論文
*RESEARCH ARTICLE*

# Cognitive and Non-cognitive Skill Formation：The Impact of Summer Activities in a Quarter System[1]

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**Abstract**

The adoption of quarter systems by an increasing number of universities has led to a rise in summer program opportunities for students. These programs not only enhance academic knowledge but also potentially develop students' internal abilities. In previous studies, summer program participants developed some non-cognitive skills or maintained most cognitive and non-cognitive skills during summer, while non-participants experienced a decline in several skills. However, how these changes in skills occurred is unclear. This study examined the formation of skill changes during summer and the impact of summer programs on skill development and formations to shed light on this point. Various production function forms of skills, including a dynamic factor model, were explored and employed for analysis. The Global Perspective Inventory, which measures cognitive and non-cognitive skills simultaneously, was examined for first-year and second-year students at our university. The findings indicate strong self-productivity across all skills, with weaker cross-productivity. Estimation results suggest that cognitive skills may have contributed to non-cognitive skill development to a similar extent as non-cognitive skills did to cognitive skills. However, the influence of non-cognitive skills appeared to be more consistent. Interpersonal skills demonstrated offsetting cross-productivity, while intrapersonal skills bolstered both cognitive and intrapersonal abilities. Summer programs contributed to the development of both cognitive and non-cognitive skills. The application of dynamic models provided insights into the crucial non-cognitive skills driving overall skill development even in a short period.

Keywords: cognitive skills, non-cognitive skills, off-campus activities, skill formation

[1] I am grateful to the Faculty Development Fund at Tsuda University for supporting this project to investigate the effect of off-campus summer programs on cognitive and non-cognitive skills in 2019 and to assess the impact of groupwork and summer programs on those skills in 2020. I am also thankful to students and colleagues who cooperated on the surveys. This research was supported by the Faculty Development Fund at Tsuda University in 2019 and 2020. After 2020, the author continued with personal funds.

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Received: February 21, 2025; accepted: April 6, 2025; published: June 15, 2025.

## 1. Introduction

In the face of consecutive unprecedented global events, higher education institutions have an increasingly vital role in preparing graduates for effective communication in diverse communities and contributions to global society. The business sector seeks culturally adept individuals who can adapt to new technologies and exhibit leadership in the era of global economic integration. In 2010, the Japanese Ministry of Education, Culture, Sports, Science and Technology (MEXT) established the Association for Promotion of Global Human Resources through the Industry-Academia Collaboration ("*Sangaku renkei niyoru Global jinzai ikusei suishin kaigi*") to explore favorable conditions and roles for businesses, government, and universities in boosting international student exchange (MEXT, 2011). The MEXT organized the Conference on Diversification of Academic Calendars and Gap Terms ("*Gakujireki no tayouka to Gap term ni kansuru kentou kaigi*") in 2014 to examine the benefits and challenges of implementing quarter systems in universities (MEXT, 2014). The quarter system's primary advantage is its two-month terms aligning with overseas summer schools, thus facilitating students' participation in international summer programs or internships. By 2016, approximately 30% of Japanese public universities[3] had adopted a quarter system, with an additional 60% in the process of transitioning or planning to do so (Nishimoto, 2018). Concurrently, Japanese universities began offering more off-campus summer programs (Hojyo, 2019).

With the growing availability of off-campus activities for students, there is potential for the development of skills that may contribute to positive socio-economic outcomes. These abilities, such as establishing identity, and cultural understanding, can be acquired independently of the specific content or subject matter of the programs or activities. Furthermore, these skills could prove valuable in securing better opportunities in society following graduation. To date, the majority of research concerning off-campus activities has focused on their operational aspects within a quarter system. Many studies have examined the impact of summer programs on language proficiency or subject-specific knowledge. While these direct effects are significant, there is also a possibility that other abilities, including non-cognitive skills, such as intercultural understanding and self-establishment, may be cultivated through off-campus experiences. These indirect skills might be associated with participants' personal growth and could be beneficial in achieving favorable socio-economic outcomes after graduation. Moreover, developing these non-cognitive skills is also the main goals of summer programs and is requested by society. Nevertheless, studies evaluating the influence of summer programs on non-cognitive skills are scarce.

In an effort to address this research gap, this study aimed to elucidate these points by

[3] Here, public universities do not include those run by local governments.

examining 1) the mutual influence of cognitive and non-cognitive skills during summer skill development, and 2) the impact of summer activities on skill formation through the analysis of structured skill formation models.

The hypotheses to be tested are as follows: 1. Non-cognitive skills contribute to cognitive skill formation. 2. Cognitive skills contribute to non-cognitive skill formation. 3. The cross-contribution of non-cognitive skills to skill formation exceeds that of cognitive skills, since Cunha and Heckman (2008) found regarding the cross-contribution of skills that non-cognitive skills had a stronger influence on cognitive skills than vice versa. 4. Summer activities positively affect both skill types. To test these hypotheses, a dynamic factor model based on Cunha and Heckman's (2008) skill formation model is formulated. Additionally, the study explores other potential dynamic skill production functions. The Global Perspective Inventory (GPI) is administered to first-year and second-years students in the Department of Policy Studies at the researcher's university to measure cognitive and non-cognitive skills before and after the summer term.

In this study, regarding non-cognitive skills, we focus on global competence related skills among various non-cognitive skills, so as to reflect the desired skills of global human resources, which summer activities aim to produce. To measure such skills, which are related to global competency, this study applied the GPI, one of the most commonly used inventories when it comes to examining the effects of overseas activities or service learning. The GPI has been employed in approximately 200 higher education institutions (Research Institute for Studies in Education, 2017). Moreover, the GPI has components of cognitive skills, and therefore, we are able to investigate the relationship between cognitive and non-cognitive skills based on the same unit and avoid the issue of the difference in units, which previous studies often could not.

The structure of this paper is as follows. A review of the existing literature on the connection between cognitive and non-cognitive abilities, as well as skill formation models, is presented in Section 2. The analytical model employed in this study is detailed in Section 3, while Section 4 provides an overview of the data utilized. The findings from the analyses are presented in Section 5. To validate and further investigate the outcomes obtained in Section 5, additional analyses are conducted and discussed in Section 6. Finally, Section 7 offers concluding remarks.

## 2. Literature review

This section comprises three parts, firstly, previous results pertaining to the relationship between cognitive and non-cognitive skills are reviewed, following which, secondly, the skill formation models are investigated, and finally, the findings regarding the effect of summer activities are examined.

It must first be noted that the impact of cognitive and non-cognitive abilities on academic performance and socioeconomic outcomes has been extensively studied. Researchers in child development and educational interventions have been drawn to the plasticity of these skills (Carneiro & Heckman, 2003; Carneiro, Crawford & Goodman, 2007; Cunha & Heckman, 2008; Chuna, Heckman & Schennach, 2010; Hoeschler, Balestra, &Backes-Gellner, 2018). Previous studies have demonstrated a strong connection between both cognitive and non-cognitive abilities and academic or socioeconomic results. Furthermore, investigations have been conducted to elucidate the interplay between cognitive and non-cognitive skills. The current review focuses on research involving undergraduates and skill formation.

Duckworth, Peterson, Matthews, and Kelly (2007) developed a self-report measure called the Grit Scale to assess grit, a non-cognitive trait, and explored its relationship with academic outcomes and persistence in challenging environments. Their research, based on 138 psychology undergraduates at the University of Pennsylvania, revealed that higher Grit Scale scores correlated with higher grade point averages (GPAs), even for students with low Scholastic Assessment Test (SAT) scores. Interestingly, they discovered an inverse relationship between Grit Scale and SAT scores.

Heckman, Stixrud, and Urzua (2006) examined how cognitive and non-cognitive skills influence economic and social outcomes, including wages, occupational and educational choices, work experience, and negative social behaviors. They utilized data from the National Longitudinal Surveys of Youth, 1979 (NLSY79) and employed Armed Services Vocational Aptitude Battery (ASVAB) test scores in five subjects to indicate cognitive skills. Non-cognitive skills were represented by the Rosenberg Self-Esteem Scale and Rotter Scale[4]. Their measurements included the standardized average and sums of these scores, predicted values from their structural model, and simulated latent factors of these skills. The researchers concluded that both cognitive and non-cognitive skills play crucial roles in children's favorable economic and social outcomes. Higher levels of both skill types were associated with increased educational attainment, higher wages, and a preference for white-collar over blue-collar occupations. Gender differences were observed in the effects of these skills on wages, with females experiencing stronger effects than males.

Borghans, Meijers, and Weel (2008) assessed the relationship between non-cognitive skills and cognitive skills by implementing several personality and psychological tests and posing economic preference questions, as well as IQ questions to Dutch university students. Non-cognitive skills were measured using the Big Five personality traits and the Rotter Scale. IQ questions quantified cognitive skills, while economic preference questions reflected time preference, the degree of risk aversion, and preference for leisure. They found that "Introversion"

[4] The Rotter Scale measures internal-external control as a personality of an individual (Rotter, 1966). The four-pairs of the shortened Rotter Scale of 23 paired-items were used in the NSLY79 (U.S. Bureau of Labor Statistics, 2025).

increased, and “Openness” and “Agreeableness” decreased the probability of providing the right answers being provided to cognitive questions, such as Raven matrices, sequences of numbers, and anagram etc. When students had lower discount rates or were more risk-averse, the probability of having correct answers increased.

