capital. There are region-specific characteristics in both outflows and inflows of human resources; there are some regions from which less educated workers are inclined to move out, whereas there are other regions that welcome such workers. Thus, we did not find a pattern that is common throughout Japan regarding the effect of migration of young workers on the quality of human resources.

(Figure 10)

Our last question is whether the impact of migration of young workers on qualitative differences in human capital among regions is considered significantly large in comparison to the initially observed levels of such differences. The qualitative differences in human capital among regions, as seen in Section 3 above, have drastically shrunk over the last 40 years, but around 30 percent of gaps still remained in recent years. In this regard, the influence of migration of young workers can merely explain eight percent or so, when we compare the number for Ehime Prefecture that has the largest drop in the quality of human capital (the degree of fall is 0.96 times, an inverse of the influence index number) and for Saitama Prefecture that has the largest rise in the quality of human capital (ditto, 1.04 times) as of 1990 (Figure 8). On the other hand, a comparison between Figure 7 and Figure 8 reveals a tendency that over the 20 years, although the influence of migration of young workers on aggregate human capital has been somewhat trending down, its influence on the quality of human capital has been trending up. This can be attributed to the recent transitions to service economies and knowledge-intensive industries, which should require our attention in future.

5. Conclusion

In this paper, we have proposed the methods for making quantitative as well as qualitative comparisons of human capital in relative terms among regions, while taking into consideration not only educational attainment but also other labor-input characteristics at the same time, by using the method of constructing index numbers proposed by Caves, Christensen, and Diewert (1982). Then we proceeded to calculate index numbers of quantitative differences in human capital among regions by using the data of the Japan's Population Census. After looking at the changes in qualitative gaps in human capital among regions in Japan from 1970 until recent years by using these index numbers, we have found that, although such gaps have shrunk over the 40 years, around 30 percent of them still remained. Moreover, there is clearly a positive correlation between such cross-regional gap in human capital and the gap in labor productivity, and the relationship between the two has been even getting stronger lately.

Next we carried out factor decompositions of qualitative differences in human capital among regions based on characteristics of labor input. As of 1970, the industrial-location as well as the educational-attainment were the two important causes of regional gaps. Over the subsequent 40 years, however, the industrial-location factor faded out, making the educational-attainment factor the major cause of the remaining regional gaps in the quality of human capital. The reasons for the disappearance of the industrial-location factor are that, as pointed out in previous studies on wage gaps, wage differences among industries are shrinking recently, and that non-manufacturing sectors, which used to have huge regional differences in human capital within the same industry, came to show gaps that were trending down over the past 40 years.

It may be possible to partially explain the observed regional differences in human capital by migration of young workers, if their willingness to move across prefectures varies depending on the level of their educational attainments. To test this idea, we calculated how much regional gaps in aggregate human capital and in the quality of human capital are caused by migration of young workers, by applying the method of index numbers used in this paper. Our results confirmed that migration of young workers significantly impacts regional human capital in terms of its aggregate value, causing uneven distributions of human capital across regions. When it comes to the quality of human capital, however, there is no such tendency, and the influence is minor, according to our findings.

Based on the above, one can readily speculate that each region's very ability to develop human resources has a crucial importance in regional differences in human capital. This should be seriously acknowledged as a fact, given the prospect that Japanese industry sectors likely to have comparative advantages in future are knowledge-intensive sectors. One of information types of labor characteristics not considered in this paper was occupations. Whether incorporation of this in the same analysis will produce robust results is a subject for future research.

