Demographic Change, Human Capital, and Economic Growth in the Republic of Korea¹

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Abstract

In this study, we construct a measure of human capital for the Republic of Korea using micro datasets on labor composition of age, gender, education, skill, and wage rate. Over the past three decades, human capital has grown steadily at about 1% per year, contrasting to a continuously declining trend of total work-hours. This growth has been driven by the rise of better-educated and skilled baby boom cohorts. A growth accounting exercise shows that human capital contributes significantly to economic growth; it accounted for 0.8% points of annual GDP growth over the period. Human capital is projected to remain a major growth factor over the next two decades as the increase in educational attainment continues. Increased employment rate of elderly or female workers reduces the aggregate human capital growth while increasing the available labor. On the other hand, improving cognitive skills, given the level of education, can contribute significantly to human capital growth.

Keywords: Demographic change, Education, Growth, Human capital, Skill

JEL Classification Codes: I25, J24, O47, O53

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1. Introduction

The Republic of Korea (henceforth, Korea) is known for its economic accomplishments. It grew at an average rate of 8.1% each year from 1965 to 2010,⁴ making it one of the fastest growing economies in the world. Numerous studies on the backdrop of Korea's economic achievement have pointed out the improvement in human resources, alongside higher savings and investment ratios, greater trade openness, and improvements in rule of law, as significant factors for this growth (Lee, 2016).

The expansion and upgradation of the workforce have played a critical role in helping Korea catch up with the economic development of advanced economies. In the early stages, Korea enjoyed a large demographic dividend as large baby boom cohorts reached working age, boosting the nation's productive capacity. The nation has also accumulated a stock of educated workforce at an unprecedented rate, backed by a strong household demand for higher education, and high public investment in the education sector. The abundant supply of well-educated labor force has allowed Korea to improve the competitiveness of its industries, transforming the economy into one of the world's top exporters.

The purpose of this paper is to investigate how Korea developed human capital during the period from 1986 to 2016, and assess the sources of human capital growth. We construct a measure of human capital using extensive micro labor-survey datasets on the composition of age, sex, education, and wage rates. Human capital growth is defined as an improvement in labor quality or worker productivity through education, skills, and experience. We then analyze the extent to which human capital contributed to GDP growth during this period using the growth accounting technique. We also construct projections of human capital growth over 2017 - 2040

⁴ GDP growth rates are based on the data from Penn World Table (PWT) 8.1 (Feenstra et al., 2015).

considering changes in population structure, educational attainment, employment rate and skills.

The importance of human capital accumulation for economic growth is well-established in the literature (Lucas, 1988; Mankiw et al., 1992; Barro and Sala-i-Martin, 2003). Previous studies show that human capital growth is mainly driven by rising educational attainment (Aaronson and Sullivan, 2001; Jorgenson and Fraumeni 1992; Jorgenson et al., 2002; Fernald and Jones, 2014; Jorgenson et al., 2016). Many researchers have used total schooling years as a measure for country-level human capital (Barro and Lee, 1994; Cohen and Soto, 2007; Lee and Lee, 2016). Others have used the estimated rate of return on schooling across the levels of education to construct the aggregate measure of human capital stock (Hall and Jones, 1999 and Jones, 2014). Recent studies have tried to incorporate explicitly the difference in quality of education across countries and over time. Juhn et al. (2005) used data from the 1940-1990 United States (US) Census, and established that the average quality of college graduates declined as college education expanded. Klenow and Bils (2000) considered teachers' quality, while evaluating the quality of education. Seshadri and Manuelli (2014) and You (2016) focused on government expenditure on education. Furthermore, Bratsberg and Terrell (2002) and Schoellman (2012) used the estimated returns on schooling of immigrants in the US to measure the quality of education in their countries of origin. Various studies assessed the impact of educational quality on workers' earnings, both within and across different countries (refer survey in Hanushek and Woessman, 2008). Some studies focused on the labor quality differences across cohorts with the same levels of educational attainment. Hendricks and Schoellman (2014) used test scores as a direct measure of cognitive ability, with data from the National Longitudinal Study of Youth, 1979. Hanushek et al. (2015) adopted skill proficiency of adults in Organisation for Economic Co-operation and Development (OECD) countries in three domains, namely, literacy, numeracy, and problem solving.

Based on this existing literature, we estimate human capital growth in the Korean economy by utilizing micro datasets over the period 1986–2016 and investigate the sources of human capital growth by quantitatively assessing the effect of changes in demographic structure, employment rate, educational attainment, and wage rates among different worker types on human capital growth in the Korean economy. We then analyze the contribution of human capital growth towards Korea's economic growth, using the growth accounting approach. Although there is a considerable body of literature on human capital in the US and other countries, only a few papers have explicitly focused on measuring Korea's human capital growth using micro data and analyzing quantitatively its role in economic growth. Some studies such as Young (1995), Kim and Topel (1995) and Lee (2016) have analyzed labor resources and economic growth in Korean economy, but our analysis incorporates more extensive data over the period of 1986-2016 and focuses on analyzing the measurement, sources and role of human capital growth. This paper fills this gap and also contributes to the literature by measuring the skill proficiencies of Korean workers using the Programme for the International Assessment of Adult Competencies (PIAAC) survey data. This method assesses the extent to which skill proficiencies have impacted human capital growth. Furthermore, this paper provides projections of labor-quantity and quality growth, with various hypothetical assumptions over the period from 2017 to 2040. It further examines the role of human capital growth in Korea's economic growth in the coming decades.

The remainder of this paper is organized as follows. Section 2 discusses the methodology and data used to measure human capital, and briefly overviews Korea's labor market developments since 1986. Section 3 constructs the estimates of labor quantity and human capital from 1986 to 2016, and discusses the sources of Korea's human capital growth. Section 4 investigates how adult skill proficiencies are related to human capital. In Section 5, we estimate the contribution

of human capital to Korea's economic growth. Section 6 presents projections of human capital growth over the period 2017-2040. Finally, Section 7 presents the concluding remarks.

2. Data and measurement of human capital growth

2.1 Definition of human capital growth

We define the overall labor input as an aggregate of labor inputs from different categories classified by gender, schooling, experience (age), and other characteristics of labor input. The overall labor input (H) incorporates both the quantity and quality of the labor force.

(1)
$$H = L \cdot h$$
,

where labor quantity (L) is measured by the number of total work hours, and labor quality (h) is related to the average productivity of worker developed through education, skills, and experience. We use labor quality as a measure of human capital stock (per worker) in an economy.

The growth rate of aggregate labor input is expressed as the share-weighted aggregate of the components where the weight is determined by the relative productivity or relative wage (Jorgenson and Stiroh, 2000; Jones, 2014).

(2)
$$\Delta ln H = \sum_g v_g \Delta ln L_g$$
,

where L_g indicates the quantity of the labor input in category g. The weight is the share of labor income attributed to each labor input in category g:

(3)
$$v_g = \frac{W_g \times L_g}{\sum_g W_g \times},$$

where w_g is the wage rate of labor input in category g. Equations (2) and (3) reflect substitution

among heterogeneous types of labor in each category with different marginal products.

The growth of human capital is defined as:

(4)
$$\Delta lnh = \Delta lnH - \Delta lnL = \sum_g v_g \Delta lnL_g - \Delta lnL.$$

As can be shown in Equation (4), we can define the growth in human capital or labor quality as the difference between the weighted growth, and the unweighted growth of work hours, wherein the weights are the shares of labor income.⁵ The unweighted growth of work hours (ΔlnL) indicates the growth in labor quantity. In Equation (4), human capital growth is determined by changes in the composition of total work hours and wage rates among the different categories. For a given total of work hours, human capital improves when the employment of more-productive, higher-wage workers increases and substitutes forthat of lessproductive, lower-wage workers in production.