A study by Egan, Daly, Delaney, and Boyce (2016) utilized the British Cohort Study (BCS) to examine whether non-cognitive skills, specifically four of the Big Five personality traits, could lower unemployment rates. Their analysis controlled for cognitive abilities and various socio-economic factors, including intelligence measured at age 10, gender, and paternal occupation. The findings revealed that conscientiousness during adolescence was associated with reduced unemployment rates across various indicators. The research also presented contemporaneous correlations between the four personality traits and intelligence. Among the statistically significant relationships, the strongest positive correlation (0.47) was observed between “Agreeableness” and “Conscientiousness.” The connections between “Intelligence” and non-cognitive variables were statistically significant but weak.

Malanchini et al. (2020, 2024) examined how the connections between cognitive abilities, non-cognitive skills, and academic performance evolve during childhood and adolescence. Their study utilized twin samples from England and Wales, ranging from 7 to 16 years old. The researchers discovered that, as children aged, particularly beyond 12 years, the associations between non-cognitive skills and academic achievement, as well as between self-reported cognitive and non-cognitive abilities, strengthened. They employed Cholesky decomposition to analyze academic achievement and explored correlations among cognitive and non-cognitive skills. The team also conducted further investigations to determine whether socio-economic status affected the impact of non-cognitive skills on academic performance, using fitted multivariable models. After accounting for socio-economic status, the link between cognitive polygenic scores (PGS) and academic achievement remained relatively stable. However, they observed an even more pronounced increase in the effects of non-cognitive PGS on academic achievement over time, although each individual effect was somewhat diminished. The study clearly demonstrated the influence of both cognitive and non-cognitive skills on academic achievement throughout child development.

Thus far, research has demonstrated the importance of both cognitive and non-cognitive skills in achieving favorable academic and socio-economic outcomes. It is also likely that contemporaneous associations between cognitive and non-cognitive skills are negative, whereas those associations among some non-cognitive skills may be positive. In addition, it is possible that these skill sets may have influenced each other’s development, even when their immediate relationships appeared weak. For example, non-cognitive abilities might have facilitated the growth of cognitive skills in conjunction with educational interventions. While numerous studies have explored the effects of cognitive and non-cognitive skills on academic and socio-economic achievements, comparatively fewer investigations have concentrated exclusively on the evolution of these skills.

Second, studies on skill development and the effect of educational investments are examined. Cunha and Heckman (2008) explicitly investigated the development of cognitive and non-cognitive abilities and the impact of parental investment. Their study utilized data from white male children in the Children of the National Longitudinal Survey of Youth, 1979 (CNLSY/79) in the United States. Through the application of dynamic factor models, which assumed a linear relationship between present and future skills, they discovered that both cognitive and non-cognitive abilities evolved over time. Their findings revealed substantial self-productivity of skills and present skills of children themselves contributing to their future skills, in both skill types, with the sensitive period for parental investments occurring earlier for cognitive skills than for non-cognitive skills. Additionally, they noted that the influence of previous non-cognitive skills on cognitive skills surpassed the effect of previous cognitive skills on non-cognitive skills.

In a related study, Cunha and Heckman (2007) proposed a skill production function model. This model suggested that cognitive and non-cognitive skills from one period contribute to those in the subsequent period, along with parental skills, educational background, and investments, though not necessarily in a linear fashion. They explored the interchangeability of early and late educational investments by examining outcomes, such as high school graduation, college enrollment, conviction, probation, and welfare. Their research emphasized the cost-effectiveness and efficacy of early investment, noting that it could enhance the returns on later investments.

Cunha, Heckman, and Schennach (2010) expanded on this work by developing multistage production functions for cognitive and non-cognitive skills. In their model, skills were formed by previous period skills and parental investments, as well as time-independent parental skills, which were treated as a form of endowment. They employed a constant elasticity of substitution (CES) for skill formation and adult outcome production functions. To address input endogeneity, they devised a method using nonlinear factor models to construct latent inputs. Their research revealed increasing self-productivity in both cognitive and non-cognitive skills throughout child development. Furthermore, they observed that the complementarity between cognitive skills and parental investment grew over time, while the opposite trend was found for non-cognitive skills and parental investment. Simply, when endowed cognitive skills of children at the earlier stage are high, giving those children more books to read may help strengthen cognitive skill in the next stage and this trend may be enforced as children develop. The aforementioned means that high cognitive skills at an early stage are important when it comes to making parental investment effective. In the production of cognitive skills, the elasticity of substitution between parental investment and endowed skills decreased as child development progressed. Conversely, this elasticity exhibited a slight increase in the production of non-cognitive skills. All said, in the skill formation models, cognitive and non-cognitive skills are influenced by each other's development. Additionally, educational investments, mainly parental investments here, positively contributed to both cognitive and non-cognitive skills although the effective periods may differ by skills.

Finally, previous findings concerning the effects of summer programs on cognitive and non-cognitive skills are reviewed. Several studies have attempted to evaluate skills related to personal development and examine how extracurricular activities impact non-cognitive abilities in relation to summer programs.

Kiyofuji and Hashimoto (2021) investigated the influence of virtual study abroad programs on non-cognitive skills using the Beliefs, Events, and Values Inventory (BEVI; Shely, 2016; Nishitani, 2018). The BEVI is also often used to assess non-cognitive abilities before and after studying abroad as is the GPI. Their findings revealed almost no change, with a slight decline or increase, in "Socio-cultural Openness" and "Global Resonance" among participants since those scores were already high; however, no significant change or significant declines in "Self-Awareness" or "Socio-emotional Convergence" were observed. They concluded this was due to the fact that, for those who had already been exposed to other cultures, to some extent before the participation, the summer program of two weeks may not have deepened socio-emotional understandings, while for others without much prior exposures, the program contributed to their inner growth. However, in the aforementioned study, there was no measure of non-cognitive skills for non-participants during summer, which can be viewed as a counterfactual comparison.

Shinkai and Oshima (2020, 2021, 2022a, 2022b, 2023, 2024, 2025) employed the GPI (RISE, 2017) from the Research Institute for Studies in Education at Iowa State University, conducting GPI surveys over five years from 2019 to assess cognitive and non-cognitive skills for both participants and non-participants of a summer program. The GPI, comprising 35 core items, enables researchers to measure three groups-one cognitive skill group and two non-cognitive skill groups, which are intrapersonal and interpersonal skill groups-at the same time. In each category, there are two subgroups, for example, "Knowing" and "Knowledge" for cognitive skills, "Identity" and "Affect" for intrapersonal skills, and "Social Responsibility" and "Social Actions" for interpersonal skills, based on the theory of "holistic human development based on cultural development and intercultural communication," The definition of the GPI originates from the ability and tendency to interact with others with recognition and respect (Research Institute for Studies in Education, 2017). This application of the GPI to universities is the first one in Japan and the results, based on the GPI-measured skills of the surveys collected over five consecutive years, varied before and after the COVID-19 outbreak (Shinkai & Oshima, 2022a, 2024, 2025). The GPI scores are also self-reported figures as is the case with similar inventories. The GPI is designed so that it is influenced neither by the specific contents of programs for evaluation, nor by age, culture, race, or nationality. Using Difference-in-Differences estimation, the Wilcoxson signed-rank test, and the sign test, these studies found a potential increase in non-cognitive skills among participants in off-campus activities after summer prior to the COVID-19 outbreak. Once the pandemic's emergency phase subsided and most off-campus activities resumed in-person, Shinkai and Oshima (2024, 2025) discovered that, among non-participants in off-campus activities, four out of six GPI-measured skills (two cognitive, "Knowing" and "Knowledge," and two non-cognitive, "Affect" and "Social Responsibility") significantly decreased after the summer term. Contrastingly, participants maintained almost all cognitive and non-cognitive skills which were measured at the same time and exhibited a slight declining trend in only one non-cognitive skill (Shinkai & Oshima, 2024, 2025). It can be interpreted that the declines in cognitive skills of non-participants stemmed from the level of exposure to international and societal issues, which declined after the first term ended. Consequently, some non-cognitive skills were intertwined with cognitive contacts and deteriorated. Shinkai (2025) showed the contemporaneous correlations between cognitive and non-cognitive skills, measured based on the GPI, for participants and non-participants in summer programs, and compared those correlations before and after summer. It was found that the correlations, which the non-cognitive skill "Affect" had with "Identity" and "Social Responsibility," and the correlation which the cognitive skill "Knowledge" had with non-cognitive skills, namely "Identity" and "Social Responsibility," became statistically non-significant for non-participants. However, the process by which these differences in changes emerged during summer remains unclear, as does the role of summer interventions, specifically off-campus activities, in the development of cognitive and non-cognitive skills during summer.

Thus far, we have reviewed previous studies on the relationship between cognitive and non-cognitive skills, the skill development models and the effects of educational investments, as well as the effect of summer programs on cognitive and non-cognitive skills. In addition to stressing the importance of non-cognitive skills on later socio-economic outcomes, determinants of non-cognitive skills are also of great concern. The sorts of investments which are significant for non-cognitive skills, and when to effectively invest in child development have been discussed in the literature (Carneiro & Heckman, 2003; Cunha & Heckman 2008; Cunha, Heckman & Schennach 2010). Non-cognitive skills are found to be malleable in adolescence (Hoeschler, Balestra, & Backes-Gellner, 2018) even in the short term (Shinkai & Oshima 2020, 2021, 2022a, 2022b, 2023, 2024, 2025). Additionally, Cunha and Heckman (2008) found that non-cognitive skills had a stronger influence on cognitive skills than vice versa. However, to date, almost no studies have investigated the effect of students' own investments on non-cognitive skills in skill formation in the context of summer activities, to my knowledge. This study applies skill formation models to investigate the relationship between cognitive and non-cognitive skills as well as the effect of students' own investment in the skill development sphere.