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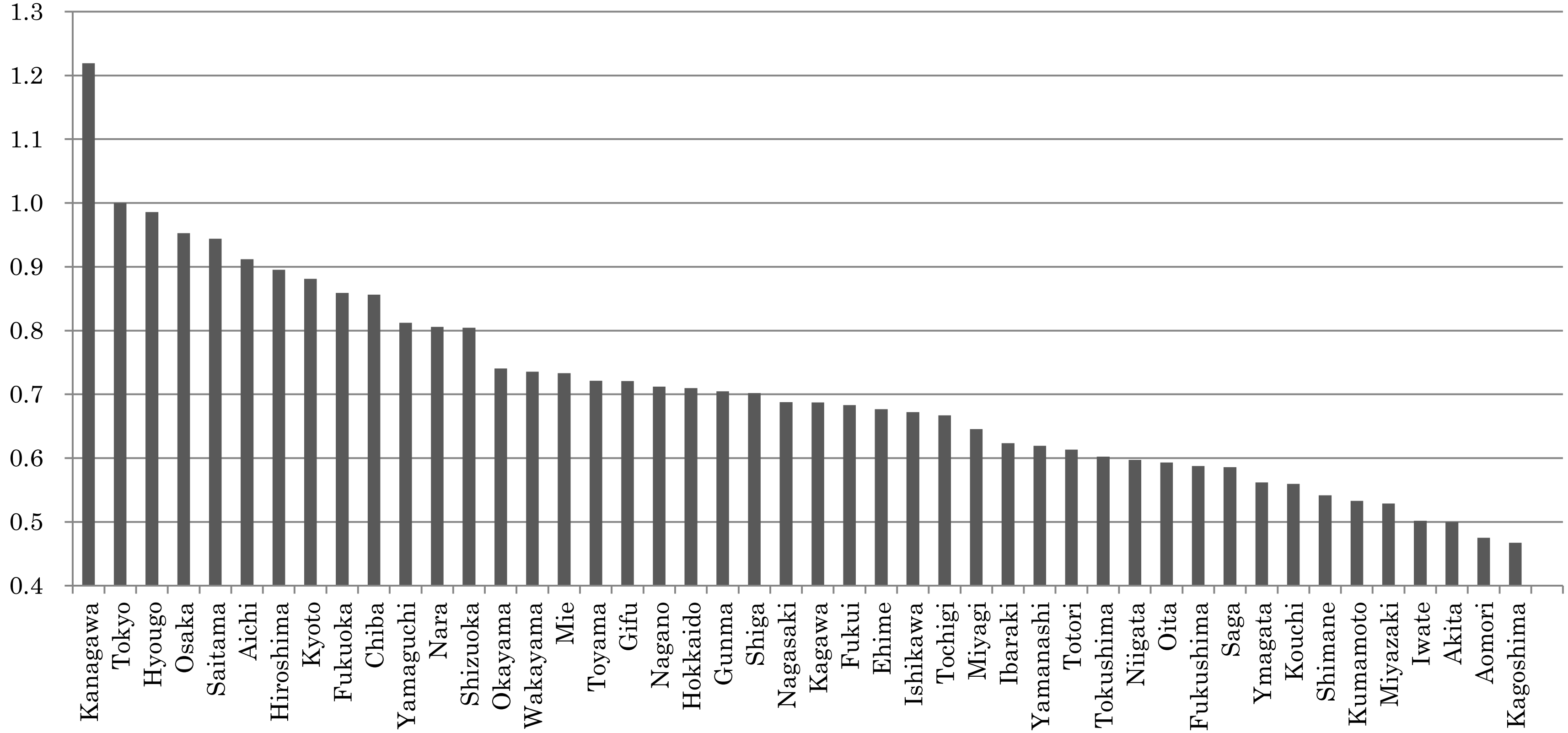
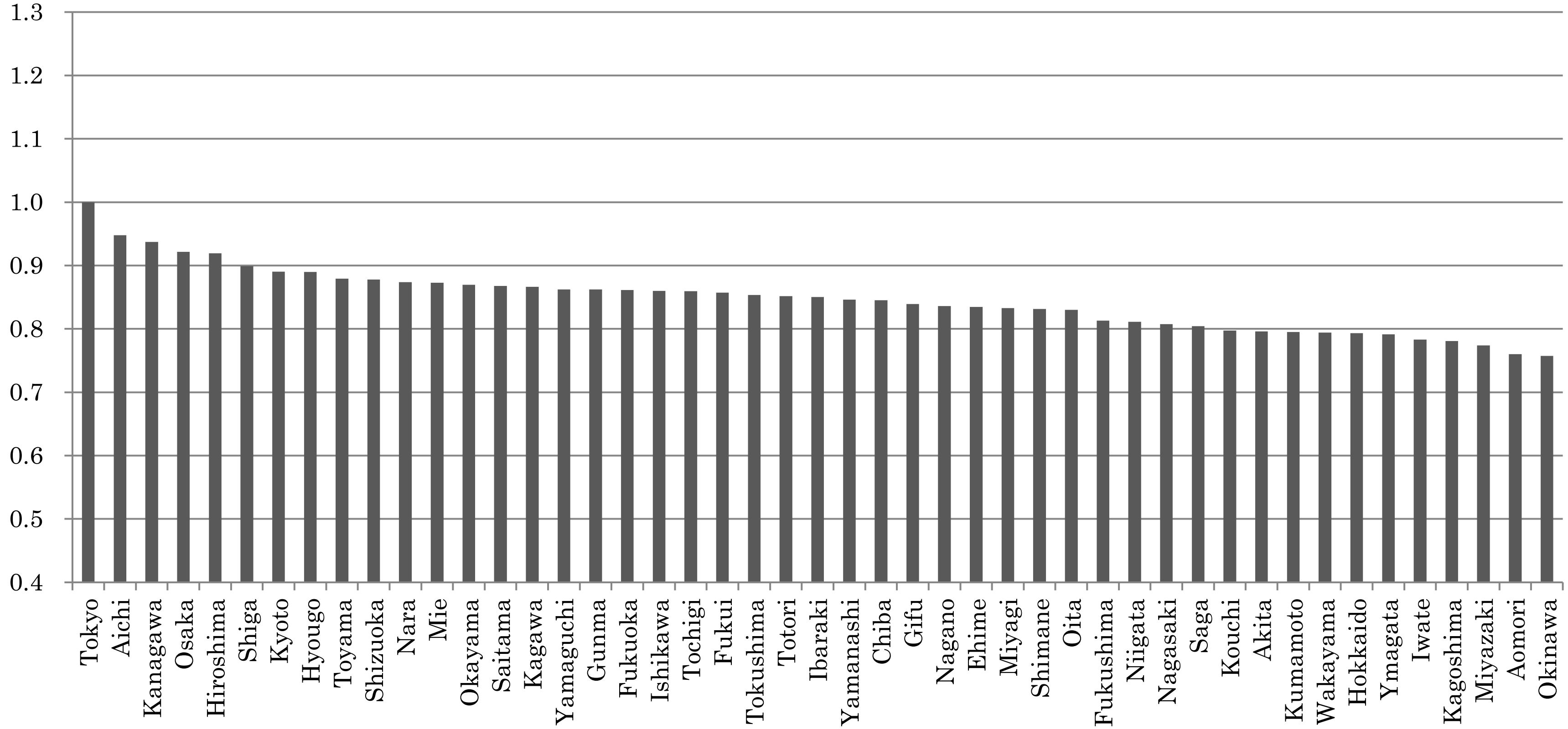
Figure 1: Regional Comparison of Labor Quality, 1970