Labor quantity, i.e., total work hours, L is the sum of hours worked by workers in each type g, L_g , which is the product of (i) average work hours per month of workers of this type, μ_g , (ii) the employment rate of workers of this type, E_g , and (iii) the population of these workers , P_g . This can be expressed as:

(5)
$$L = \sum_l L_g = \sum_g \mu_g E_g P_g .$$

2.2 Data

In order to construct the human capital index, the labor quantity variables and wage rates are required. Unfortunately, Korea does not have a unified data set that contains the total work hours and wage rates like the Current Population Survey (CPS) in the US. Therefore, we

⁵ A drawback of this approach is that the labor income share can increase for reasons other than changes in labor productivity.

combine two data sets to construct the human capital index. Labor quantity variables, the number of workers, and the hours worked are taken from the *Annual Report on the Economic Active Population Survey* (EAPS) collected by the National Statistics Office (NSO). The datasets contain underlying micro data based on employment status information collected from approximately 32,000 households every year and are used by the Korean government to estimate official labor market variables such as the unemployment rate in Korea. EAPS has collected employment status data since 1986 and wage rate data since 2001. In order to consider a longer wage series, we combine two other micro datasets, namely the *Basic Survey on Wage Structure* (BSWS) from 1980 to 2007, and the *Survey on Work Status by Employment Type* (WSET) from 2008 to 2016. The advantage of the BSWS and WSET datasets is that the wage rates are directly collected from establishments and, therefore, are less exposed to measurement error than EAPS' household survey data. Due to the limited coverage of EAPS data, our estimation of human capital covers the period from 1986 to 2016.

Group	Num. of Groups	Description		
Sex	2	Male, Female		
Education	4	Secondary School Dropouts	(HSD, <12)	
		Secondary School Graduates	(HSC, =12)	
		College Dropouts	(SMC, 13-15)	
		College Graduates	(CLC, ≥16)	
Age	8	25-64 years, by 5-year-intervals		

Table 1: The classification of groups

Labor quantity is calculated by the number of monthly hours worked by employed individuals between ages 25 and 64.⁶³ The human capital index is estimated by utilizing data on

⁶ The workers in this analysis include those who are self-employed and family workers, as well as temporary

the composition of workers, as well as their wage rates, cross-classified by sexes (2), educational levels (4), and age (experience) groups (8), and end up with 64 ($=2\times4\times8$) types of workers. Data on work hours, employment rate, population, and wage are computed for each category. Once the worker type is defined, we construct the human capital index using the weighted sum of total work hours across individuals in each of the 64 categories, using Equation (4).

The choice of worker type can be further disaggregated by incorporating other characteristics of workers. If different categories of labor inputs cannot be distinguished from the data, the labor input is measured using the aggregate labor input weighted by the overall labor share. This can underestimate the true contribution of labor inputs if the composition of labor shifts over time toward types of high quality. In Section 4, we examine our estimates by adding cognitive skills measured by adult skill proficiency scores as another category of labor input.

2.3 Overview of Korean labor market

In this section, we illustrate the evolution of population, employment rate, and work hours, which constitute the labor quantity. First, we present the trend on each component from 1986 to 2016, and then the life-cycle patterns of employment rates and work hours for selected years. Figure 1 shows that the annual growth rates of the population aged between 25 and 64 years have declined continuously over time, from about 3% in the late 1980s, to below 1% in the 2010s. It also shows the projections by Statistics Korea (2016) from 2017 up to 2030. The growth rates of the population aged 25-64 are forecasted as negative, and consequently, the size of the population aged 25-64 is expected to decline in the coming decades. Due to this fact, the shrinking working age population is a major concern for long-term growth in Korea.

employees. We assume the wage rates for these workers are equal to those of the wage workers in each category.

Figure 1: Population projection: 1985-2030

Figure 2: Population structure: 1985-2040



Figure 2 shows the change in the age structure of the population in selected years—1985, 2000, 2015, 2030, and 2040. There were continuous increases in the percentage of the working age population from 1985 to 2015 due to the Korean baby boom in late 1950s, and early 1960s. However, the projected values for 2030 and 2040 show that due to low fertility rates and longer life expectancy, the share of the population over the age of 60 will rise rapidly in the coming decades due to low fertility rates and longer life expectancy.









Figure 3 presents the trend of employment rates by gender, at the aggregate level for the period from 1986 to 2016. The aggregate employment rates had increased in the 1980s and 1990s, but suffered a severe drop during the Asian financial crisis in 1997-1998. They have shown a mild recovery since then. The increase in overall employment rates after the crisis is mostly driven by the steady rise in female employment rates. Female employment rates have exceeded the pre-crisis level, whereas the male employment rates have barely been restored to their pre-crisis levels. Nevertheless, the employment rates for males remain far higher than females. Korean females tend to manage household affairs and child rearing, and correspondingly, participate less in the labor market.

Figure 4 displays the average monthly hours worked by gender. These average work hours are computed only for employed workers. The average monthly hours of males were higher than those of females throughout the period. However, the average work hours for both males and females have continued to decline since late 1980s with significant drops during the Asian financial crisis.



Figure 5: Change in employment rate by age group, selected years

(a) Male



We have also examined the life-cycle patterns of employment rates and working hours during selected years – 1986, 1996, 2006, and 2016. Figure 5 presents the change in employment rates over the life cycle by gender. The cross-sectional age-employment rate profiles are inverted-U shaped curves for males, as their employment rates tend to rise with age in their 20s and 30s, staying high in their 40s and 50s, and then the rates begin to decline. The data show that employment rates for males over 50 years are significantly higher in 2016, than in the earlier years. In contrast, the rates for the males aged 25-29 in 2016 are relatively lower than in the earlier years. These phenomena reflect the increased labor market participation of old-aged people but a relatively high youth unemployment in recent years. Unlike males' employment, females' one in Korea follows an M-shaped pattern because there are significant drops in their 30s, attributed to a career interruption after marriage or childbirth but tend to rise during their 40s and 50s. This pattern is more prominent in recent data, as employment rates for females in their 20s and 40s are much higher than for those in their 30s.



Figure 6: Change in work hours by age group, selected years

(a) Male

(b) Female

Figure 6 shows the life cycle patterns of average work hours by gender for the selected years. The average work hour profiles move downwards from 1986. These results are consistent with the decreasing patterns of average monthly worked hours in Figure 4. The cross-sectional profiles for work hours are similar to those for employment rates. The patterns show mildly inverted-U shaped curves for males, and M-shaped curves for females. The work hours for females are less than those for males across all ages.

To construct a measure of human capital index based on Equation (4), wage rates across different worker types are important. For instance, the change in population age structure has a direct effect on human capital growth, based on the age-wage profiles of the workforce. Patterns of age-wage profiles are also examined. The typical estimates of the return on age using Mincer wage regressions show that earnings grow as a concave function of age, implying that the productivity of prime-age workers (35-54 years) is high relative to young-age workers (25-35 years) or old-aged workers (55-64 years). As can be seen in Figure 7, the cross-sectional age-wage profiles for males confirm this pattern. For the females, however, the wage begins declining in their late 30s, reflecting a career interruption after marriage and child rearing, and re-entry to lower-wage jobs in older ages. Noting that the cross-sectional Korean labor census data compare different people born in different years at different points of their life cycles, the cross-sectional profile does not distinguish between "age effects"-the direct consequences of growing older, and "cohort effects"-the consequences of being born at different times (Paccagnella, 2016). Hence, the cross-sectional age-wage profiles can understate the life cycle earnings growth when there is growth in average wages.



