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ANALYZING ECONOMIC GROWTH WITHIN THE FRAMEWORK OF THE KNOWLEDGE ECONOMY ECOSYSTEM MODEL

by

Dilaka Lathapipat

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Dilaka Lathapipat

World Bank

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ABSTRACT This paper builds on Chen and Dahlman (2006)'s Knowledge Economy concept by introducing the Knowledge Economy Ecosystem model consisting of five pillars: ICT infrastructure, innovation infrastructure, financial infrastructure, quality of institutions, and educated and skilled workers. The subindices for the first four pillars contribute to the Knowledge Economy Infrastructure (KEI) Index, while the human capital pillar is represented by the learning-adjusted years of schooling (LAYS), a measure introduced by the World Bank in 2018. The utilization of LAYS in our model is important, because it recognizes that mean years of schooling is a poor measure of human capital simply because the quality of education can differ greatly across countries. Employing a dynamic panel data framework, we empirically examine the influence of the KEI Index and LAYS on total factor productivity (TFP) and GDP per capita growth. Our findings affirm the substantial positive impact of both LAYS and the KEI Index on TFP and economic growth. This empirical evidence underscores the essential role of sustained investments in these five pillars for fostering long-term economic growth, offering vital insights for policymakers. Drawing on Thailand as a case study, the analysis illuminates the nation's specific challenges within the Knowledge Economy Ecosystem framework, especially in the realms of human capital development, innovation, and institutional quality. The study underscores the considerable obstacles Thailand encounters in these domains, impeding its transition toward a knowledge-based economy.

Introduction

This study scrutinizes the pressing issue of Thailand's inadequate human capital and skills within the context of its economic growth and development. It delves into multifaceted challenges that have hindered Thailand's progress in upgrading its production sectors and fostering high-value-added jobs that demand enhanced skills. As emphasized in World Bank (2016), Thailand needs substantial investments in both physical and knowledge capital, as well as investments in enhancing the business and institutional climate. However, a protracted period of low gross fixed capital formation, especially since 1998 and a further downward trend after 2012, reflects the country's struggle to mobilize the necessary resources. The repercussions of this struggle are manifest in Thailand's dismal economic growth performance over the last fifteen years. Thailand's inability to sufficiently accumulate capital is also intricately linked to a less-discussed decline in wages among college graduates, even those with degrees in the Science, Technology, Engineering, and Mathematics (STEM) fields. Despite accounting for a meagre 3 percent of the adult population in 2022, the noteworthy decline in their wages throughout the 2005-2022 period underscores a pronounced lack of demand for these highly skilled individuals. This observation raises significant concerns about Thailand's long-term growth prospects, signifying a deficiency in the development of productive capabilities necessary for advancing into higher value-added sectors.

This paper contends that the presence of a critical mass of highly skilled individuals is pivotal in shaping a country's economic trajectory. The shortage of highly skilled workers hampers investments in technological advancement in production, limits productivity, and erodes competitive advantage. Thailand's declining education system quality relative to peers and consistently poor learning outcomes underscore the urgency of the situation. This challenge is presenting a growing obstacle in a world marked by accelerating technological innovation.

The primary analysis in this study is rooted in the Knowledge Economy framework initially articulated by Chen and Dahlman (2006). Their model highlights the importance of knowledge utilization and creation for achieving sustainable, long-term economic growth. To successfully transition into the Knowledge Economy, Chen and Dahlman argue that nations must maintain investments in education, innovation, information and communication technologies (ICT), and establish a conducive economic and institutional environment, forming the four pillars of the Knowledge Economy. However, they have not updated their model or the accompanying Knowledge Economy Index since 2014, which diminishes their usefulness. In this study, we expand the Knowledge Economy concept by introducing a model with five pillars: ICT infrastructure, innovation infrastructure, financial infrastructure, quality of institutions, and educated and skilled workers. The subindices for the first four pillars contribute to the Knowledge Economy Infrastructure Index, while the "Educated and skilled worker" pillar is represented by "Average learning-adjusted years of schooling (LAYS) for adults aged 25 or more" in this new Knowledge Economy Ecosystem model.