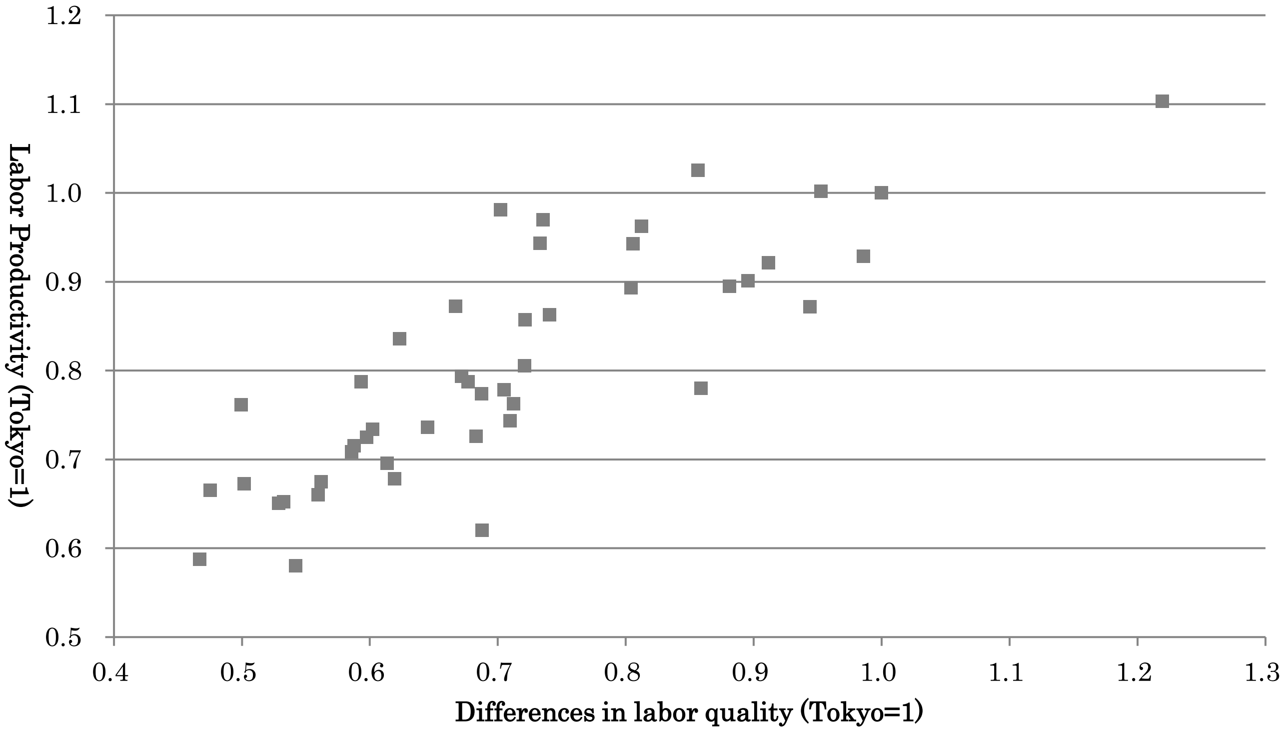
Source: Authors' calculation / R-JIP 2017 database