Figure 7: Age-wage rate profiles by gender, selected years (hourly wage)

The age-wage profiles also depend on education, work experience, job characteristics, and other factors that influence the productivity of older workers relative to younger workers. Identifying the "pure" biological effect of age requires excluding the effects of any other characteristics related to age. The age-productivity profile of Korean workers reflects the significant difference in educational attainment across age groups. The higher educational attainment of younger workers compared to older workers contributed significantly to the productivity gap between old-aged and young-age workers. As completion of education among adults as well as old-aged people has risen over time, the age-productivity profile shifted upwards and changed the shape of the age-productivity profile, by making the average wage of old-aged workers decline gradually.



Figure 8: Age-wage rate profiles by education, selected years (hourly wage)

(a) Secondary school graduates

(b) College graduates

Figure 8 presents the cross-sectional age-wage profiles by education level for the selected years – 1986, 1996, 2006, and 2016. We observe wide gaps in wage levels between higher-secondary graduates and college graduates. The age-wage profiles for higher-secondary graduates show the mildly inverted-U curve, as the wage of old-age workers is lower than that of prime-age workers. In contrast, the college graduates' age-wage profiles show strong upward trends as wages continue to rise until the peak at 50-54 years and then begin to decline throughout the selected years, except in 1986. This may reflect higher productivity of college graduates, especially those who stay employed despite their old age. Nonetheless, this continuously upward sloping profile may also indicate the rigidity of the Korean labor markets, especially for the college educated workers. The lifetime employment, seniority-based wages, and promotion system allow little flexibility to adjust wages in line with observed productivity

3. Estimates of human capital growth

3.1 Labor quantity growth

We first construct our benchmark labor quantity index based on Equation (5). It is plotted as a black solid line in Figure 9. The average annual growth rate of labor quantity (i.e. total hours worked) from 1986 to 2016 was 1.31% (see Table 4). Labor quantity by this measure grew rapidly in the earlier period, at about 3.28% per year from 1986 to 1995. It experienced a severe drop to 0.13% during the 1997-98 financial crisis and then showed a mild recovery. Over the recent years, from 2011 to 2016, its average growth rate was at 0.50% per year.



Figure 9: Labor quantity index - benchmark and counterfactuals

Figure 9 presents the growth rates of labor quantity for three counterfactual cases. Using Equation (5), we can generate three different counterfactuals by holding one of the three factors, i.e., work hours, employment rate, or population across workers' types, fixed at its 1986 level. As can be observed from the green-dotted line (CF1) in Figure 9, the labor quantity index which was constructed based on the counterfactual assumption that the average work hours across workers' types did not change since 1986, grew much faster compared to the baseline. As observed in Figure 6, the average work hours have decreased since 1986 for all age groups.

When we adjust the average work hours in 1986, the negative impact of average work hours on the total work hours is eliminated, and the labor quantity grows faster than in the benchmark case.

The second counterfactual index (CF2), denoted by the red-dotted line, shows that labor quantity would have improved at a slower pace if employment rates had not changed since 1986. This is based on the fact that employment rates have continuously increased over the sample period except during the Asian financial crisis (Figure 3). Hence, once the employment rates are replaced with the 1986 values, the labor-quantity growth rates are lower than the benchmark rates. The last counterfactual (CF3) demonstrates that labor quantity would have decreased significantly if the population across worker type had been fixed at the 1986 level. This indicates that the population structure change with the rise of baby boom cohorts was a major contributing factor of labor quantity growth during the past three decades.

3.2 Human capital growth

Our benchmark human capital index is constructed based on Equation (4) and is presented in Figure 10. The index for human capital showed steady growth over the sample period. The average annual growth rate of human capital from 1986 to 2016 was 1.01% (see Table 4). Human capital grew at about 0.88% per year from 1986 to 1995, and at 0.72% per year from 2011 to 2016. It showed faster growth during the 1996-2010 period, at over 1.1% per year.

We construct four different counterfactuals by holding one of the four factors, i.e. μ_g , E_g , P_g , and w_g , constant at its 1986 level. As indicated by Equations (4) and (5), the changes in the structure of average work hours, employment rate, and population across worker type, and their corresponding wage share values are important for the estimation of human capital index. Note that the growth rates of work hours, employment rate, and population at the aggregate level do not have any impact on these counterfactual indices for human capital, while they affect those for

labor quantity.



Figure 10: Human capital index - benchmark and counterfactuals

The four counterfactual indices for human capital are also displayed in Figure 10. The first counterfactual (CF1) assumes no change in the structure of average work hours across worker type at the 1986 level. As observed in the figure, the change in average work hours has almost no effect on human capital. This result implies that the compositional change by work hours are not large enough to change the human capital growth. Next, we fix the employment structure across workers in 1986 (CF2). It has a small but positive effect on human capital. Note that the employment increases are mainly driven by the female employment increases (see Figure 3.). Therefore, if the employment rate is fixed in 1986, human capital may grow faster than the benchmark because it eliminates the increases of less-productive or lower-paid female workers although its effect on human capital is small. Human capital growth, however, would have decreased significantly, if no change had occurred to population structure across workers' types (CF3). The continued accumulation of a more-productive baby boom generation was a main contributing factor to human capital growth in Korea since 1986. Lastly, we apply a similar

counterfactual analysis assuming that the wage rate for worker type is set at the 1986 level (CF4). The counterfactual human capital index is higher than the benchmark. This indicates that the wage rate has increased more, for less-productive or lower-paid female workers since 1986. Thus, if relative wage rates had not changed since 1986, human capital would have grown faster over the past three decades. We will investigate this issue in detail in the next sub-section.

3.3 Source of human capital growth

In our framework, a worker's average level of human capital stock is equal to the sum of the shares of workers, weighted by relative wage rates across workers, cross-classified by gender, education, and age, divided by total number of workers. Human capital, therefore, is determined by substitution among heterogeneous workers with different marginal products or wage rates. When the share of worker types with higher-productivity increases, it promotes human capital growth.



Figure 11. Educational level by age group, selected years

Korea is well known for rapid improvement in educational attainment. Among the population

aged 15 and above, the percentage of workers with at least some secondary schooling soared from 37% in 1970 to 87% in 2010. The proportion of college educated persons has increased from 6% to 42% over the same period (Barro and Lee, 2013). Figure 11 displays the change in educational level by age group from EAPS data. There has been continuous growth in the shares of secondary and tertiary school graduates among workers, especially in the prime age group. The increase in population share of high-educated workers must not only reflect an increase in supply of high-educated workers, but also a demand for them. EAPS data shows that the employment rates for high-educated workers have been high, compared to low-educated workers.

Empirical investigation based on the Mincer-type wage regression shows that an additional year of schooling is associated with a significant increase in earnings or labor productivity. We estimate the Mincer-type wage equation using Korean labor data from 1986 to 2016.⁷ The estimates, shown with a black line in Figure 12, indicate that the premium of college education over secondary education ranged from 0.387 to 0.642. This implies that the marginal rate of return on college education was about 1.5-2 times higher than that on secondary education. Thus, the expansion of a college-educated workforce, combined with a relatively high wage rate, contributes to the strong human capital growth in Korea. An expansion in the supply of high-educated workers, leading to the equilibrium in the labor market. When the elasticity of substitution between high-educated and low-educated workers is greater than one, this raises the wage share of high-educated workers (Acemoglu, 2008). The increase in the supply of higher-educated workers leads to human capital growth, as long as their labor income share does not decline proportionally more.