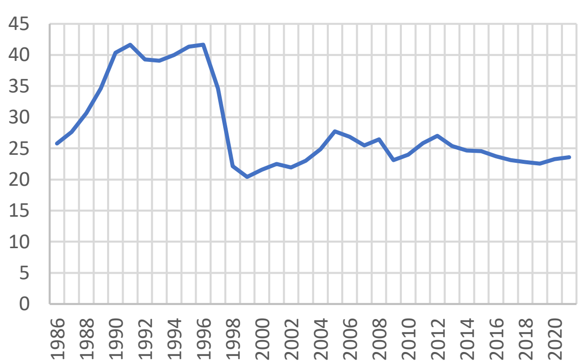
In order to establish empirical support to our framework, we formally investigate the impacts of LAYS and the Knowledge Economy Infrastructure Index on economic growth, emphasizing their statistically significant positive effects on total factor productivity (TFP) and GDP per capita growth. We focus on TFP because it captures the efficiency and technological progress that influence the overall productivity of an economy. When an economy experiences a boost in TFP, it tends to see higher returns on capital investments, which, in turn, attracts more investment. This cycle of productivity and investment can contribute significantly to sustained economic growth.

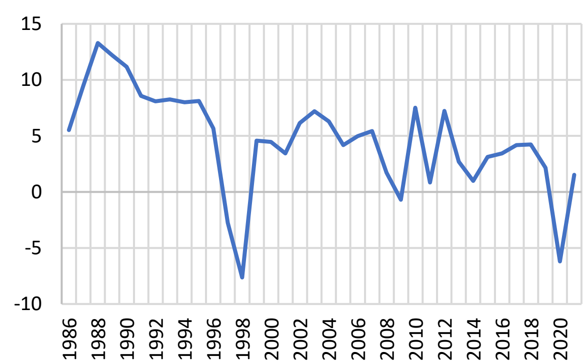
The study then evaluates Thailand's performance within this Knowledge Economy Ecosystem, comparing the country's progress in each pillar to that of international peers at a similar stage of technological development (as measured by distance from the TFP frontier). Our findings reveal areas of progress and concern, particularly underscoring the need for further investments in human capital, innovation infrastructure, and institutional environment. This benchmarking exercise underscores the crucial importance of cultivating a critical mass of highly skilled workers to effectively engage in the Knowledge Economy, catalyze the next phase of structural transformation, and ensure Thailand's sustained growth and prosperity.

Inadequacy of Thailand’s Human Capital and Skills

World Bank (2016) emphasized that Thailand needs to upgrade its production sectors and create high value-added jobs that require more skills. This has proven to be especially challenging as it required substantial investments in terms of physical and knowledge capital, as well as investments in improving the business and institutional climate. At the aggregate level, the lack of investment is reflected in the prolonged period of low gross fixed capital formation since 1998 and a more recent downward trend observed after 2012. The slump in investment has clearly hurt Thailand’s economic growth, which averaged less than 3 percent per annum from 2013 to 2019. This dismal growth rate is less than one-third of the 9.28 percent average rate observed during the economic boom decade from 1986 to 1996 (see Figure 1).

Figure 1: Gross fixed capital formation (% of GDP)   GDP growth rate (%)





The pace of capital accumulation has likely been insufficient for Thailand to upgrade its domestic productive capabilities to the level of sophistication required to enable it to escape from the low-growth equilibrium and reach high income status by the 2037 target. A measure of a country’s progress in its productive capacity is capital deepening, which points to an increase in the aggregate net capital stock-per-worker ratio. Thailand has not performed well on this front, as is evident from Figure 2, which presents average rates of capital deepening over the 2000-2019 period for 70 PISA 2018-participating economies with available data. Specifically, Thailand’s 1.6 percent average rate puts the country 46th overall and 16th out of 22 upper middle-income countries (ahead of only Argentina, Mexico, Brazil, Macedonia, Jordan, and

Russia), which averaged as high as 3.2 percent per year. Lower-middle income-, ASEAN (excluding Thailand)- and high-income countries, on the other hand, averaged 3.9, 3.3 and 2.7 percent per year respectively over the period.