Figure 2: Regional Comparison of Labor Quality, 2010



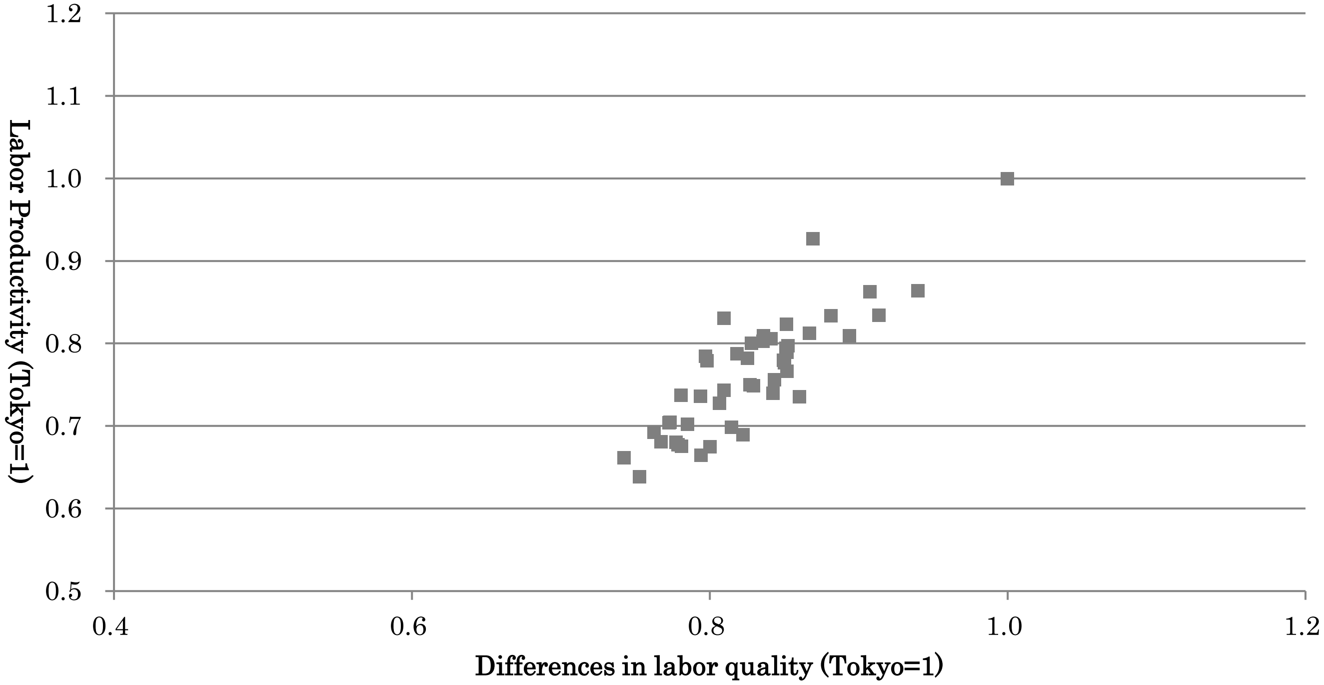
Source: Authors' calculation / R-JIP 2017 database

Figure 3: Correlation between Regional Labor Quality and Labor Productivity, 1970