The subsequent section will outline the model employed in this paper.

## ３． The model of analysis

This study employs a dynamic factor model to investigate the skill development process before and after summer break. The model examines how both cognitive and non-cognitive abilities in the current period influence these skills in the subsequent period. Initially, we implemented a linear dynamic factor model, as proposed by Cunha and Heckman (2008), which assumes inputs are perfect substitutes.

$$\begin{pmatrix} S_{c,1,t+1} \\ \vdots \\ S_{c,I,t+1} \\ S_{N,1,t+1} \\ \vdots \\ S_{N,J,t+1} \end{pmatrix} = \begin{pmatrix} {\alpha^0}_{c,1} \\ \vdots \\ {\alpha^0}_{c,I} \\ {\alpha^0}_{N,1} \\ \vdots \\ {\alpha^0}_{N,J} \end{pmatrix} + \begin{pmatrix} \alpha^C_{11} & \cdots \alpha^C_{1,I} & \alpha^C_{1,I+1} \cdots & \alpha^C_{1,I+J} \\ \vdots & & \vdots & \vdots \\ \alpha^C_{I,1} & \cdots \alpha^C_{I,I} & \alpha^C_{I,I+1} \cdots & \alpha^C_{I,I+J} \\ \alpha^N_{1,1} & \cdots \alpha^N_{1,I} & \alpha^N_{1,I+1} \cdots & \alpha^N_{1,I+J} \\ \vdots & & \vdots & \vdots \\ \alpha^N_{J,1} & \cdots \alpha^C_{J,I} & \alpha^C_{J,I+1} \cdots & \alpha^C_{J,I+J} \end{pmatrix} \begin{pmatrix} S_{c,1,t} \\ \vdots \\ S_{c,I,t} \\ S_{N,1,t} \\ \vdots \\ S_{N,J,t} \end{pmatrix} \tag{1}$$

where $t$ denotes the period before summer and $t+1$ represents after summer. The variables $S_{c,i}$. $S_{N,j}$ are cognitive and non-cognitive skills when $i \in \{1, \cdots I\}, j \in [1, \cdots, J]$. Our scenario involves two factors for cognitive skills and four factors for non-cognitive skills. The term $\alpha$ refers to a collection of parameters. Todd and Wolpin (2007) proposed a similar linear dynamic specification for the production function of cognitive skills. In their specification, cognitive test scores of children depended on the lagged test scores and concurrent or both concurrent and cumulative home environments in a linear form.

For the estimation of the effect of summer activities, the following equation is applied.

$$\begin{pmatrix} S_{c,1,t+1} \\ \vdots \\ S_{c,I,t+1} \\ S_{N,1,t+1} \\ \vdots \\ S_{N,J,t+1} \end{pmatrix} = \begin{pmatrix} {\alpha^0}_{c,1} \\ \vdots \\ {\alpha^0}_{c,I} \\ {\alpha^0}_{N,1} \\ \vdots \\ {\alpha^0}_{N,J} \end{pmatrix} + \begin{pmatrix} \alpha^C_{11} & \cdots \alpha^C_{1,I} & \alpha^C_{1,I+1} \cdots & \alpha^C_{1,I+J} \\ \vdots & & \vdots & \vdots \\ \alpha^C_{I,1} & \cdots \alpha^C_{I,I} & \alpha^C_{I,I+1} \cdots & \alpha^C_{I,I+J} \\ \alpha^N_{1,1} & \cdots \alpha^N_{1,I} & \alpha^N_{1,I+1} \cdots & \alpha^N_{1,I+J} \\ \vdots & & \vdots & \vdots \\ \alpha^N_{J,1} & \cdots \alpha^C_{J,I} & \alpha^C_{J,I+1} \cdots & \alpha^C_{J,I+J} \end{pmatrix} \begin{pmatrix} S_{c,1,t} \\ \vdots \\ S_{c,I,t} \\ S_{N,1,t} \\ \vdots \\ S_{N,J,t} \end{pmatrix} + \begin{pmatrix} \beta_{c,1} \\ \vdots \\ \beta_{c,I} \\ \beta_{N,1} \\ \vdots \\ \beta_{N,J} \end{pmatrix} I_t + \begin{pmatrix} \varepsilon_{c,1,t} \\ \vdots \\ \varepsilon_{c,I,t} \\ \varepsilon_{N,1,t} \\ \vdots \\ \varepsilon_{N,J,t} \end{pmatrix} \tag{2}$$

Here, $I_t$ denotes personal investment during summer, such as internships or study abroad programs. It is assigned a value of zero for individuals who did not engage in any summer program and one for those who did participate. The variables $\alpha$ and $\beta$ are parameters, while $\varepsilon$ represents an error term. The model considers two periods: before and after summer. $t \in$

$[1, \dots T], T = 2$. The inputs exhibit perfect substitutability, resulting in a straight-line isoquant. When inputs are positioned on the isoquant line with a slope equal to the ratio of their marginal products, the elasticity of substitution between inputs becomes infinite.

Subsequently, we move away from the assumption of perfect input substitution and implement a Cobb-Douglas technology for skill productions.

$$S_{c,i,t+1} = A_{c,i} S_{c,1,t}^{\alpha_{i1}^{c}} \cdots S_{c,I,t}^{\alpha_{iI}^{c}} S_{N,1,t}^{\alpha_{iI+1}^{c}} \cdots S_{N,J,t}^{\alpha_{i\,I+J}^{c}} \qquad (3\text{-}1)$$

$$S_{N,j,t+1} = A_{N,j} S_{c,1,t}^{\alpha_{j1}^{N}} \cdots S_{c,I,t}^{\alpha_{jI}^{N}} S_{N,1,t}^{\alpha_{jI+1}^{N}} \cdots S_{N,J,t}^{\alpha_{j\,I+J}^{N}} \qquad (3\text{-}2)$$

By applying a logarithmic function to both sides of the equations, we derive the following expression.

$$ln\, S_{c,i,t+1} = lnA_{c,i} + \alpha_{i1}^{c} lnS_{c,1,t} \cdots + \alpha_{iI}^{c} lnS_{c,I,t} + \alpha_{i\,I+1}^{c} lnS_{N,1,t} \cdots + \alpha_{iI+J}^{c} lnS_{N,J,t} \qquad (4\text{-}1)$$

$$ln\, S_{N,j,t+1} = lnA_{N,j} + \alpha_{j1}^{N} lnS_{c,1,t} \cdots + \alpha_{jI}^{N} lnS_{c,I,t} + \alpha_{jI+1}^{N} lnS_{N,1,t} \cdots + \alpha_{jI+J}^{N} lnS_{N,J,t} \qquad (4\text{-}2)$$

For this scenario, the marginal rate of substitution between inputs is calculated through multiplying the ratio of input powers by the ratio of inputs themselves. The inputs exhibit a unitary elasticity of substitution. Skill formation can also be represented using the CES technology model. In the CES technology model, the elasticity of substitution between inputs remains constant across all inputs but is not equal to one.

Similar to the previous scenario, personal investment is incorporated to examine its impact on skill enhancement.

$$ln\, S_{c,i,t+1} = lnA_{c,i} + \alpha_{i1}^{c} lnS_{c,1,t} \cdots + \alpha_{iI}^{c} lnS_{c,I,t} + \alpha_{i\,I+1}^{C} lnS_{N,1,t} \cdots + \alpha_{iI+J}^{C} lnS_{N,J,t} + \beta_{c,i} I_t + \varepsilon_{c,i,t}$$
(5-1)

$$ln\, S_{N,j,t+1} = lnA_{N,j} + \alpha_{j1}^{N} lnS_{c,1,t} \cdots + \alpha_{jI}^{N} lnS_{c,I,t} + \alpha_{jI+1}^{N} lnS_{N,1,t} \cdots + \alpha_{jI+J}^{N} lnS_{N,J,t} + \beta_{N,j} I_t + \varepsilon_{N,j,t}$$
(5-2)

The Translog production function offers a more generalized approach by relaxing the constant elasticities of substitution. This function was suggested by Christensen, Jorgenson, and Lau (1973) and can be viewed as a second-order Taylor series approximation of a more general production function with logged variables.

$$ln\, S_{c,i,t+1} = lnA_{c,i} + \alpha_{i1}^{c} lnS_{c,1,t} \cdots + \alpha_{iI}^{c} lnS_{c,i,t} + \alpha_{i\,I+1}^{c} lnS_{N,1,t} \cdots + \alpha_{i\,I+J}^{c} lnS_{N,J,t}$$

$+\frac{1}{2}\sum_{l=1}^{I}\beta_{c,i,c,l}(lnS_{c,l,t})^2+\frac{1}{2}\sum_{l=1}^{J}\beta_{c,i,N,l}(lnS_{N,l,t})^2+\sum_{l=1}^{I}\sum_{m=1}^{I}\beta_{c,i,c,l,c,m}\, lnS_{c,l,t}lnS_{c,m,t}$

$+\sum_{l=1}^{I}\sum_{m=1}^{J}\beta_{c,i,c,l,N,m}\, lnS_{c,l,t}lnS_{N,m,t}+\sum_{l=1}^{J}\sum_{m=1}^{J}\beta_{c,i,N,l,N,m}\, lnS_{N,l,t}lnS_{N,m,t}$ (6-1)