⁷ The estimation applies to the cross-sectional data, and the estimated coefficients on the dummy for college education levels are reported.



Figure 12: Estimates of wage premium to college education: 1986-2016

Note: The estimation uses two micro datasets - *the Basic Survey on Wage Structure* (1980 – 2007) and *the Survey on Work Status by Employment Type* (2008 – 2016) from 1986 to 2016. The sample in these surveys includes permanent employees who earn wage and salary from their employers, excluding self-employed and family members. We restrict our sample to establishments with 10 or more permanent employees to ensure time series consistency between two datasets.

Figure 12 also presents the ratio of average wages between college graduates and secondary graduates, measured in the logarithmic scale. The values on blue line show that the relative wage rates have moved closely with the college premium estimates from the Mincer equation. The change in the relative wage by educational attainment is influenced by the change in the composition of labor force by sex and age. Keeping the sex and age composition fixed at the 1986 level, we calculate the relative wage rates, and present them using the red line. These adjusted values have also shown movements that broadly similar to other estimates. However, the adjusted relative wage rates are much higher than the college premium estimates (in black), or the unadjusted relative adjusted wage rates (in red) until 2007. They also showed little change over the period of 1997–2003 in contrast to the rising trend of the other estimates. The differences are possibly due to the changes in the supply of female college graduates, as well as

in the age composition of college educated workers. As shown in Figures 7 and 8, the wage gap between the genders has been large, and the age-wage profiles have varied a lot by educational attainment.

In order to appraise the effect of change in educational attainment, sex and age among workers on human capital, we construct three alternative wage series by cross-classifying wage in broader categories; i.e. (1) across sexes and age groups, (2) across education and age groups, and (3) across sexes and education. We compute the average wages for each broader cross group and match them to the labor input cross-classified in the benchmark in Section 2. Comparing these human capital indices with the benchmark, constructed from the benchmark wage series using cross-classification by sex, education, and age-group, we can identify the independent effect on human capital due to changes in composition of labor inputs across gender, education, or age-groups.

Figure 13 presents the alternative human capital indices, together with the benchmark. The two alternative human capital indices classified by education and age group, and by education and sex, are not very different from the benchmark. The index that is constructed using an alternative wage series with a broader classification of education and age is placed slightly above the original index. This implies that the alternative index, under the counterfactual that female wage rates are the same as male wage rates, underestimates the decline in productivity due to substitution of males with females. When an alternative wage series without the age variation is used, the human capital index is placed slightly below the original index. This is because the former underestimates wage increases caused by substitution of low-wage young workers with high-wage and more experienced workers, especially for males. This result indicates that a part of the human capital improvement is attributed to a pure age-effect, caused by the shift in employment toward higher-productive age groups.



Figure 13: Human capital indices with alternative classification of worker types

Note: The benchmark index is constructed based on the classification of workers cross-classified by two sexes, four educational levels, and eight age groups. Other alternative indices use wage series constructed with broader classifications.

As anticipated, the alternative human capital index, where education variation is excluded, deviates largely from the benchmark. This index displays almost no growth throughout the sample period. Therefore, the improvement in labor quality in Korea since 1986 was driven almost entirely by the substitution of less-educated, lower-productive workers with more-educated, higher-productive workers in employment. In the previous section, we find that the highly productive baby boom generation was a main contributing factor to human capital growth in Korea since 1986. Viewed in light of the findings in this section, this suggests that the higher productivity of the baby boom generation is majorly attributed to the growth in educational attainment.

4. Estimating human capital growth with adult skills

4.1 The effect of adult skills on wage

To measure the human capital index in section 3, we assumed that the productivity of workers depends on their education, gender, and age (experience). Another important factor to consider for productivity of labor is the skill proficiency of workers. A few studies have shown a significantly positive effect of adult skills on earnings, after controlling for other factors, including education level and experience. Using PIAAC⁸ data, Hanushek at al. (2015) show that adult skills have a significantly positive impact on earnings. Furthermore, Lee and Wie (2015) show that, based on Korean PIAAC data, an increase in adult literacy skills by one standard deviation is associated with an 8.3% wage increase among prime age workers on average.

Figure 14. Adult literacy proficiency by gender and education (a) By gender (b) By education



⁸ In 2008, the OECD developed the Programme for the International Assessment of Adult Competencies (PIAAC). The PIAAC assessed the skill proficiencies of adults aged 16 to 65 in three domains, namely literacy, numeracy, and problem solving, in technology rich environments (OECD, 2013).

Figure 14 (a) presents the age-skill profiles by gender in Korea, using literacy as a skill measure.⁹ Following Schwerdt et al. (2015), we normalize the scores with the mean and standard deviation to standardize them. The data on the distribution of skills proficiency by age group suggest that younger people tend to have higher skill proficiencies compared to older peers. The literacy gap between younger and older adults in Korea is larger compared to other OECD countries (Lee and Wie, 2017). The significant part of the age-skill relationship must reflect the impacts of educational attainment related to skill. Figure 14 (b) shows that young workers are better educated and more skilled than the older ones. Thus, the slope of the age-skill profile in Figure 14 (b) reflects the differences in both skill and educational attainment across age groups.

Ignoring the skill differences by education level overestimates the effect of education on productivity, and thus on human capital. The significant part of the age-wage relationship reflects the impacts of skill proficiency and educational attainment on wages. The age profile of skills and its effect on worker productivity is considered one of the major determinants for the age-wage profile (Maestas et al. 2016). The upward shifts of the age-wage profiles over time (shown in Figure 7) suggest that a continuous increase in both educational attainment and skill proficiency of workers contributed significantly to the productivity and wages.

In the previous section, the measure of human capital index was based on the crossclassification of worker types based on sex, age, and education. Because the skill proficiency level of workers was not distinguished from educational attainment and other characteristics of workers in the data, the human capital index was measured using the aggregate labor input weighted by the aggregate labor income share for each worker type in the categories crossclassified by sex, age, and education. This method may not accurately estimate the true contributions of age and educational attainment, if the composition of labor shifts over time from

⁹ Using numeracy score as an alternative measure of skill proficiency does not change the results qualitatively.

low-skilled to high-skilled, both across and within the same education and age group. The positive effect of education on human capital growth, as described in the previous section, can be significantly explained by an improvement in skills across age groups over time. Workers' skill proficiencies are not only positively related to their access to formal schooling, but also influenced by other individual and job characteristics such as age, gender, parents' education levels and income, immigrant status, occupation, job-related training, and so on (OECD, 2013). In this regard, we attempt to measure to what extent the change in skill proficiency has influenced human capital growth. From the Korean sample of PIAAC data, the distribution of skill proficiency and wage within each worker type across sex, education, and age groups are calculated. Then, this imputed cross-sectional distribution is applied to all labor census data over the sample period. We assume that while the standard deviation of the skill score remains the same for each worker type, its mean can shift over time with age effects and cohort effects.¹⁰ Using data cross-classified by age, gender, education and imputed skill, we construct a new human capital index (section 4.2).

Because the PIAAC test scores are available for only one year over the sample period, we investigate the determinants of skills, focusing on the effects of age and education, on skills. We first estimate the skill production function using a sample of Korean participants in the PIAAC survey. The regression uses literacy test scores as a skill measure.

¹⁰ Our framework in table 2 attempts to identify the cohort effects using the relationship between skill scores and father's education and the age effects using the relationship between skill scores and age in table 2. Applying the cross-section age-skill profile to the estimation of the profiles across cohorts in other years raises an issue regarding the separation of "age effects" from "cohort effects." Paccagnella (2016) combines PIACC with previous international skills surveys, to disentangle age and cohort effects. Pooling information from the different surveys allows to create "synthetic cohorts," while assessing the average skill proficiency of a given age group over time. The results are mixed: the cross-sectional differences can cause an underestimation of the age effect in some countries, but an overestimation in others.