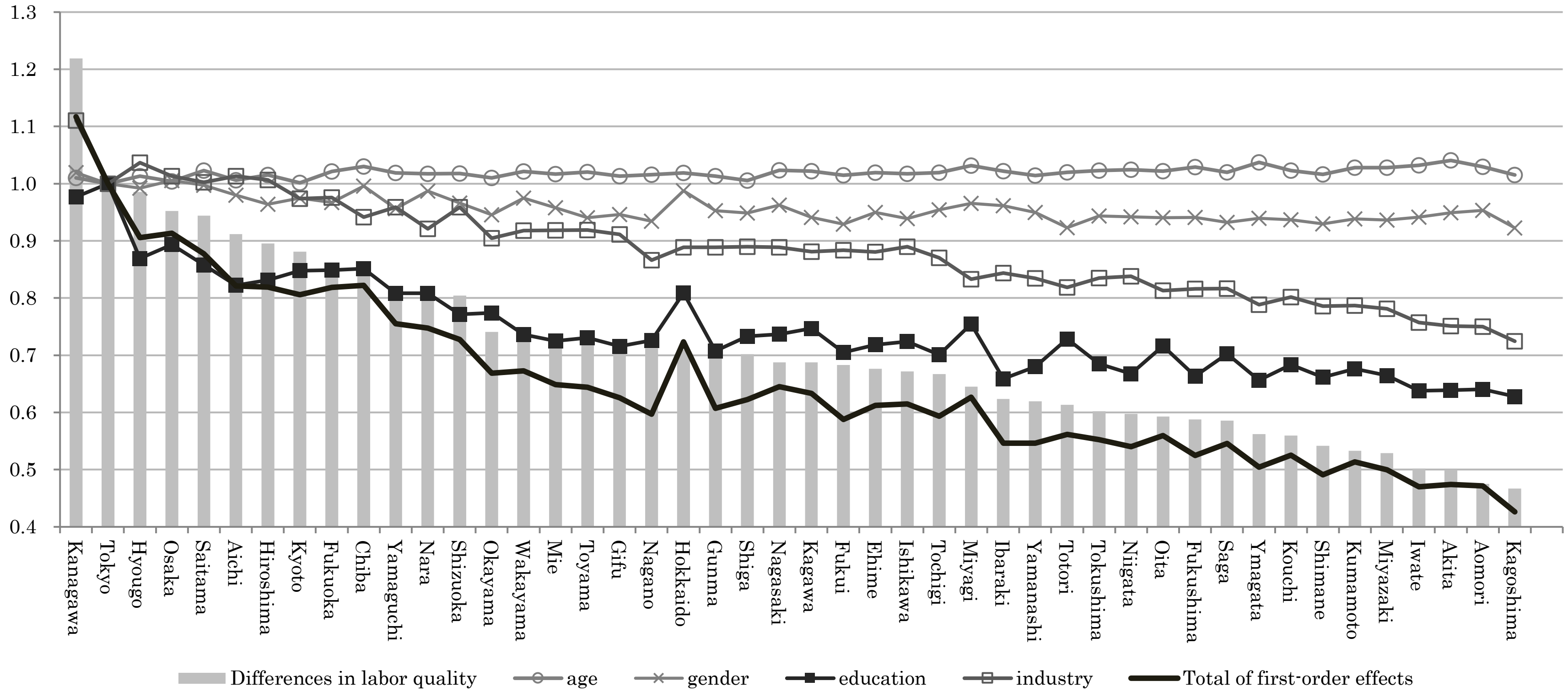
Source: Authors' calculation / R-JIP 2017 database

Figure 4: Correlation between Regional Labor Quality and Labor Productivity, 2010



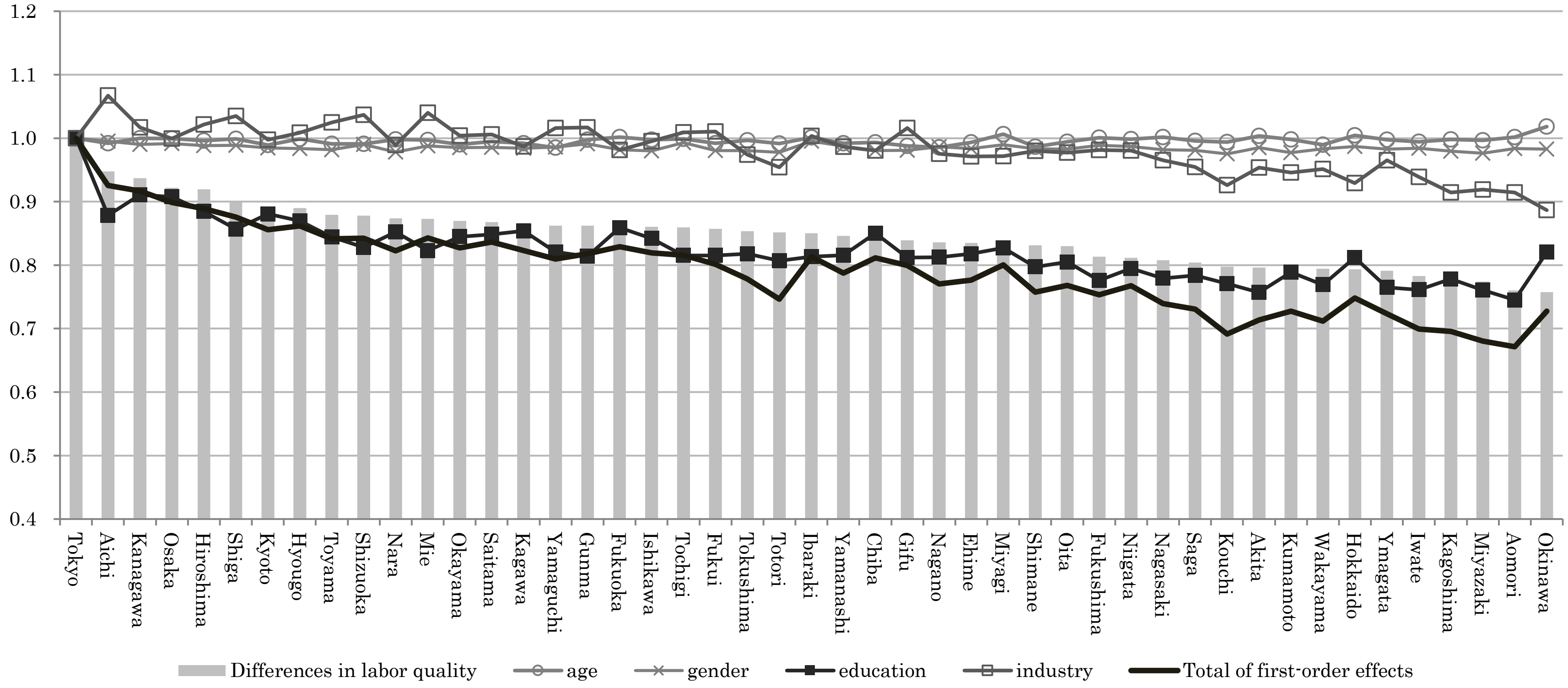
Source: Authors’ calculation / R-JIP 2017 database