$ln\, S_{N,j,t+1}=lnA_{N,j}+\alpha_{j1}^{N}lnS_{c,1,t}\cdots+\alpha_{jI}^{N}lnS_{c,i,t}+\alpha_{jI+1}^{N}lnS_{N,1,t}\cdots+\alpha_{j\,I+J}^{N}lnS_{N,J,t}$

$+\frac{1}{2}\sum_{l=1}^{I}\beta_{N,j,c,l}(lnS_{c,l,t})^2+\frac{1}{2}\sum_{l=1}^{J}\beta_{N,j,N,l}(lnS_{N,l,t})^2+\sum_{l=1}^{I}\sum_{m=1}^{I}\beta_{N,j,c,l,c,m}\, lnS_{c,l,t}lnS_{c,m,t}$

$+\sum_{l=1}^{I}\sum_{m=1}^{J}\beta_{N,j,c,l,N,m}\, lnS_{c,l,t}lnS_{N,m,t}+\sum_{l=1}^{J}\sum_{m=1}^{J}\beta_{N,j,N,l,N,m}\, lnS_{N,l,t}lnS_{N,m,t}$ (6-2)

when $\beta_{c,l,N,m}=\beta_{N,m,c,l}$ , $l\neq m.$

For estimation, the following equations can be used:

$ln\, S_{c,i,t+1}=lnA_{c,i}+\alpha_{i1}^{c}lnS_{c,1,t}\cdots+\alpha_{iI}^{c}lnS_{c,i,t}+\alpha_{i\,I+1}^{c}lnS_{N,1,t}\cdots+\alpha_{i\,I+J}^{c}lnS_{N,J,t}$

$+\frac{1}{2}\sum_{l=1}^{I}\beta_{c,i,c,l}(lnS_{c,l,t})^2+\frac{1}{2}\sum_{l=1}^{J}\beta_{c,i,N,l}(lnS_{N,l,t})^2+\sum_{l=1}^{I}\sum_{m=1}^{I}\beta_{c,i,c,l,c,m}\, lnS_{c,l,t}lnS_{c,m,t}$

$+\sum_{l=1}^{I}\sum_{m=1}^{J}\beta_{c,i,c,l,N,m}\, lnS_{c,l,t}lnS_{N,m,t}+\sum_{l=1}^{J}\sum_{m=1}^{J}\beta_{c,i,N,l,N,m}\, lnS_{N,l,t}lnS_{N,m,t}+\beta_{c,i}I_t+\varepsilon_{c,i,t}$
(7-1)

$ln\, S_{N,j,t+1}=lnA_{N,j}+\alpha_{j1}^{N}lnS_{c,1,t}\cdots+\alpha_{jI}^{N}lnS_{c,i,t}+\alpha_{jI+1}^{N}lnS_{N,1,t}\cdots+\alpha_{j\,I+J}^{N}lnS_{N,J,t}$

$+\frac{1}{2}\sum_{l=1}^{I}\beta_{N,j,c,l}(lnS_{c,l,t})^2+\frac{1}{2}\sum_{l=1}^{J}\beta_{N,j,N,l}(lnS_{N,l,t})^2+\sum_{l=1}^{I}\sum_{m=1}^{I}\beta_{N,j,c,l,c,m}\, lnS_{c,l,t}lnS_{c,m,t}$

$+\sum_{l=1}^{I}\sum_{m=1}^{J}\beta_{N,j,c,l,N,m}\, lnS_{c,l,t}lnS_{N,m,t}+\sum_{l=1}^{J}\sum_{m=1}^{J}\beta_{N,j,N,l,N,m}\, lnS_{N,l,t}lnS_{N,m,t}+\beta_{N,j}I_t+$
$\varepsilon_{N,j,t}$
(7-2)

The marginal product of $lnS_{c,1,t}$ is:

$$\frac{\partial lnS_{c,i,t*1}}{\partial lnS_{c,1,t}}=\alpha_{i1}^{c}+\beta_{c,i,c,1}lnS_{c,1,t}+\beta_{c,i,c,1,c,2}lnS_{c,2,t}+\sum_{m=1}^{J}\beta_{c,i,c,1,N.m}lnS_{N,m} \quad (8)$$

The marginal product of $lnS_{N,1,t}$ is:

$$\frac{\partial lnS_{c,i,t*1}}{\partial lnS_{N,1,t}}=\alpha_{iI+1}^{c}+\beta_{c,i,N\,1}lnS_{N,1,t}+\sum_{l=1}^{I}\beta_{c,i,c,l,N,1}lnS_{c,l,t}+\sum_{m=1}^{J}\beta_{c,i,N,1,N.m}lnS_{N,m,t} \quad (9)$$

The elasticity of substitution becomes,

$$\sigma_{lnS_{c,1,t}lnS_{N,1,t}} = \frac{\Delta(\frac{lnS_{c,1,t}}{lnS_{N,1,t}})}{\frac{lnS_{c,1,t}}{lnS_{N,1,t}}} \Bigg/ \frac{\Delta(\frac{MP_{lnS_{c,1,t}}}{MP_{lnS_{N,1,t}}})}{\frac{MP_{lnS_{c,1,t}}}{MP_{lnS_{N,1,t}}}} \tag{10}$$

where MP is the marginal product of each input.

When considering the production function prior to approximation in the logged form, the elasticity can be expressed as:

$$\sigma_{S_{c,1,t}S_{N,1,t}} = \frac{\Delta(\frac{S_{c,1,t}}{S_{N,1,t}})}{\frac{S_{c,1,t}}{S_{N,1,t}}} \Bigg/ \frac{\Delta(\frac{MP_{S_{c,1,t}}}{MP_{S_{N,1,t}}})}{\frac{MP_{S_{c,1,t}}}{MP_{S_{N,1,t}}}} \tag{11}$$

When all $\beta$ s in equations (6-1) (6-2) are zero, the estimation equations become the same as those in the case of the Cobb-Douglas technology. When the production function is in the logged form, zero $\beta$s mean a linear specification.

To assess skill levels, we utilize the average of each skill's components, in accordance with RISE (2017). These aggregated variables prove beneficial when considering Cobb-Douglas type technology.

The subsequent section will provide an overview of the data used in our analyses.

## 4. Data summary

To examine the indirect abilities fostered by summer programs, we administered GPI-based surveys at Tsuda University's Department of Policy Studies before and after the summer term. This initiative has been ongoing for five consecutive years since 2019. The surveys aimed to evaluate the impact of off-campus summer activities on both cognitive and non-cognitive skills.

Our university transitioned to a quarter system in 2017, establishing the Center for Off-campus Learning ("*Gakugai gakushu* center") in 2016 to introduce summer programs and internships and support students' participation in summer activities. By 2023, 1,211 students from our university had engaged in various summer programs, including international summer schools, service learning, and internships. Of these participants, 67% were freshers or sophomores, and 58.2% participated in activities lasting less than one month (The Center for Off-campus Learning and Career Support, 2025). Additionally, the Department of Policy Studies was launched in 2017, with all students following a quarter system from its inception.

We chose the Department of Policy Studies for our research because it has implemented a quarter system for all students since its inception in 2017. We believed that students in this department would have ample opportunities to engage in summer activities due to the absence of semester-based courses. First-year and second-year students were targeted, as they comprise nearly 70% of summer activity participants at our university. Additionally, most of their coursework consists of required classes, and they have not yet specialized in specific disciplines. From the five surveys conducted, we selected the 2023 cohort for this paper's analysis, as it was considered unaffected by the COVID-19 outbreak while still reflecting recent class formats (Shinkai & Oshima, 2024, 2025). The GPI allows for the assessment of six skills: two cognitive skills ("Knowing" and "Knowledge" from the "Cognitive Scales") and four non-cognitive skills ("Affect" and "Identity" from the "Intrapersonal Scales," and "Social Responsibility" and "Social Interactions" from the "Interpersonal Scales"). Each item is evaluated using a Likert-type scale ranging from 1 to 5. The score for each skill is calculated by averaging the items within that skill category.

In 2023, the GPI surveys were administered at Tsuda University's Department of Policy Studies during June and September by the author[5]. The author explained the purpose of the surveys to all first-year and second-year students before the surveys and only those who agreed answered. Approximately 120 students enter this department every year. The study involved 90 first-year and second-year students, with pre- and post-summer responses matched. First-year students made up 67.78% of the sample, while second-year students accounted for 32.22%. Among the participants, 45.56% (41 students) took part in off-campus activities, either domestically or internationally. These activities included domestic internships, volunteer work, service learning, regional cooperation projects, fieldwork, and study abroad programs. Sixteen students engaged in international programs, thirty-one in domestic activities, and six participated in both. Here, a dummy variable for participation in the summer program was used to represent own investment. Ideally, if we have more observations in each program, we may be able to test the difference in the effect of different summer programs. We identified a program with a few participants. Additionally, we also found that more than a few students participated in both domestic and international programs or in multiple international or domestic programs. Therefore, we decided to gauge the aggregate effect of participation in summer programs, as in previous skill formation models, instead of the effect of the individual program[6].