Figure 2: Average Growth in Capital-per-Worker Ratio over the 2000-2019 period for PISA 2018-Participating Economies (Percent)

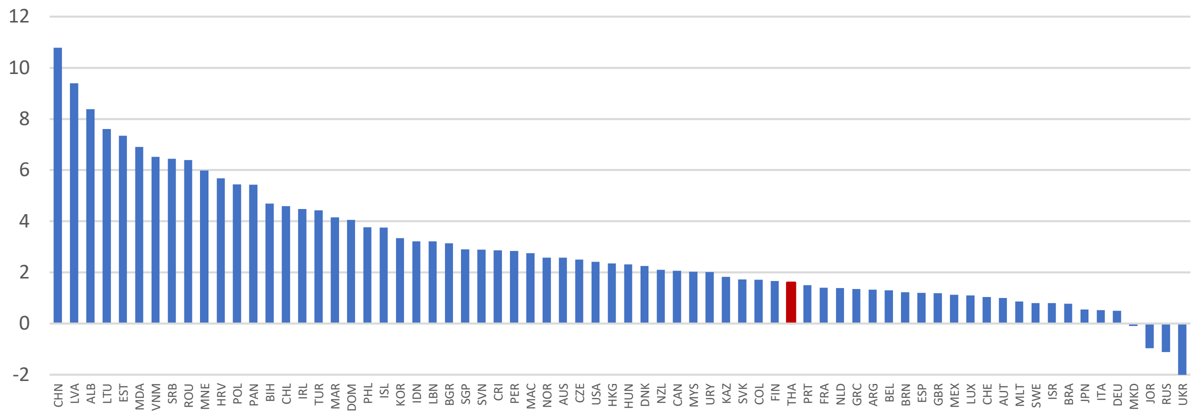
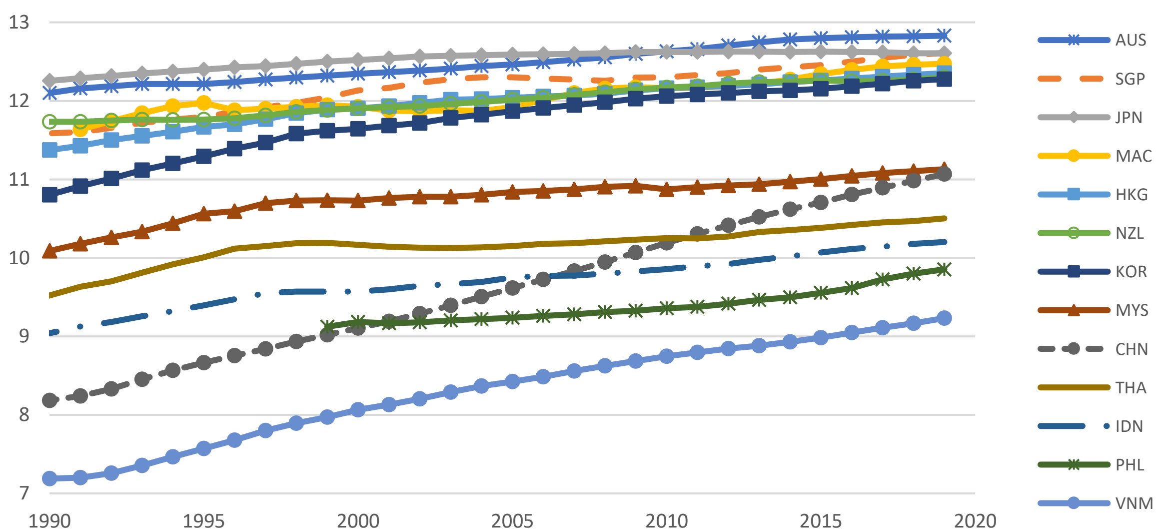


Figure 3: Trends in Log Capital-per-Worker Ratio for PISA2018-Participating EAP Economies (constant 2014 US$)