Figure 5: First-order Factor Decomposition of Regional Difference Index of Labor Quality, 1970



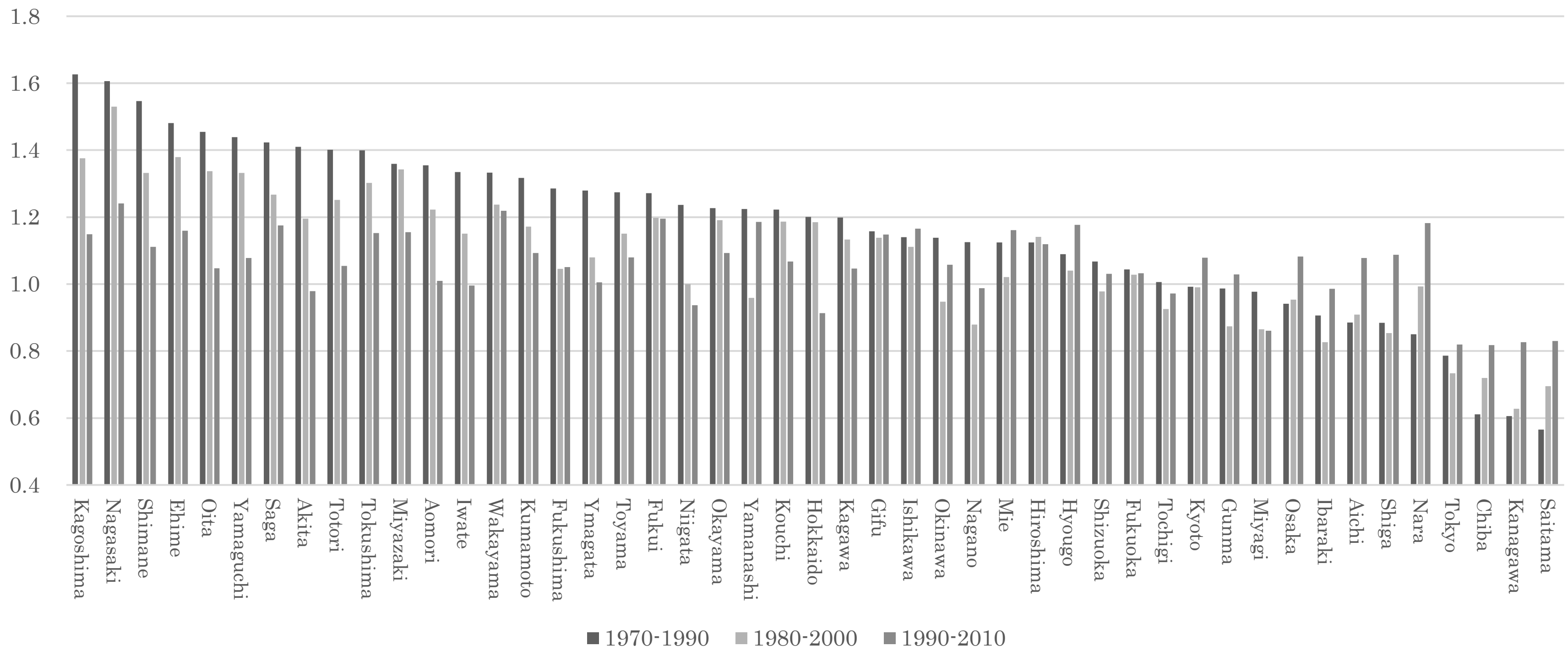
Source: Authors’ calculation

Figure 6: First-order Factor Decomposition of Regional Difference Index of Labor Quality, 2010