[5] The GPI, initially created in English by RISE at Iowa State University, comprised 35 core items, with 32 used for generating GPI scores. To implement it at our institution, we rendered the GPI into Japanese. A linguistics professor on our staff reviewed the translation, which was then tested with graduate students before being sent to the GPI headquarters at Iowa State University for evaluation. Subsequently, we sought permission to utilize the GPI and administered it to our students upon receiving approval from the GPI headquarters. This approval process has been repeated annually prior to GPI administration. Before implementation, the Research Ethics Committee at Tsuda University examined and approved the content of our survey. First year students and second year students were asked at different times but the intervals between the pre- and post- surveys were approximately the same, namely three months.

[6] To check the possibility of the difference in the effects of international summer programs and domestic summer

The Appendix's Table A1 presents the summary statistics. Notably, within the non-cognitive skills category, "Affect" scored highest, while "Social Interactions" scored lowest among all skill categories (Appendix A, Table A1).

The subsequent section will present the findings from the analyses of skill formation.

## 5. Results of analyses

This section outlines the estimation outcomes. Table 1 presents the results from estimating equations (1) and (2) across all six skill categories. To assess multicollinearity, variance inflation factors (VIF) were evaluated for each estimation, with no factors exceeding a value of two. Additionally, we conducted the Ramsey regression equation specification error (RESET) test to verify the appropriateness of linear specification and check for omitted variables (Ramsey, 1969). None of the equations rejected the hypothesis of "no omitted variables" based on squared, cubed, and quartic fitted values.

programs, an analysis with separate dummies for international and domestic programs was conducted. The results are quite similar to those with one integrated dummy with an emphasis on the effects on international programs. However, since more than a few students participated in both international and domestic programs, the coefficients of international and domestic programs may have integrated the effects of both programs. Therefore, it is difficult to articulate the effect of either program on its own.

Table 1 Results of the estimation of a linear dynamic factor model

Table 1-1 Cognitive Scales

| | Knowing(Post) | | | | | | Knowledge(Post) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat |
| Knowing (Pre) | 0.515 | ** | 4.090 | 0.487 | ** | 3.830 | 0.163 | | 1.520 | 0.135 | | 1.250 |
| Knowledge(Pre) | 0.053 | | 0.470 | 0.047 | | 0.420 | 0.633 | ** | 6.590 | 0.626 | ** | 6.560 |
| Affect(Pre) | -0.071 | | -0.590 | -0.073 | | -0.610 | 0.111 | | 1.090 | 0.109 | | 1.080 |
| Identity(Pre) | 0.053 | | 0.580 | 0.045 | | 0.490 | 0.174 | ** | 2.260 | 0.166 | ** | 2.170 |
| Social Responsibility(Pre) | 0.012 | | 0.140 | 0.014 | | 0.160 | -0.099 | | -1.360 | -0.097 | | -1.350 |
| Social Interactions(Pre) | -0.046 | | -0.780 | -0.054 | | -0.910 | -0.035 | | -0.700 | -0.043 | | -0.860 |
| Participated(=1) | | | | 0.136 | | 1.280 | | | | 0.139 | | 1.550 |
| Constant | 1.570 | ** | 2.39 | 1.675 | ** | 2.540 | 0.029 | | 0.050 | 0.137 | | 0.250 |
| Obs. | 90 | | | 90 | | | 90 | | | 90 | | |
| Adjusted $R^2$ | 0.128 | | | 0.135 | | | 0.501 | | | 0.510 | | |
| Ramsey's RESET test | F(3, 80) = | | | F(3, 79) = | | | F(3, 80) = | | | F(3, 79) = | | |
| | 1.81 | | | 1.54 | | | 0.72 | | | 0.53 | | |

Table1-2 Non-cognitive Scales; Intrapersonal Scales

| | Affect (Post) | | | | | | Identity (Post) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat |
| Knowing (Pre) | 0.001 | | 0.010 | -0.023 | | -0.210 | 0.214 | | 1.450 | 0.177 | | 1.190 |
| Knowledge(Pre) | -0.010 | | -0.110 | -0.016 | | -0.170 | -0.104 | | -0.780 | -0.112 | | -0.850 |
| Affect(Pre) | 0.596 | ** | 5.880 | 0.593 | ** | 5.880 | 0.186 | | 1.310 | 0.182 | | 1.300 |
| Identity(Pre) | 0.112 | | 1.470 | 0.105 | | 1.380 | 0.628 | ** | 5.890 | 0.618 | ** | 5.820 |
| Social Responsibility(Pre) | 0.079 | | 1.100 | 0.081 | | 1.130 | -0.063 | | -0.620 | -0.060 | | -0.610 |
| Social Interactions(Pre) | -0.057 | | -1.130 | -0.063 | | -1.270 | -0.097 | | -1.390 | -0.107 | | -1.530 |
| Participated(=1) | | | | 0.117 | | 1.320 | | | | 0.181 | | 1.460 |
| Constant | 0.942 | | 1.700 | 1.033 | * | 1.860 | 0.531 | | 0.690 | 0.671 | | 0.870 |
| Obs. | 90 | | | 90 | | | 90 | | | 90 | | |
| Adjusted $R^2$ | 0.442 | | | 0.447 | | | 0.327 | | | 0.336 | | |
| Ramsey's RESET test | F(3, 80) = 0.24 | | | F(3, 79) = 0.54 | | | F(3, 80) = 0.25 | | | F(3, 79) = 0.36 | | |

Table1-3 Non-cognitive Scales; Interpersonal Scales

| | Social Responsibility (Post) | | | | | | Social Interactions (Post) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat |
| Knowing (Pre) | 0.240 | * | 1.880 | 0.188 | | 1.490 | -0.075 | | -0.440 | -0.089 | | -0.520 |
| Knowledge(Pre) | 0.072 | | 0.630 | 0.059 | | 0.530 | -0.132 | | -0.870 | -0.136 | | -0.890 |
| Affect(Pre) | -0.116 | | -0.950 | -0.121 | | -1.020 | 0.262 | | 1.620 | 0.261 | | 1.610 |
| Identity(Pre) | 0.042 | | 0.460 | 0.027 | | 0.300 | -0.072 | | -0.590 | -0.076 | | -0.620 |
| Social Responsibility(Pre) | 0.656 | ** | 7.540 | 0.659 | ** | 7.800 | 0.035 | | 0.300 | 0.036 | | 0.310 |
| Social Interactions(Pre) | -0.165 | ** | -2.740 | -0.180 | ** | -3.060 | 0.676 | ** | 8.480 | 0.672 | ** | 8.350 |
| Participated(=1) | | | | 0.259 | ** | 2.470 | | | | 0.071 | | 0.490 |
| Constant | 0.549 | | 0.820 | 0.749 | | 1.150 | 0.543 | | 0.610 | 0.597 | | 0.670 |
| Obs. | 90 | | | 90 | | | 90 | | | 90 | | |
| Adjusted $R^2$ | 0.494 | | | 0.523 | | | 0.468 | | | 0.464 | | |
| Ramsey's RESET test | F(3, 80) = | | | F(3, 79) = | | | F(3, 80) = | | | F(3, 79) = | | |
| | 1.38 | | | 0.96 | | | 0.24 | | | 0.21 | | |

Note: **p<0.05, *p<0.10. Compiled by the author.

The results with “Participated(=1)” are the estimation results of equation (2). Otherwise, the estimations results are based on equation (1).

Table 1 reveals that each skill demonstrated robust self-productivity, with all instances being statistically significant. “Social Interaction” exhibited the highest self-productivity, followed by “Social Responsibility,” “Knowledge,” and “Identity.” Regarding cross-productivity, “Identity” in one period enhanced “Knowledge” in the subsequent period. While “Knowing” in one period may have boosted “Social Responsibility” in the next, this effect vanished when accounting for summer program participation (Table 1-3). The coefficient of “Knowing” in one period became statistically insignificant with a participation dummy. Conversely, some skills negatively impacted others in the following period. For instance, high “Social Interactions” in one period resulted in decreased “Social Responsibility” in the next. Summer activities were found to positively influence “Social Responsibility” in the subsequent period but had no significant impact on other skills.

Table 2 presents the results of logged variable estimation[7], assuming Cobb-Douglas technology for skill formation. The analysis tested whether the sum of coefficients equaled unity, which would indicate homogeneous skill formation of degree one. These findings aligned with the dynamic linear model results. Self-productivity remained strong and statistically significant across all skill formations, with “Social Interactions” exhibiting the highest self-productivity, followed by “Social Responsibility,” “Affect,” and “Identity.” Significant cross-productivity between cognitive and non-cognitive skills was observed between “Identity” and “Knowledge,” with a 10% increase in “Identity” leading to a 1.8% rise in “Knowledge” in the following period.

The Cobb-Douglas function estimation revealed effects not present in the linear dynamic factor model. Elevated “Affect” in one period increased “Identity” in the next, while “Knowledge” in one period fostered “Social Responsibility” in the subsequent period, even when accounting for summer program participation. High “Social Interaction” in one period continued to lower “Social Responsibility” in the following period.

In the Cobb-Douglas function analysis, off-campus summer activities significantly impacted two skill groups, as opposed to one in the previous model. Participation in summer programs enhanced both “Knowledge” (cognitive skill) and “Social Responsibility” (non-cognitive skill) in the subsequent period. Specifically, students who took part in summer activities experienced a 4.7% increase in “Knowledge” and a 6% rise in “Social Responsibility” in the following period.