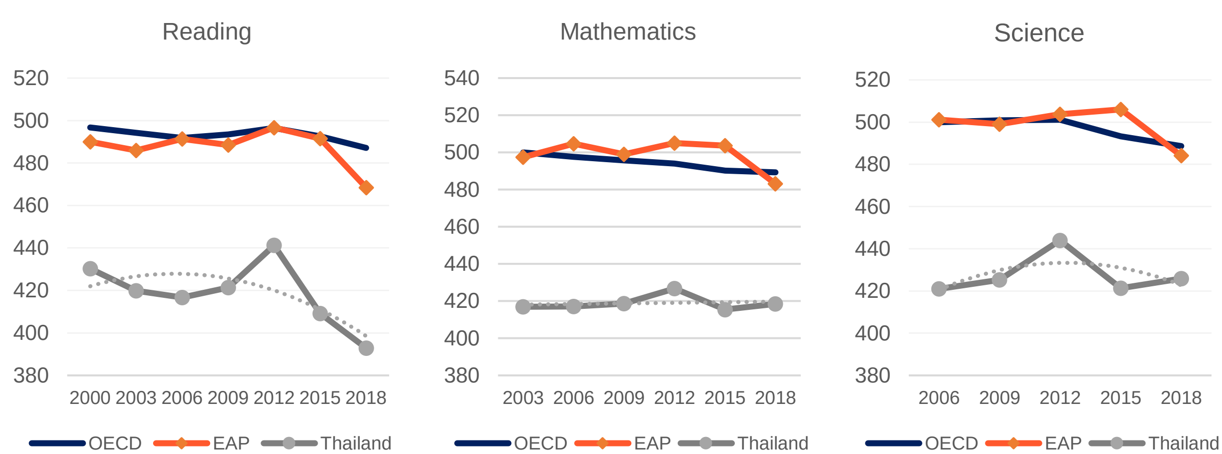


Thailand's low rate of physical capital investment relative to its peers means that more advanced countries have been surging ahead, while less advanced ones have been catching up. Among the 13 EAP economies which participated in PISA 2018, Thailand was ahead of only 3 (Indonesia, Philippines, and Vietnam) in regards to capital intensity in production. Moreover, it can be seen from Figure 3 that the rates of capital deepening for these 3 countries have been higher than that of Thailand over the last decade. In other words, these countries have been catching up to Thailand in terms of production sophistication. For instance, Thailand's capital-per-worker ratio of US$ 36,408 (in constant 2014 US$) was around 3.6 times higher than that of Vietnam in 2019. The gap came down from as high as 8.2 times at the turn of the millennium. On the other hand, high-income countries such as Australia and Singapore were around 8.8 and 7.2 times more capital intensive than Thailand in 2000. By 2019, the gaps to these two countries have widened further to as much as 10.2 and 8.2 times.

Shortage of skill critical mass is a prime suspect behind Thailand's stagnant capital investment and economic growth. Shortage of skill critical mass can lower the returns on a country's capital investment by reducing productivity, hindering technological advancement, and undermining competitive advantage. The insufficient supply of highly skilled workers will likely hamper Thailand's innovation and technology absorption capacity and limits the country's future growth potential. This constraint is at the heart of the problem of many middle-income countries including Thailand, and will likely become more binding in a world where technological innovation is progressing at an ever-faster pace.

Improving access to high-quality education is a top priority for improving Thailand's economic growth prospects. A better-educated and skilled workforce is critical to Thailand's economic growth prospects. For individuals, having the necessary skills and competencies to obtain productive employment can help them secure a better future and, for those who are poor, help them break out of the cycle of poverty. World Bank (2016) states that the quality of Thailand's education system is perceived to have worsened relative to its upper middle-income peers and ASEAN neighbors. Since then, however, Thai students' learning outcomes have failed to improve. In the latest PISA 2018, Thailand ranked 68th in reading out of the 79 PISA-participating countries and economies (59th in mathematics, and 55th in science), ahead of only Indonesia and the Philippines in EAP. Furthermore, all the trends have been moving in the wrong direction. Thailand's reading performance shows an increasingly negative trajectory, while scores in math and science have stagnated over the last 2 decades (see Figure 4).

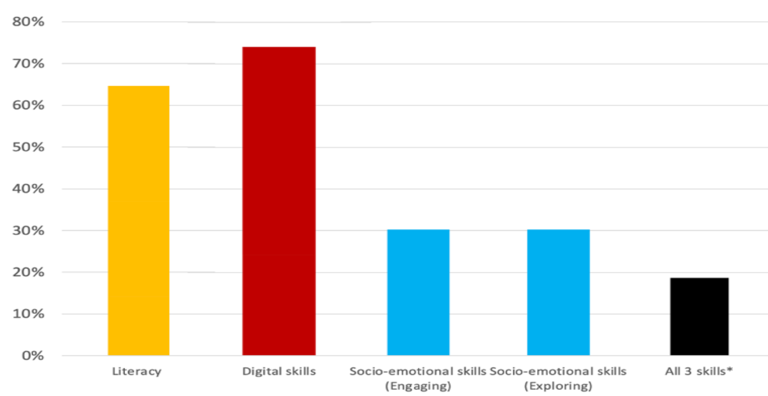
Figure 4: Trends in Student Learning Outcomes in the Three PISA Domains