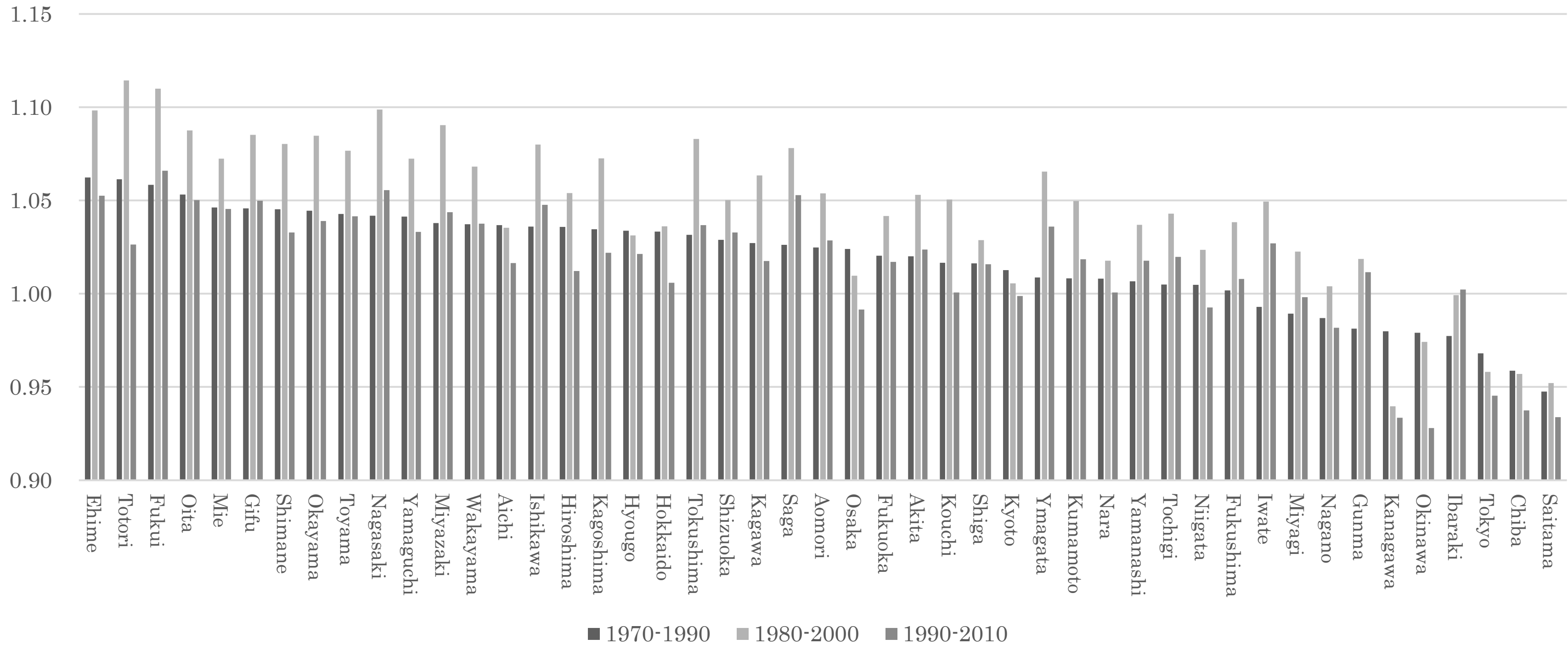
Source: Authors' calculation

Figure 7: Quantitative Impact on Regional Human Capital by Migration of Young Workers