The homogeneity of degree one was rejected by “Knowing” at a 5% significance level in

[7] Several outliers were observed in the “Identity” and “Social Responsibility” categories regarding the difference in score logarithms. Data points that fell more than three standard deviations above or below the mean were excluded from logarithmic analyses. In contrast, no such outliers were identified in the preceding instance. We also tried the estimation of the Translog production function. However, the results of the VIF were way beyond five and detected multicollinearity. Therefore, we did not include the results in the table.

the test on the sum of coefficients of skill categories. Similarly, “Affect” with a summer program participation dummy variable also rejected the homogeneity of degree one. Other skills accepted the null hypothesis.

Cunha and Heckman (2008) used different measures of cognitive and non-cognitive skills than this paper but found strong self-productivity in both, though non-cognitive skills’ self-productivity decreased as children developed. Non-cognitive skills had a stronger impact on cognitive skills than vice versa. Initially, parental investments affected cognitive skills more than non-cognitive skills, although this relationship eventually became unclear. The relationship varied based on the adult outcomes used for anchoring skill variables.

In a two-stage model, Cunha, Heckman, and Schennach (2010) discovered strong self-productivity of skills in both stages, with greater strength in the second stage of child development. Non-cognitive skills contributed to cognitive skill development but not vice versa. They determined that parental investments had a stronger effect on both cognitive and non-cognitive skills in the first period, from age 0 to ages 5-6 in their data set, compared to the second, from ages 5-6 to ages 13-14. Investment effects surpassed cross-productivity of other skills in the same period when skills were anchored by years of schooling. Their study focused on parental investments rather than children’s self-investments.

This study examined undergraduate students and their self-investments through summer program participation. We found that cognitive skills’ cross-productivity contributions to non-cognitive skills were comparable to the reverse, although non-cognitive skills’ contributions to cognitive skills are more stable. Self-productivities were stronger than cross-productivities, aligning with previous findings. However, investment effects were weaker than cross-productivities of other skills, possibly due to the sample’s age.

While Duckworth et al. (2007) and Egan et al. (2016) found contemporaneous negative correlations between cognitive and non-cognitive skills in adolescents, the current study estimated the dynamic relationship between these skills. We observed positive contributions between cognitive and non-cognitive skills in skill formation, as well as negative contributions between non-cognitive skills within interpersonal scales. Additionally, our cognitive skill measurements differed from test scores, and we constructed both cognitive and non-cognitive skills using GPI Scales, avoiding potential scaling issues. This consistent scaling approach may have influenced the results.

Table 2 Results of the estimation of a production function with the Cobb-Douglas Technology

Table 2-1 Cognitive Scales

| | Ln(Knowing (Post)) | | | | | | Ln(Knowledge(Post)) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat |
| Ln(Knowing (Pre)) | 0.454 | ** | 3.420 | 0.432 | ** | 3.220 | 0.137 | | 1.240 | 0.108 | | 0.980 |
| Ln(Knowledge(Pre)) | 0.041 | | 0.340 | 0.034 | | 0.280 | 0.624 | ** | 6.320 | 0.615 | ** | 6.280 |
| Ln(Affect(Pre)) | -0.085 | | -0.600 | -0.089 | | -0.630 | 0.130 | | 1.100 | 0.126 | | 1.070 |
| Ln(Identity(Pre)) | 0.054 | | 0.610 | 0.048 | | 0.540 | 0.181 | ** | 2.450 | 0.173 | ** | 2.370 |
| Ln(Social Responsibility(Pre)) | 0.004 | | 0.050 | 0.006 | | 0.080 | -0.071 | | -1.120 | -0.068 | | -1.090 |
| Ln(Social Interactions(Pre)) | -0.038 | | -0.820 | -0.042 | | -0.910 | -0.043 | | -1.120 | -0.048 | | -1.260 |
| Participated(=1) | | | | 0.035 | | 1.040 | | | | 0.047 | * | 1.680 |
| Constant | 0.669 | ** | 2.59 | 0.700 | ** | 2.690 | -0.003 | | -0.020 | 0.039 | | 0.180 |
| Obs. | 90 | | | 90 | | | 90 | | | 90 | | |
| Adjusted $R^2$ | 0.082 | | | 0.083 | | | 0.491 | | | 0.510 | | |
| Ramsey's RESET test | F(3, 80)= 1.81 | | | F(3, 79) = 1.54 | | | F(3, 80) = 0.81 | | | F(3, 79) = 0.73 | | |
| Test of Coefficients | F(1,83)=7.42 | | | F(1,82)=8.23 | | | F(1,83)=0.06 | | | F(1,82)=0.29 | | |

Table 2-2 Non-cognitive skills; Intrapersonal scales

| | Ln(Affect (Post)) | | | | Ln(Identity (Post)) | | | |
|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat |
| Ln(Knowing (Pre)) | 0.001 | 0.010 | -0.020 | -0.210 | -0.022 | -0.160 | -0.040 | -0.280 |
| Ln(Knowledge(Pre)) | 0.013 | 0.150 | 0.007 | 0.080 | 0.016 | 0.140 | 0.007 | 0.060 |
| Ln(Affect(Pre)) | 0.638 ** | 6.140 | 0.635 ** | 6.140 | 0.300 ** | 2.120 | 0.294 ** | 2.080 |
| Ln(Identity(Pre)) | 0.059 | 0.910 | 0.053 | 0.830 | 0.581 ** | 6.650 | 0.575 ** | 6.580 |
| Ln(Social Responsibility(Pre)) | 0.047 | 0.850 | 0.049 | 0.890 | -0.059 | -0.780 | -0.056 | -0.750 |
| Ln(Social Interactions(Pre)) | -0.029 | -0.870 | -0.033 | -0.980 | -0.059 | -1.300 | -0.064 | -1.390 |
| Participated(=1) | | | 0.034 | 1.390 | | | 0.037 | 1.110 |
| Constant | 0.326 * | 1.720 | 0.356 * | 1.880 | 0.216 | 0.840 | 0.248 | 0.960 |
| Obs. | 90 | | 90 | | 89 | | 89 | |
| Adjusted $R^2$ | 0.412 | | 0.418 | | 0.448 | | 0.449 | |
| Ramsey's RESET test | F(3, 80) = 0.14 | | F(3, 79) = 0.50 | | F(3, 79) = 1.13 | | F(3, 78) = 1.10 | |
| Test of Coefficients | F(1, 83) = 3.12 | | F(1, 82) = 3.99 | | F(1, 82) = 1.37 | | F(1, 81) = 1.82 | |

Table 2-3 Non-cognitive skills; Interpersonal scales

| | Ln(Social Responsibility (Post)) | | | | | | Ln(Social Interactions (Post)) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat |
| Ln(Knowing (Pre)) | 0.066 | | 0.510 | 0.038 | | 0.300 | -0.290 | | -1.170 | -0.312 | | -1.230 |
| Ln(Knowledge(Pre)) | 0.202 | * | 1.840 | 0.184 | * | 1.700 | -0.124 | | -0.560 | -0.131 | | -0.590 |
| Ln(Affect(Pre)) | -0.135 | | -0.990 | -0.136 | | -1.010 | 0.433 | | 1.630 | 0.430 | | 1.610 |
| Ln(Identity(Pre)) | 0.012 | | 0.140 | 0.005 | | 0.070 | -0.226 | | -1.370 | -0.231 | | -1.390 |
| Ln(Social Responsibility(Pre)) | 0.782 | ** | 9.340 | 0.776 | ** | 9.430 | 0.011 | | 0.080 | 0.013 | | 0.090 |
| Ln(Social Interactions(Pre)) | -0.125 | ** | -2.950 | -0.131 | ** | -3.150 | 0.738 | ** | 8.550 | 0.734 | ** | 8.440 |
| Participated(=1) | | | | 0.060 | * | 1.980 | | | | 0.034 | | 0.540 |
| Constant | 0.132 | | 0.560 | 0.181 | | 0.780 | 0.362 | | 0.750 | 0.393 | | 0.800 |
| Obs. | 88 | | | 88 | | | 90 | | | 90 | | |
| Adjusted $R^2$ | 0.609 | | | 0.622 | | | 0.469 | | | 0.464 | | |
| Ramsey's RESET test | F(3, 78) = 1.04 | | | F(3, 77) = 0.61 | | | F(3, 80) = 0.12 | | | F(3, 79) = 0.08 | | |
| Test of Coefficients | F(1, 81) = 1.08 | | | F(1, 80) = 1.92 | | | F(1, 83) = 1.37 | | | F(1, 82) = 1.55 | | |

Note: **p<0.05, *p<0.10. Compiled by the author.

The results with “Participated(=1)” are the estimation results of equation (5-1) or (5-2). Otherwise, the estimations results are based on equation (4-1)or(4-2).

## 6. Additional estimation

This study examines the outcomes of assessing cognitive and non-cognitive skill development using a linear dynamic model and the Cobb-Douglas function. In this context, education investment is defined as students’ involvement in a summer program. While parental attributes may have less influence on adolescent skills compared to those of younger children, home environments could still impact skill levels. A positive correlation between these factors might lead to an upward bias in skill coefficients. Although instrumental variables could address this bias, the available data lacks sufficient information on parental background or home environments. An alternative approach to mitigate this bias involves analyzing differences in individual skills. Since an individual’s home environment remains constant before and after summer, these factors should cancel out. Consequently, the coefficients of differenced independent variables would not be affected by potential variations in home environments across individuals. In this scenario, the coefficient of one’s own skill represents self-productivity minus one, rather than self-productivity alone.