	(1)	(2)	(3)	(4)
Female	-0.081***	-0.092***	-0.086***	-0.092***
	(0.023)	(0.023)	(0.023)	(0.023)
HSD.	-0.675***	-0.643***	-0.661***	-0.642***
	(0.039)	(0.040)	(0.039)	(0.040)
SMC.	0.350***	0.331***	0.338***	0.329***
	(0.032)	(0.032)	(0.032)	(0.032)
CLC.	0.731***	0.676^{***}	0.701***	0.674***
	(0.029)	(0.031)	(0.030)	(0.031)
Age	-0.020***	-0.019***	-0.019***	-0.019***
-	(0.001)	(0.001)	(0.001)	(0.001)
Father Education		0.020***		0.019***
		(0.003)		(0.004)
Mather education			0.016***	0.003
			(0.004)	(0.005)
Constant	0.812***	0.590***	0.656***	0.584***
	(0.062)	(0.073)	(0.078)	(0.080)
R-Square	0.370	0.373	0.371	0.373
Ν	5504	5454	5475	5449

Table 2 Skill production function

Notes: The dependent variable is PIAAC literacy test scores, which are normalized with mean and standard deviation to standardize the scores. The sample consists of Korean PIAAC participants aged 25-64 excluding migrants. The specification has three educational level variables including secondary school drops (HSD), college dropouts (SMC), and college graduates (CLC), while excluding secondary school graduates (HSC). Robust standard errors are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 2 reports the estimates of the impact of individual and family characteristics, such as age, gender, education, and parents' education, on literacy scores. In Column (1), which includes gender, age, and education variables, female respondents have significantly lower scores than males, and age has a significantly negative effect on skills. This specification includes three education groups—high school dropouts, college dropouts, and college completes—to the regression. Therefore, the estimates show the impact of each level of educational attainment on

skills, relative to high school graduates. The estimates show that a higher level of educational attainment is positively related to a higher level of literacy skills, after controlling for age and gender variables. Column (2) adds father's education (measured by average years of schooling). It shows that father's education has a positive and significant effect on adult literacy skills. In Columns (3) and (4) show that with father's education controlled for, mother's education does not have a significant effect on literacy skills. This result suggests that a worker whose father's education level is higher, with the same age and education levels, tends to have a higher literacy skill score. Considering that parent's average educational attainment had increased steadily in Korea, it has had a positive effect on worker's skill over cohorts during the sample period.

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.324***	-0.287***	-0.350***	-0.309***	-0.319***	-0.284***
	(0.027)	(0.033)	(0.029)	(0.034)	(0.027)	(0.033)
Age	0.055^{***}	0.059^{***}	0.057^{***}	0.062^{***}	0.056^{***}	0.059^{***}
•	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)
Age^2/100	-0.054***	-0.060***	-0.060***	-0.067***	-0.053***	-0.059***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
HSD	-0.266***	-0.169***			-0.215***	-0.149***
	(0.050)	(0.051)			(0.054)	(0.054)
SMC	0.336***	0.169^{***}			0.305^{***}	0.160^{***}
	(0.036)	(0.037)			(0.037)	(0.037)
CLC	0.545***	0.278***			0.485***	0.257***
	(0.033)	(0.037)			(0.035)	(0.037)
			o ***	· · · · · · · · · · · · · · · · · · ·	o o - /***	· · · · · **
Literacy score			0.197	0.075	0.074	0.037
			(0.015)	(0.016)	(0.017)	(0.017)
a	0.000***	7 000***	0.040***	7 01 1***	7 00 2***	- 0 - 1***
Constant	8.029	7.889	8.249	7.914	7.993	7.8/1
<u> </u>	(0.237)	(0.245)	(0.247)	(0.243)	(0.238)	(0.246)
Occupation and	Ν	Ŷ	N	Y	Ν	Y
industry control						
R-Square	0.195	0.258	0.128	0.243	0.201	0.259
Ν	2837	2816	2837	2816	2837	2816

Table 3: Wage regression

Notes: The dependent variable is the log value of hourly earnings, including bonuses. The sample consists of employees aged 25–64 who work at least 40 hours per week. The standardized literacy test scores are used as a skill

measure. Robust standard errors are reported in parentheses. The specification has three educational level variables including secondary school drops (HSD), college dropouts (SMC), and college graduates (CLC), while excluding secondary school graduates (HSC). *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

We also examine the wage effects of adult skills using the Mincer-type wage equation. Columns (1) to (6) of Table 3 report the estimation results of the Mincer-type equation, with and without occupation, and industry fixed effects. The estimates on skills are shown in Columns (3) and (4), without controlling for the education variables, and in Columns (5) and (6), controlling for the education variables. The estimates in Columns (5) and (6) indicate that a one standard deviation increase in literacy scores leads to a wage increase of 7.4% and 3.7%, with and without controlling for occupation and industry fixed effects, respectively. The returns on formal schooling in Columns (5) and (6), where we control for skills, decline as compared to those in Columns (1) and (2) respectively.

4.2. Human capital growth with adult skills

To examine the effect of skill changes among workers on human capital, we construct alternative data series for worker types, cross-classified by skill groups, in addition to sex, education levels, and five-year age groups. The Korean labor market data used in Section 3 do not provide any information about individual skill levels. Hence, we impute individuals' skill levels with their characteristics examined in the PIAAC analysis. From the skill production estimation in Table 2, the skill levels are determined based on the age, sex, education, and father's education. Furthermore, the skills have their own contribution to wage. Using these relationships, an individual's skill is imputed.

We maintain the 64 cross groups (gender (2) x education (4) x age groups (8)) in Section 3, and assume that the skill distribution within these cross-classified groups does not change over time except the mean value of skill scores. Since skill has its own impact on an individual's wage,

we use the correlation between wage and literacy scores from the wage regression in Table 3. The actual procedure is as follows:

(Step 1) Create 64 cross-classified groups (gender (2) x education (4) x age groups (8)).

(*Step 2*) Normalize test scores, and log wage within each group. Since gender, education, and age are controlled, these characteristics have no effect on the normalized log wage.

(Step 3) Calculate the correlation, ρ , between normalized test scores and normalized log wages.

(Step 4) Generate random variables, $u_{i,g}$ from the standard normal distribution.

(Step 5) Simulate test scores for workers i in group g with the correlation obtained in (Step 3) using following formula.

$$\tilde{\mu}_{i,g,t} = \operatorname{nrm.} \ln w_{i,g,t} + \sqrt{1 - \rho^2} \, u_{i,g,t}$$

The covariance matrix provides the statistical relationship between log wage and the test score. We already know that the test score has a positive impact on the log wage, after controlling for sex, education, and age. Hence, this positive impact of test score needs to be taken into account for the log wage. We use the lower triangular matrix obtained by a Cholesky decomposition of the covariance matrix. Since the lower triangular matrix is expressed with the correlation coefficient, we only need the correlation coefficient to link the log wage and test scores within the groups.

$$\mathbf{L} = \begin{bmatrix} 1 & 0\\ \rho & \sqrt{1 - \rho^2} \end{bmatrix}$$

(*Step 6*) Estimate adjusted group-specific means, $\hat{\mu}_{g,t}$, using the statistical relationship between father's education and test scores.