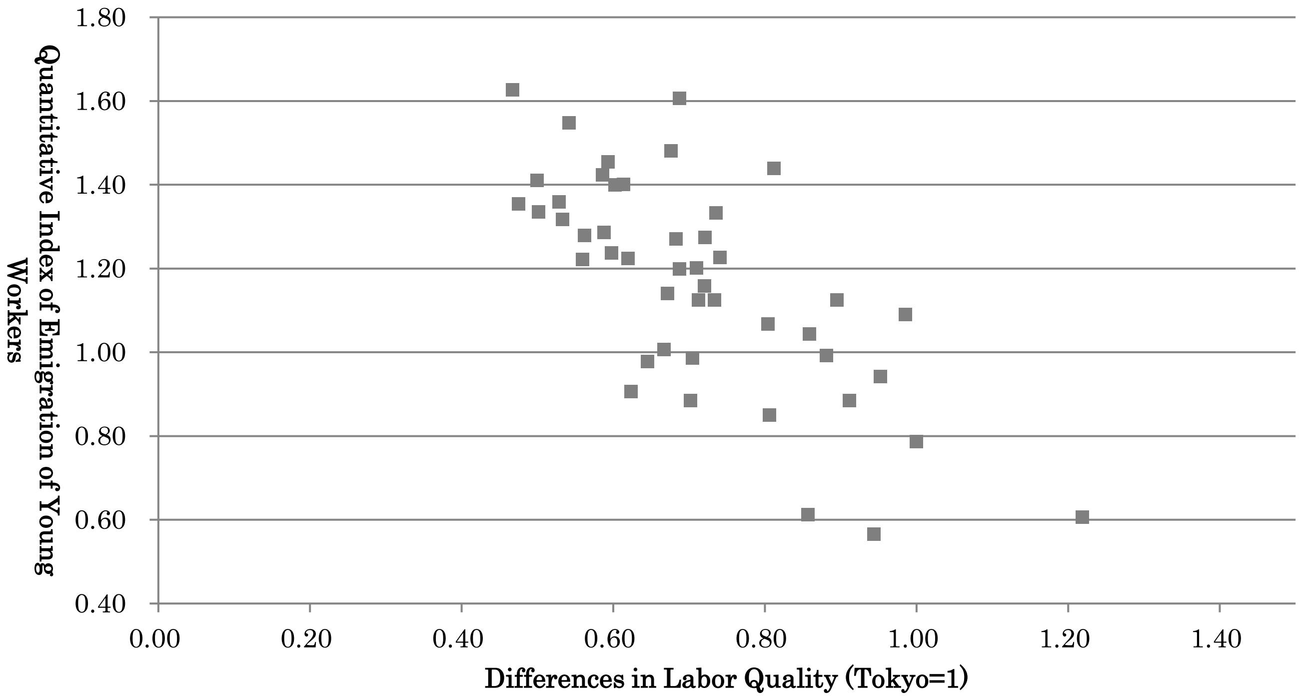
Source: Authors' calculation

Figure 8: Qualitative Impact on Regional Human Capital by Migration of Young Workers



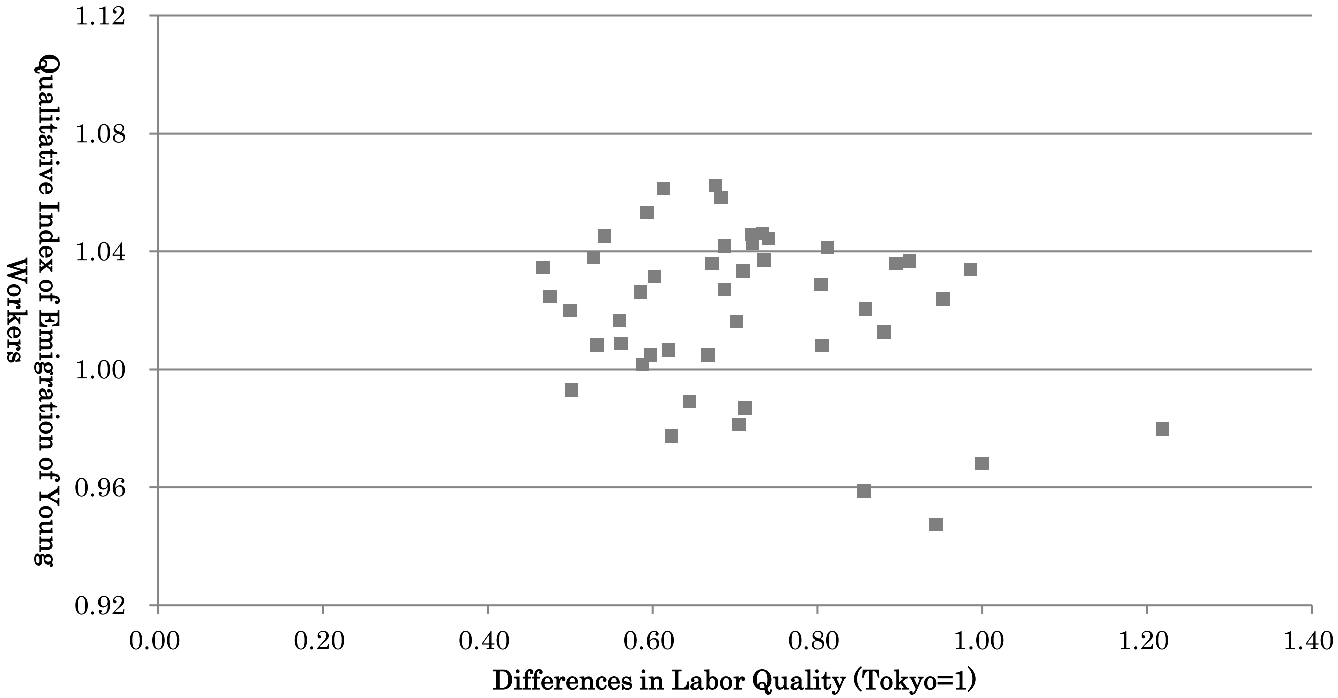
Source: Authors' calculation

Figure 9: Is there Agglomeration Effect on the Amount of Human Capital by Migration of Young Workers?



Source: Authors' calculation

Figure 9: Is there Agglomeration Effect on the Quality of Human Capital by Migration of Young Workers?



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