Equations (5-1) and (5-2) can be written as:

$$ln\, S_{c,i,t+1} - lnS_{c,i,t} = lnA_{c,i} + \alpha_{i1}^{c} lnS_{c,1,t} \cdots + (\alpha_{ii}^{c} - 1) lnS_{c,i,t} \quad \cdots + \alpha_{iI}^{c} lnS_{c,I,t} + \alpha_{i\,I+1}^{C} lnS_{N,1,t} \quad \cdots \quad + \quad \alpha_{iI+J}^{C} lnS_{N,J,t} + \beta_{c,i} I_t + \varepsilon_{c,i,t} \quad (12\text{-}1)$$

$$ln\, S_{N,j,t+1} - ln\, S_{N,j,t} = lnA_{N,j} + \alpha_{j1}^{N} lnS_{c,1,t} \cdots + \alpha_{jI}^{N} lnS_{c,I,t} + \alpha_{jI+1}^{N} lnS_{N,1,t} \cdots + (\alpha_{jj}^{N} - 1) lnS_{N,j,t} \cdots + \quad \alpha_{jI+J}^{N} lnS_{N,J,t} + \beta_{N,j} I_t + \varepsilon_{N,j,t} \quad (12\text{-}2)$$

Table 3 presents the outcomes of the equation estimations mentioned earlier. As in previous analyses, we conducted VIF examinations and implemented Ramsey’s RESET test. Consistent with our prior findings, no factors exceeded a value of two in any of the estimations.

Table 3 Results of the additional estimation

Table 3-1 Cognitive Scales

| | Diff. in Ln(Knowing (Post)) | | | | | | Diff. in Ln(Knowledge(Post)) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat |
| Ln(Knowing (Pre)) | -0.546 | ** | -4.110 | -0.568 | ** | -4.230 | 0.137 | | 1.240 | 0.108 | | 0.980 |
| Ln(Knowledge(Pre)) | 0.041 | | 0.340 | 0.034 | | 0.280 | -0.376 | ** | -3.810 | -0.385 | ** | -3.940 |
| Ln(Affect(Pre)) | -0.085 | | -0.600 | -0.089 | | -0.630 | 0.130 | | 1.100 | 0.126 | | 1.070 |
| Ln(Identity(Pre)) | 0.054 | | 0.610 | 0.048 | | 0.540 | 0.181 | ** | 2.450 | 0.173 | ** | 2.370 |
| Ln(Social Responsibility(Pre)) | 0.004 | | 0.050 | 0.006 | | 0.080 | -0.071 | | -1.120 | -0.068 | | -1.090 |
| Ln(Social Interactions(Pre)) | -0.038 | | -0.820 | -0.042 | | -0.910 | -0.043 | | -1.120 | -0.048 | | -1.260 |
| Participated(=1) | | | | 0.035 | | 1.040 | | | | 0.047 | * | 1.680 |
| Constant | 0.669 | ** | 2.590 | 0.700 | | 2.690 | -0.003 | | -0.020 | 0.039 | | 0.180 |
| Obs. | 90 | | | 90 | | | 90 | | | 90 | | |
| Adjusted $R^2$ | 0.137 | | | 0.138 | | | 0.154 | | | 0.172 | | |
| Ramsey's RESET test | F(3, 80) = 0.69 | | | F(3, 79) = 0.49 | | | F(3, 80) = 0.12 | | | F(3, 79) = 0.23 | | |

Table 3-2 Non-cognitive Scales; Intrapersonal Scales

| | Diff. in Ln(Affect (Post)) | | | | | | | Diff. in Ln(Identity (Post)) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat |
| Ln(Knowing (Pre)) | 0.001 | | 0.010 | -0.020 | | -0.210 | -0.022 | | -0.160 | -0.040 | | -0.280 |
| Ln(Knowledge(Pre)) | 0.013 | | 0.150 | 0.007 | | 0.080 | 0.016 | | 0.140 | 0.007 | | 0.060 |
| Ln(Affect(Pre)) | -0.362 | ** | -3.480 | -0.365 | ** | -3.540 | 0.300 | ** | 2.120 | 0.294 | ** | 2.080 |
| Ln(Identity(Pre)) | 0.059 | | 0.910 | 0.053 | | 0.830 | -0.419 | ** | -4.800 | -0.425 | ** | -4.870 |
| Ln(Social Responsibility(Pre)) | 0.047 | | 0.850 | 0.049 | | 0.890 | -0.059 | | -0.780 | -0.056 | | -0.750 |
| Ln(Social Interactions(Pre)) | -0.029 | | -0.870 | -0.033 | | -0.980 | -0.059 | | -1.300 | -0.064 | | -1.390 |
| Participated(=1) | | | | 0.034 | | 1.390 | | | | 0.037 | | 1.110 |
| Constant | 0.326 | * | 1.720 | 0.356 | * | 1.880 | 0.216 | | 0.840 | 0.248 | | 0.960 |
| Obs. | 90 | | | 90 | | | 89 | | | 89 | | |
| Adjusted $R^2$ | 0.076 | | | 0.086 | | | 0.272 | | | 0.274 | | |
| Ramsey's RESET test | F(3, 80) = 0.60 | | | F(3, 79) = 1.42 | | | F(3, 79) = 4.73 | | | F(3, 78) = 3.05 | | |

Table 3-3 Non-cognitive Scales; Interpersonal Scales

| | Diff. in Ln(Social Responsibility (Post)) | | | | | | Diff. in Ln(Social Interactions (Post)) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Explanatory variables | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat | Coefficient | | t-stat |
| Ln(Knowing (Pre)) | 0.066 | | 0.510 | 0.038 | | 0.300 | -0.290 | | -1.170 | -0.312 | | -1.230 |
| Ln(Knowledge(Pre)) | 0.202 | * | 1.840 | 0.184 | * | 1.700 | -0.124 | | -0.560 | -0.131 | | -0.590 |
| Ln(Affect(Pre)) | -0.135 | | -0.990 | -0.136 | | -1.010 | 0.433 | | 1.630 | 0.430 | | 1.610 |
| Ln(Identity(Pre)) | 0.012 | | 0.140 | 0.005 | | 0.070 | -0.226 | | -1.370 | -0.231 | | -1.390 |
| Ln(Social Responsibility(Pre)) | -0.218 | ** | -2.600 | -0.224 | ** | -2.720 | 0.011 | | 0.080 | 0.013 | | 0.090 |
| Ln(Social Interactions(Pre)) | -0.125 | ** | -2.950 | -0.131 | ** | -3.150 | -0.262 | ** | -3.040 | -0.266 | ** | -3.060 |
| Participated(=1) | | | | 0.060 | * | 1.980 | | | | 0.034 | | 0.540 |
| Constant | 0.132 | | 0.56 | 0.181 | | 0.780 | 0.362 | | 0.750 | 0.393 | | 0.800 |
| Obs. | 88 | | | 88 | | | 90 | | | 90 | | |
| Adjusted $R^2$ | 0.139 | | | 0.169 | | | 0.126 | | | 0.118 | | |
| Ramsey's RESET test | F(3, 78) = 0.63 | | | F(3, 77) = 0.49 | | | F(3, 80) = 1.85 | | | F(3, 79) = 1.50 | | |

Note: **p<0.05, *p<0.10. Compiled by the author.

The skill group coefficients remained nearly identical to those from previous analyses. If significant factors were omitted in the Cobb-Douglas production function estimation and these factors correlated with skills, the explanatory variable coefficients should have changed. However, these coefficients, along with the summer program participation dummy variable coefficients, remained stable.

Our earlier findings have proven to be quite robust. Nevertheless, for the differenced logarithm of variables, the value of $R^2$ in the estimation of “Affect” was notably low, under 0.1. Such a finding casts doubt on the explanatory power of this estimation equation. When plotting the distribution of equation (12-2) for the “Affect” logarithm difference, the residuals appeared to follow multiple density types, at least two (Appendix B, Figure B1). This suggests the existence of several groups within the “Affect” logarithm difference. For example, one group might have exhibited little change before and after summer, while another group may have experienced a decrease in “Affect” post-summer, with these groups exhibiting distinct behaviors. However, determining the exact factors that caused individuals to fall into each group may not be possible. The residual distribution apparently shows two peaks. Consequently, instead of a single equation, we consider the possibility of two equations for the “Affect” logarithm difference, with each individual potentially following one of these. The conditional probability density function thus becomes:

$$f(y_{N,j}) = \alpha_1 g_1(y_{N,j,A1}) + \alpha_2 g_2(y_{N,j,A2}) \tag{13}$$

when $y_{N,j} = lnS_{N,j,t+1} - LnS_{N,j,t},\ \alpha_1 + \alpha_2 = 1,\ g_i \sim N(\mu_i, \sigma_i^2),\ where\ i = 1, 2$

The likelihood function is:

$$L(\theta) = \sum_{l=1}^{2} \alpha_l \prod_{m=1}^{n} g_{l,m}(\, y_{N,j,m} | s,\ \theta\,) \tag{14}$$

where $n$ is the number of observations, $s$ is the vector of explanatory variables and the $\theta$ is the vector of the parameters of this model.

Table 4 demonstrates the results of the estimation of the log-likelihood function.