(*Step 7*) Finally, convert the normalized $\mu_{i,g,t}$ with the adjusted group-specific means and standard deviations.

$$\mu_{i,g,t} = \hat{\mu}_{g,t} + \sigma_g \cdot \tilde{\mu}_{i,g,t}$$

We use the imputed skill measures, and alternative data series to construct an alternative human capital index. While the OECD (2013) classifies six skill groups according to PIAAC literacy scores, we reclassify them into four groups, merging Groups 0 and 1, and Groups 4 and $5.^{11}$



Figure 15: Share of skill (literacy) group

Figure 15 displays the share of the four skill groups over time. In terms of skill levels, most workers belong to the Medium-High and Medium-Low skill group. High skill and Medium-High skill groups increase over time. The share of High skill groups increased from 3% to 8% over the

¹¹ According to OECD classification, the skill groups correspond to the range of literacy scores as flows: 0(0 - 176), 1(176 - 226), 2(226 - 276), 3(276 - 326), 4(326 - 376), and 5(376 - 500).

period and the share of Medium-High skill groups jumped from 21% to 37%. In contrast, the share of Medium-Low and Low skill groups has decreased continuously since 1986.



Figure 16: The share of skill group by education

In order to investigate the skill distribution further, we disaggregate the share of skill groups within each education level in Figure 16. Since we assume that the skill distribution does not change within the demographic groups, the share of skill groups belonging to a certain level of education is relatively stable over the sample periods. These results indicate that the dramatic

changes in the share of skill groups in Figure 15 are mainly driven by the compositional change of the gender, education, and age groups.



Figure 17: Human capital with imputed skill

Human capital growth with imputed skills is shown in Figure 17. The benchmark result from Figure 10 has also been provided for comparison. As shown in the figure, the skill has a minor effect on human capital growth, compared to education. This reflects that the changes in imputed skills are mainly driven by the change in father's educational attainment. The independent effect of changes in skills and accompanying relative wage ratio is relatively small, compared to that of education.

5. The Impact of human capital on economic growth

This section appraises the contribution of human capital to output growth by adopting the growth accounting method of Solow (1957). The basic proposition of this approach is that human capital contributes to output through improvement of overall labor productivity,

controlling for other contributing factors, such as physical capital stock, and technological advances.

Let us assume a standard production function:

(6)
$$Y = F(K, H, A) = F(K, L \cdot h, A),$$

where *Y* is the output (real GDP), *K* is the physical capital stock, and *A* measures the level of technology, or "total factor productivity (TFP)."

The growth accounting method appraises the contribution of labor resources - labor quantity and human capital - to output growth by decomposing the growth rate of aggregate output into contributions from the growth of *Y*, into each of the three productive inputs, *K*, *H* and *A*, as shown in Equation (7):

(7)
$$\Delta lnY = \frac{F_K \cdot K}{Y} \cdot \Delta lnK + \frac{F_H \cdot H}{Y} \cdot \Delta lnH + \Delta lnA,$$

where ΔlnX represents the change in the logarithm of the variable X between time t and t-1, and F_K and F_H are the marginal products of capital and labor respectively. When the marginal products can be measured by factor prices, we rewrite equation (2) using the labor share, v_H , and the capital share, v_{K} .¹², as follows:

(8)
$$\Delta lnY = v_K \cdot \Delta lnK + v_H \cdot \Delta lnH + \Delta lnA.$$
$$= v_K \cdot \Delta lnK + v_H \cdot \Delta lnL + v_H \cdot \Delta lnh + \Delta lnA$$

 $^{^{12}} v_k = F_K \times \frac{K}{Y} = rK/Y$, and $v_H = F_H \times \frac{H}{Y} = wH/Y$, where *r* is the rental price of capital, and *w* is the wage rate. In practice, the factor share is measured by an average of the shares in time T and T-1.

The second term on the right-hand side (RHS) of the equation measures the contribution of labor inputs to output growth. An increase in human capital contributes to output, alongside labor quantity, physical capital, and technology.



Figure 16: Labor quantity, human capital, and GDP growth rates: 1986-2016

Note: The growth rates are three-year moving averages of benchmark labor quantity and quality growth (benchmark indices), and GDP growth rates.

Figure 16 and Table 4 present the growth rates of human capital and quantity from 1986 to 2016. The real GDP growth rate is also included for comparison. The Korean economy had experienced high GDP growth rates until 1997, when it was hit by the Asian financial crisis. The average annual GDP growth rate was 8.84% from 1986 to 1995. Both labor quantity and quality growth contributed to GDP growth during this period, but the contribution made by labor quantity was larger than that by human capital. The annual labor-quantity growth rate was 3.28%, on an average, but the labor-quality growth rate was only around 0.9% during that period. During the crisis, labor quantity dropped drastically, owing to the decline in employment rates, and average work hours. In contrast, the human capital growth rate rose during the crisis. From 1996

to 2005, the human capital growth rate was at 1.15% per year, compared to 0.56% for labor quantity. The countercyclical property of the human capital growth rate—in contrast to the procyclical movement of the labor quantity— also showed up clearly during other recession periods such as in 2003 (bubble burst), and 2008-2009 (global financial crisis). This feature confirms the cleansing effect of recession (Caballero and Hammour, 1994; Davis et al., 1998). Many studies on wage cyclicality find that low-wage workers are likely to be separated from their employment during the recession (Bils, 1985; Keane et al., 1988; Solon et al., 1994). Due to this compositional change over the business cycle, the average productivity increases during the recession.

	1986	1986	1996	2006	2011
	-2016	-1995	-2005	-2010	-2016
GDP growth rate	5.57%	8.84%	4.98%	4.03%	2.93%
Labor-quantity growth	1.31%	3.28%	0.56%	0.25%	0.50%
Contribution to GDP growth	1.08%	2.78%	0.43%	0.20%	0.35%
	(19.41%)	(31.47%)	(8.60%)	(4.96%)	(11.99%)
Human capital growth	1.00%	0.90%	1.17%	1.14%	0.75%
Contribution to GDP growth	0.78%	0.77%	0.93%	0.86%	0.51%
	(14.08%)	(8.66%)	(18.64%)	(21.40%)	(17.39%)

Table 4: Annual growth rates of labor quantity, human capital, and GDP: 1986-2016

Source: GDP data are from the Bank of Korea and authors' calculations of other data.

Notes: Human capital is constructed using the weighted sum of work hours across workers aged 25-64, cross classified by gender, age, and educational attainment. The weights are relative productivity, measured by the share of labor income for each worker type. Labor quantity is total hours worked by all worker types. The contribution to GDP growth by labor quantity or quality is measured using the growth accounting formula. Data on labor income share are from OECD (2017) and the labor income share is the ratio of total labor compensation to GDP. Total labor compensation is calculated as compensation of employees multiplied by the number of hours worked by all persons employed (employees and self-employed), divided by the hours worked by employees, assuming that an hour worked by self-employed receives the same compensation as the average hourly compensation received by an employee.

Korea's average GDP growth rates have continuously declined after the Asian financial crisis, averaging 4.03% from 2006 to 2010, and 2.93% from 2011 to 2016. The GDP growth slowdown was accompanied by a significant decline in labor quantity. The total work hours had continuously declined from about 5.5% in late 1980s to -0.7% in 2016. It grew only at 0.25% from 2006 to 2010, and 0.50% from 2011 to 2016. However, the persistent growth of human capital has supported economic growth in the recent decades; the average human capital growth rates were at 1.14% from 2006 to 2010, and 0.75% from 2011 to 2016.