In the latest PISA 2018, around half of Thai students scored below the minimum proficiency level (Level 2) in math and science, while almost 60 percent scored below basic proficiency in reading. In other words, these 15-year-old students can be considered functionally illiterate and/or innumerate in spite of their having attended school for nearly nine years. At the other end of the proficiency scale, while 21 percent of students in Singapore, 12 percent each in Korea and Vietnam attained level 5 or higher in science, only 0.7 percent of Thai students managed to do so. The gaps to these countries are even greater in the mathematics domain.

The poor learning outcomes of the initial education system results in a large proportion of youth and adults without foundational skills. According to employers, one of the most important areas of skills shortages is foundational skills. Yet 62 percent of youth and adults do not have foundational literacy, which means that they cannot read and understand lengthy texts to solve problems. Furthermore, 72 percent of youth and adults do not have foundational digital skills, which reflects their lack of capacity to accurately use a mouse and a keyboard and manage online information to solve a problem. Moreover, about 30 percent of youth and adults do not perceive that they are open to 'exploring new horizons' (i.e., widen one's views, seek new knowledge, and appreciate different points of views). A similar proportion do not perceive that they have the tendency to 'engage with others' (i.e., connect and build rapport with other people). Literacy, digital, and socio-emotional skills are strongly correlated with diverse measures of positive labor market outcomes such as having a higher labor income, engaging in non-routine tasks, exercising innovations at work, and flexibly teleworking during Covid-19. The low quality of education and poor learning outcomes of those who are currently in initial education and training, therefore, suggest that Thailand will continue to face challenges in human capital development in the foreseeable future.

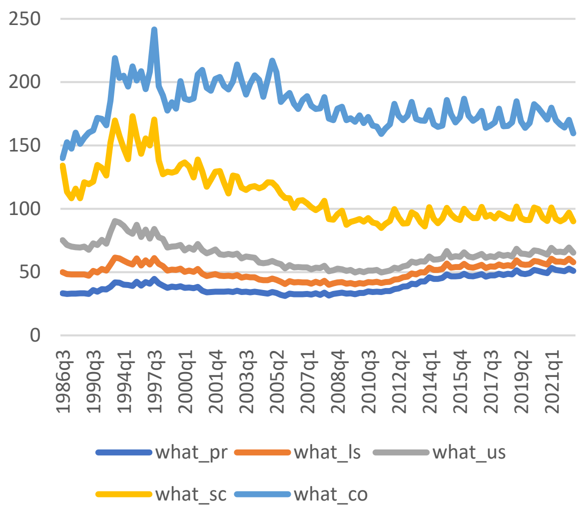
Figure 5: Proportion of youth and adults exhibiting skills below the threshold levels of foundational skills



Source: World Bank (2022): Adult Skills Assessment in Thailand, 2022.

The Thai economy is showing signs and symptoms of a country stuck in the middle-income trap. As defined in Asian Development Bank Institute (2017), "*the 'middle income trap captures a situation where a middle-income country can no longer compete internationally in standardized, labor-intensive goods because wages are relatively too high, but it can also not compete in higher value-added activities on a broad enough scale because productivity is relatively too low. The result is slow growth, stagnant or falling wages, and less potential for rising living standards for more people.*" To see these symptoms, this section investigates the evolution of Thailand's educational wage structure over the 1986-2022 period by constructing composition-adjusted real hourly wages (or real hourly wage indices) across five education groups (see Figure 6).

Figure 6: Composition-adjusted real hourly wage rates by education group (const 2019 THB)



Composition-adjusted real hourly wage rates by education group (1986Q3=1)