Table 4 Results of the mixture model: Difference in Ln(Affect)

| | Diff. in Ln(Affect (Post)) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Group | | | Second Group | | | First Group | | | Second Group | | |
| Explanatory variables | Coefficient | | z-stat | Coefficient | | z-stat | Coefficient | | z-stat | Coefficient | | z-stat |
| Ln(Knowing (Pre)) | 0.011 | | 0.120 | -0.112 | | -1.070 | 0.062 | | 0.690 | 0.011 | | 0.090 |
| Ln(Knowledge(Pre)) | 0.013 | | 0.170 | 0.147 | | 0.860 | 0.007 | | 0.080 | -0.031 | | -0.320 |
| Ln(Affect(Pre)) | -0.359 | ** | -3.520 | -1.065 | ** | -6.110 | -0.327 | ** | -2.740 | -0.685 | ** | -4.550 |
| Ln(Identity(Pre)) | 0.115 | | 1.620 | -0.233 | ** | -2.920 | 0.120 | | 1.700 | -0.099 | | -1.200 |
| Ln(Social Responsibility(Pre)) | 0.023 | | 0.450 | 0.172 | ** | 2.550 | -0.002 | | -0.040 | 0.096 | | 1.280 |
| Ln(Social Interactions(Pre)) | -0.021 | | -0.650 | -0.112 | ** | -3.480 | -0.028 | | -0.820 | -0.093 | ** | -2.520 |
| Participated(=1) | | | | | | | -0.026 | | -1.080 | 0.071 | ** | 2.010 |
| Constant | 0.299 | | 1.540 | 1.346 | ** | 5.560 | 0.264 | | 1.360 | 0.835 | ** | 3.260 |
| Marginal prob. | 0.789 | | | 0.211 | | | 0.661 | | | 0.339 | | |
| Marginal means | -0.010 | | -0.780 | -0.200 | ** | -15.410 | 0.012 | | 0.710 | -0.153 | ** | -7.010 |
| Obs. | 90 | | | | | | 90 | | | | | |
| Log-likelihood | 84.580 | | | | | | 83.117 | | | | | |

Note: **p<0.05, *p<0.10. Compiled by the author.

The initial cluster, representing the latent first class, exhibited coefficients comparable to previous findings. The self-productivity of “Affect” was 0.641 without the participation dummy variable and 0.673 with it. In contrast, the second cluster presented a distinct pattern. Its “Affect” self-productivity was considerably different from that of the first cluster, while “Social Interactions” negatively influenced “Affect” growth. The second cluster’s predicted mean was lower than the first’s, and more cases were assigned to the initial cluster. The summer program participation dummy variable’s coefficient was statistically significant and positive in the second cluster. This suggests that, for individuals experiencing substantial changes in “Affect,” summer program involvement may enhance “Affect” in the subsequent period. Conversely, for those with minimal “Affect” changes during summer, participation might not yield significant effects. Based on the results, it is possible that the impact of summer program participation varies, depending on the level of change in an intrapersonal skill, namely “Affect”.

## 7. Conclusion

With the growing adoption of quarter systems in universities, students are presented with more chances to participate in off-campus summer activities, including study abroad programs, internships, fieldwork, and service learning. These summer experiences not only broaden subject knowledge but may also foster non-cognitive abilities. Research by Shinkai and Oshima (2024, 2025) revealed that participants in summer programs generally maintained both cognitive and non-cognitive skills, while non-participants experienced a decline in certain skills. However, the mechanisms behind these skill changes remained unclear. It is possible that cognitive and non-cognitive skills interacted, leading to positive or negative changes. Additionally, off-campus programs might have contributed to skill development and offset potential negative effects in skill formation.

This study employed linear dynamic factor models and other potential nonlinear dynamic functional forms of skill formation to elucidate how cognitive and non-cognitive skills develop during summer, and to determine the impact of summer activity participation on skill formation. Four hypotheses were tested. The first hypothesis, stating that non-cognitive skills contribute to cognitive skill formation, was confirmed by the positive effect of “Identity” in one period on “Knowledge” in the subsequent period. The second hypothesis, proposing that cognitive skills contribute to non-cognitive skill formation, was also validated through the observed cross-productivity between pre-summer “Knowledge” and post-summer “Social Responsibility.” When examining cross-productivity coefficients, the “Knowledge” coefficient was slightly larger than or comparable to that of “Identity,” even when accounting for summer program participation. Consequently, the third hypothesis, suggesting that non-cognitive skills contribute more to skill formation than cognitive skills, remains uncertain. The contribution of non-cognitive skills was more consistent, since it appeared regardless of what the production function form was. The coefficients for summer activity participation were significant in the formation of log-transformed “Knowledge” and “Social Responsibility,” supporting the fourth hypothesis that summer activities positively affect both cognitive and non-cognitive skills.

Despite the relatively short skill formation period of one summer, strong self-productivity and weak but significant cross-productivity were observed among cognitive and non-cognitive skills. For non-participants, “Knowing” may have deteriorated after summer (Shinkai & Oshima, 2025). “Knowing” was only significantly affected by self-productivity, emphasizing the importance of improving this skill to maintain it during summer. As regards “Knowledge,” another skill that declined for non-participants after summer, “Identity” may be able to raise “Knowledge” in the following period. Participants exhibited an upward trend in “Identity,” which may have contributed to maintaining “Identity” and increasing “Knowledge.” “Social Responsibility” showed a downward trend for all participants. Since this non-cognitive skill can be improved by “Knowledge,” having a strong “Knowledge” skill is crucial for developing “Social Responsibility.”

The concept of “Social Responsibility” is explored, revealing that, while “Social Interactions” demonstrated strong self-productivity, it may have weakened another interpersonal skill. Both “Social Responsibility” and “Social Interactions” fall into the category of interpersonal abilities. It is possible that “Social Responsibility” may play the role of a substitute for “Social Interactions” instead of the two complementing each other in the group of interpersonal abilities.

Intrapersonal abilities were found to enhance both cognitive and intrapersonal skills but not interpersonal ones. Participation in the summer program was shown to boost both cognitive and interpersonal capabilities. Although improving all cognitive and non-cognitive skills is beneficial, non-cognitive skills are particularly valued in existing literature for their role in achieving positive socio-economic outcomes. Analysis of skill formation models highlighted crucial skills in the development of six cognitive and non-cognitive abilities, as well as the positive impact of the summer program on cognitive and interpersonal skills. The summer program’s effect on non-cognitive skills surpassed its impact on cognitive skills. Summer programs contributed to the development of both skill types and occasionally offset the negative effects of potential cross-productivity.

The research findings underscored the importance of evaluating cognitive and non-cognitive skills in skill formation in conjunction with educational investments. The application of dynamic models in the study provided insights into the essential non-cognitive skills, which strengthen overall skill development even in a short period.

Appendix A: Descriptive Statistics

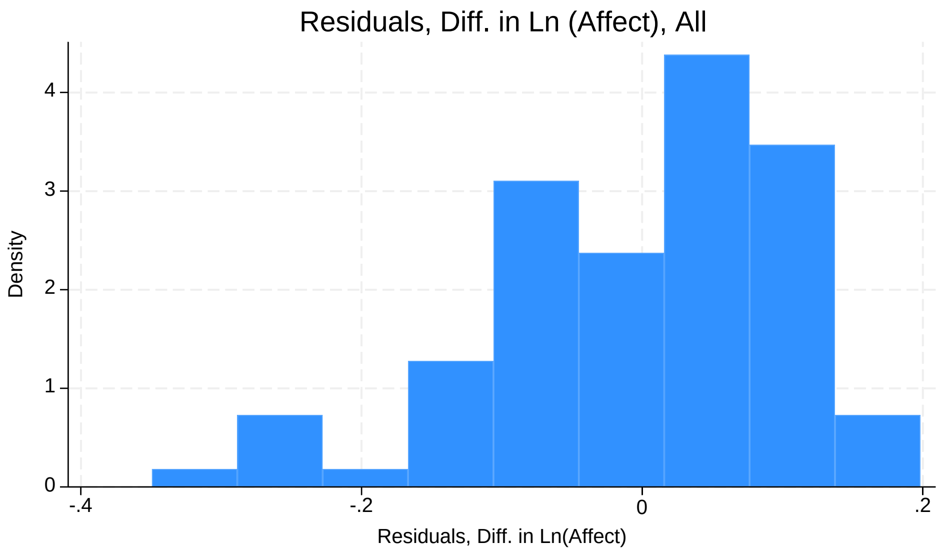
Table A1 GPI scores before and after summer

| Variables | N | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| Knowing（Pre） | 90 | 3.437 | 0.434 | 2.143 | 4.714 |
| Knowing（Post） | 90 | 3.343 | 0.524 | 2 | 4.571 |
| Knowledge（Pre） | 90 | 3.347 | 0.573 | 2 | 5 |
| knowledge（Post） | 90 | 3.278 | 0.589 | 1.800 | 5 |
| Affect（Pre） | 90 | 3.840 | 0.532 | 2.800 | 5 |
| Affect（Post） | 90 | 3.689 | 0.552 | 2.600 | 5 |
| Identity (Pre) | 90 | 3.269 | 0.730 | 1.500 | 5 |
| Identity（Post） | 90 | 3.226 | 0.701 | 1.333 | 5 |
| Social Responsibility（Pre） | 90 | 3.387 | 0.713 | 1 | 5 |
| Social Responsibility（Post） | 90 | 3.104 | 0.701 | 1 | 5 |
| Social Interactions（Pre） | 90 | 2.569 | 0.948 | 1 | 5 |
| Social Interactions（Post） | 90 | 2.472 | 0.904 | 1 | 4.750 |

Note: Author’s calculations.

Appendix B: Distribution of Residuals

Figure B1 Distribution of residuals in the estimation of equation (12-2)




Note: Author’s calculations.

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