In growth accounting terms, the contribution of human capital to GDP growth was significant. According to Equation (8), assuming the aggregate labor income share in national accounts as 0.682, human capital growth contributed 0.8% points of annual GDP growth over 1986–2016. Human capital's contribution to economic growth increased significantly in the recent decade. The share of GDP growth explained by human capital rose from about 8.7% in 1986–1995, to about 19.4% in 2006-2016. In contrast, the contribution of labor quantity to GDP growth dropped from about 31.5% in 1986–1995, to about 4.9% in 2006–2016.

6. Projections of human capital growth, 2017–2040

In this section, we consider the projections of labor quantity and quality growth up to 2040. As discussed in the previous section, the change in labor quantity was driven by increases in population and employment rates across worker-types. The population aged between 25 and 64 is projected to decline until 2040 (Figure 1). Hence, unless employment rates rise fast and offset the decline in population size in the coming decades, the labor quantity is expected to decline continuously. On the other hand, the change in human capital was largely driven by an increase in more-educated cohorts over time. As more educated cohorts join the working-age population, human capital should increase.

To estimate the population structure by age group, we use Statistics Korea's projections (Statistics Korea 2016). The projections of education are constructed using the forward extrapolation method by Barro and Lee (2015). Thus, data on education levels in 2016 by age group are used as benchmark figures to calculate the education level of the population in five-year age groups, until 2040, at five-year intervals. Data on the educational attainment for the population aged 25-29, at five-year intervals, are constructed using the school enrollment rates for younger cohorts in their earlier years. Educational attainment for the population aged 25-64 changes over time with the continuous inflow of better-educated younger cohorts (25-29 years old), relative to the outflow of less-educated older-age cohorts (65-69 years old).

For employment rates, we set up a baseline scenario that assumes that the employment rate for a worker type is set at the 2016 level. We consider three alternative scenarios: (i) the employment rates of elderly workers of both sexes, aged between 55 and 64 years, increase gradually to Japan's level until 2040, (ii) the employment rates of female workers across all age groups increase gradually to Japan's level until 2040, and (iii) the skill distribution for employed workers gradually converges with Japan's distribution levels until 2040 under the baseline employment rate assumption. The employment rates of old-age workers, between 55 and 64, and of female workers have been rising in the recent decade in Korea (Figure 3). Considering the fact that Korea has followed Japan's demographic changes with a lag of about 20 years, Japan is a good benchmark for gauging the future employment rates in Korea. OECD statistics show that the employment rates for all age groups and for both sexes in Japan are higher than those in Korea.¹³ Note that we do not model the employment rates for workers by their education levels.

¹³ The employment rates in Japan, for example, were 90.6% and 76.8% for male ages 55–59 and 60–64, respectively in 2016, while the corresponding rates in Korea were 84.3% and 71.7% in the same year. For females, Japan's employment rates are higher by 8~13% points than the Korea's corresponding rates in each five-year age group of 25-60 years old

The employment rates for all worker types are assumed to increase proportionally.



Figure 17: Skill distribution: Korea vs. Japan

The third alternative scenario is based on the significant difference in skill distribution between Japan and Korea. In Japan, the labor market consists of more skilled workers than the Korean labor market in every age group, as shown in Figure 17. Hence, by assuming that the skill distribution among employed workers in each cross-classified group gradually approaches Japan's skill distribution levels, we assess the impact of skill improvement on human capital growth, independent from other human capital factors such as age, gender, and educational attainment. While the other alternatives incorporate the change in quantity of labor force, there is no quantity change in this scenario. The demographic structure and employment rates are same as the baseline, which sets the employment rate at 2016. The only difference is that the skill distribution moves towards Japan's structure. In Korea, the college enrollment rate is the highest in the world. Thus, improving human capital by increasing the quantity of those who undergo formal schooling does not work. However, adult cognitive skills can be improved by better quality of schooling (leading to higher returns on schooling), or job-related training. Therefore, the third alternative is plausible, and can help to assess the quantitative impact of developing adult skills for human capital growth.



Note: The projections are based on the baseline scenario in which employment rates are fixed at the 2016 level, and three alternative scenarios: (i) employment rates of old-age workers of both sexes, aged between 55 and 64, increase gradually to the levels in Japan until 2040, (ii) employment rates of female workers across all age groups increase gradually to the levels in Japan until 2040, and (iii) the skill distribution for employed workers across cross groups increase gradually to the levels in Japan until 2040.

Figure 18 (a) shows projections of the labor quantity index for the 2017–40 period, depending on the three alternative employment rate assumptions. In the first scenario, the annual labor-quantity growth rates are projected to fall dramatically from 0.2% in 2017, to -1.5% in 2040, with no change in the employment rate. The other two scenarios also show rapid decline in the trends. While the increasing labor employment rates can offset the decrease in the supply of workers to a certain extent, the decline in labor quantity is an inevitable process, which will have a significantly negative impact on Korea's economic growth in the future. The labor quantity

growth in the last scenario, however, is almost same as the baseline, because only the skill distribution within each employed group is changed.

In contrast, the projections for the human capital index in Figure 18 (b) show that Korea can maintain significant growth in human capital over the next two decades owing to the continuous increase of better-educated workers. The annual human capital growth rates are projected to decline slowly from 0.7% in 2017 to 0.1% in 2040, with no change in the employment rate. Hence, the contribution of human capital to GDP growth will remain positive and significant, though declining, over the next decades, in contrast to the negative contribution of labor quantity.¹⁴ The other two scenarios assume that increases in employment rates result in slower human capital growth paths. This reflects the increasing share of less productive demographic groups in total employment. An increase in the availability of old-aged or female workers reduces the average wage or productivity growth rates of workers in the economy, if the average wage or productivity for the old-aged or female workers is lower than that of the average worker. Hence, a notable feature of the projections is that they show the opposite effect of employment increase in old-aged and female workers on labor quantity and quality. Note that we do not consider the labor market participation of groups over the age of 65. Considering that the share of people aged 65 and above is expected to increase rapidly until 2040, the increased employment of the elderly will increase the country's workforce but reduce human capital growth. In addition, the scenarios assume no change in average work hours based on the worker type, which is set at the 2016 level. If the average work-hours decrease, the labor quantity will decline faster, while its effect on human capital will be unclear, depending on the changes across worker types.

¹⁴ Note that if the increase in educational attainment and skill proficiency of workers can induce technological change that uses skilled workers more intensively, GDP growth rate can increase further.

When the skill distribution improves, the human capital growth increases significantly; the growth rate from the last scenario is about 0.13% higher than the baseline scenario. In order to mitigate the negative effect of demographic changes on economic growth, Korea needs to find new sources of growth. Because the educational attainments are already very high in Korea, providing higher education does not seems to work well in the future. Improving the quality of higher education, and providing life-long training, especially after college graduation, however, can shift the skill distribution to a higher level, mitigating the negative effects of the declining labor force in the future.

7. Concluding remarks

We estimated Korea's human capital growth by using extensive micro datasets on labor composition in terms of age, sex, education, skill, and wage rates. The labor quantity growth rate has continuously declined from about 5.3% per year in the late 1980s to -0.7% in 2016. Human capital growth, however, has persisted at around 0.8%–1.2% throughout the sample period with countercyclical patterns. The main source of human capital growth in Korea was consistent improvement of educational attainment among workers. The better-educated and more productive workforce has contributed significantly to economic growth. In the recent decades, the contribution of human capital to GDP growth has become more important than that of labor quantity.

Korea is projected to maintain its human capital growth over the next two decades while experiencing a dramatic decline in labor quantity. The annual human capital growth rates are projected to decline slowly from 0.7% in 2017 to 0.1% in 2040, given a constant employment rate in 2016. An increase in the number of aged or female workers is expected to reduce the

growth rates of aggregate human capital. In contrast, an improvement of adult cognitive skills, through better-quality education and training, can help increase human capital growth significantly.

Our human capital estimates are subject to measurement errors. We had to merge several household and labor market survey datasets to measure the changes in the labor market over the past three decades, but these datasets may not be completely consistent. The skill measure from the PIAAC is available only for one year, and our methodology to construct its estimates for other years may be skewed. Therefore, there is scope for further improvement. In assessing the role of human capital on economic growth, we adopt the growth accounting method. As the method is just a mechanical decomposition of the output growth into components associated with productive inputs, it is limited to consider the interactions among these factors. An abundant human capital stock can have a positive effect on technological progress. Conversely, technological change can raise the relative demand for skilled workers and skill premium, thus promoting human capital accumulation. We will need a structural model to identify the independent impact of human capital on output growth in the economy. Future studies can improve the human capital measure and further investigate the relationship between human capital accumulation and economic growth in the Korean economy.

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References

- Aaronson, D., Sullivan, D.G., 2001. Growth in worker quality. Economic Perspectives Federal Reserve Bank of Chicago, 25(4), 53-74.
- Acemoglu, D. 2008, Introduction to Modern Economic Growth, Princeton University Press.
- Barro, R.J., Lee, J., 1994. Sources of economic growth. Carnegie-Rochester Conference Series on Public Policy 40(1), 1–46.
- Barro, R.J., Lee, J., 2013. A new data set of educational attainment in the world, 19502010.Journal of Development Economics 104(C), 184–198.
- Barro, R.J., Lee, J., 2015. Education Matters: Global Schooling Gains from the 19th to the 21st Century. New York: Oxford University Press.
- Barro, R.J., Martin, X.S., 2003. Economic Growth, 2nd Edition, vol. 1 of MIT Press Books. The MIT Press.
- Bils, M.J., 1985. Real Wages over the Business Cycle: Evidence from Panel Data. Journal of Political Economy, 93(4), 666–689.
- Bratsberg, B., Terrell, D., 2002. School quality and returns to education of US immigrants. Economic Inquiry, 40(2), 177-198.
- Caballero, R.J., Hammour, M.L., 1994. The Cleansing Effect of Recessions. American Economic Review, 84(5), 1350–1368.
- Cohen, D., Soto, M., 2007. Growth and human capital: good data, good results. Journal of Economic Growth, 12(1), 51–76.
- Davis, S.J., Haltiwanger, J.C., Schuh, S., 1998. Job Creation and Destruction. Vol. 1 of MIT Press Books. The MIT Press.
- Feenstra, R. C., R. Inklaar, R., and Timmer, M., 2015, The Next Generation of the Penn World Table," American Economic Review, 105(10), 3150 - 82.

- Fernald, J.G., Jones, C.I., 2014. The Future of US Economic Growth. American Economic Review, 104(5), 44–49
- Hall, R.E., Jones, C.I., 1999., Why Do Some Countries Produce So Much More Output Per Worker Than Others?. Quarterly Journal of Economics, 1999, 114 (1), 83–116.
- Hanushek, E.A., Schwerdt, G., Wiederhold, S., Woessmann, L., 2015. Returns to skills around the world: Evidence from PIAAC. European Economic Review, 73(C), 103–130.
- Hanushek, E.A., Woessmann, L., 2008. The role of cognitive skills in economic development. Journal of Economic Literature, 46.3, 607-68.
- Hendricks, L., Schoellman, T., 2014. Student abilities during the expansion of US education. Journal of Monetary Economics, 63(C), 19–36.
- Jones, B.F., 2014. The human capital stock: a generalized approach. American Economic Review, 104.11 (2014): 3752-77.
- Jorgenson, D.W., FraumeniB., 1992. Investment in Education and U.S. Economic Growth.Scandanavian Journal of Economics, 96, supplement, S51-70..
- Jorgenson, D.W., Ho, M.S., Samuels, J.D., 2016. Education, Participation, and the Revival of U.S. Economic Growth. NBER Working Papers, National Bureau of Economic Research, Inc, July.
- Jorgenson, D.W., Ho, M.S., Stiroh, K.J., 2002. Projecting productivity growth: lessons from the U.S. growth resurgence. Economic Review (Q3), 1–13.
- Juhn, C., Kim, D.I., Vella, F, 2005. The Expansion of College Education in the United States: Is There Evidence of Declining Cohort Quality? Economic Inquiry, 43(2), 303–315.
- Keane, M., Moffitt, R., Runkle, D., 1988. Real Wages over the Business Cycle: Estimating the Impact of Heterogeneity with Micro Data. Journal of Political Economy, 96(6), 1232–1266.
- Kim, D.I., Topel, R.H., 1995. Labor markets and economic growth: lessons from Korea's

industrialization, 1970-1990. in Richard B. Freeman and Lawrence F. Katz, (eds), Differences and changes in wage structures. University of Chicago Press, 227-264.

- Klenow, P.J., Bils, M., 2000. Does Schooling Cause Growth? American Economic Review, 90(5), 1160–1183.
- Lee, J.W., 2016. Korea's Economic Growth and Catch-up: Implications for China. China & World Economy, 24(5), 71–97.
- Lee, J.W., Lee, H., 2016. Human capital in the long run. Journal of Development Economics, 122(C), 147–169.
- Lee, J.W., Wie, D., 2017. Returns to Education and Skill in the Labor Market: Evidence from Japan and Korea. Asian Economic Policy Review, 12(1), 139-160.
- Lemieux, T., 2006. The mincer equation thirty years after schooling, experience, and earnings. in Grossbard, Shoshana (ed), Jacob mincer a pioneer of modern labor economics. Springer US, 127-145.
- Lucas, R. Jr., 1988. On the mechanics of economic development. Journal of Monetary Economics, 22(1), 3–42
- Maestas, N., Mullen, K.J., Powell, D., 2016. The effect of population aging on economic growth, the labor force and productivity (No. w22452). National Bureau of Economic Research.
- Mankiw, N.G., Romer, D., Weil, D.N., 1992. A Contribution to the Empirics of Economic Growth. The Quarterly Journal of Economics, 107(2), 407–437.
- Manuelli, R.E., Seshadri, A., 2014. Human capital and Wealth of Nations. American Economic Review, 104(9), 2736-2762.
- Mincer, J.A., 1974. Schooling, Experience, and Earnings. Cambridge, MA: National Bureau of Economic Research.

- OECD, 2013. OECD Skills Outlook 2013: First results from the survey of adult skills. Paris: OECD Publishing.
- OECD, 2017. OECD Compendium of Productivity Indicators 2017. Paris: OECD Publishing
- Paccagnella, M., 2016. Age, Ageing and Skills: Results from the Survey of Adult Skills. OECD Education Working Papers, No. 132, OECD Publishing, Paris.
- Schoellman, T., 2011. Education quality and development accounting. The Review of Economic Studies, 79(1), 388-417.
- Solon, G., Barsky, R., Parker, J.A., 1994. Measuring the Cyclicality of Real Wages: How Important is Composition Bias? The Quarterly Journal of Economics, 109(1), 1–25.
- Solow, R.M., 1957. Technical Change and the Aggregate Production Function. ,Review of Economics and Statistics, 39(3), 312–320.
- Statistics Korea, 2016, Population Projections for Korea (2015-2065). Seoul: Korea.
- You, H.M.,2016. The contribution of rising school quality to U.S. economic growth. Journal of Monetary Economy 63(1), 95–106.
- Young, A., 1995. The tyranny of numbers: confronting the statistical realities of the East Asian growth experience. The Quarterly Journal of Economics, 110(3), 641-680.