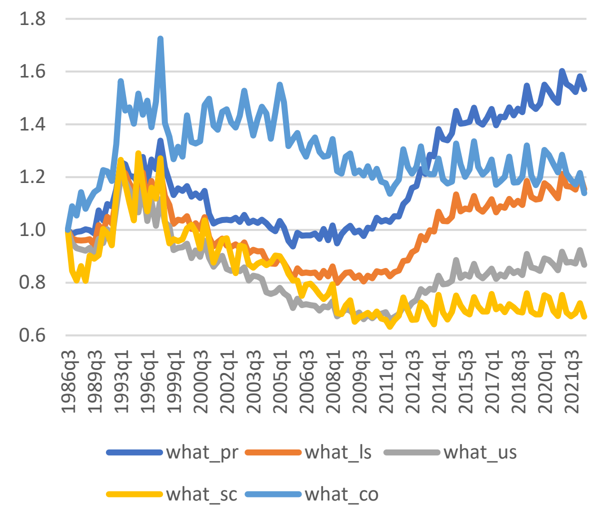
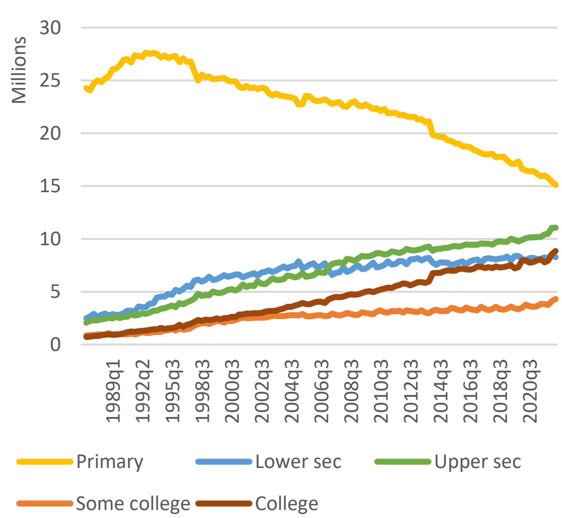
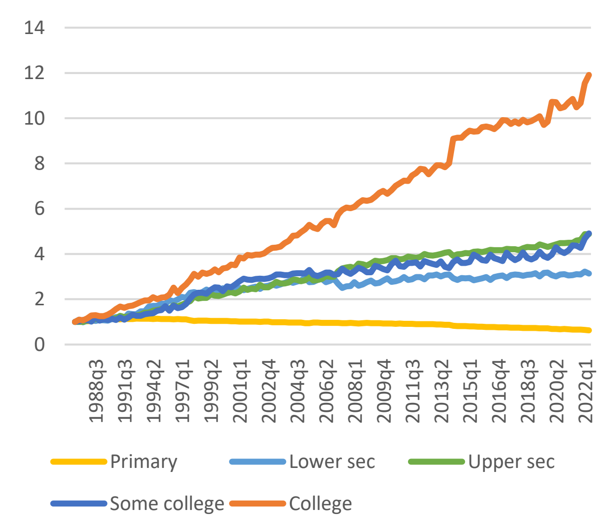


Figure 7: Labor supply by education (ages 15-64 years old)



Labor supply by education (ages 15-64 years old) (1986Q3=1)

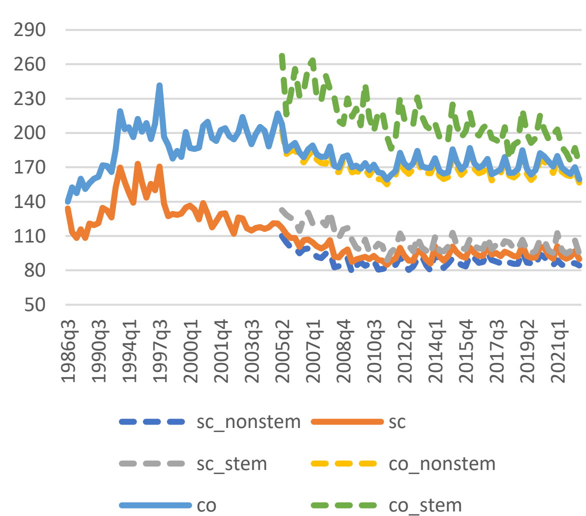


It is well-documented that the Thai labor market had undergone immense structural change during the economic boom decade prior to the 1997 economic crisis. Growth-enhancing structural transformation contributed greatly to high rates of labor productivity and economic growth, which resulted in rapidly rising real wage rates during this period (Lathapipat and Chucherd, 2013). This stage of structural transformation was an important driver of Thailand's overall economic, productivity, and real wage growth. Interestingly, we observe that the real hourly wage index for the college group (with exactly a bachelor's degree qualification) rose the most (by as much as 70 percent) compared to the other education groups. Over the same period, the supply of the college group (with a bachelor's degree qualification or higher) also increased most rapidly (by more than 230 percent from 1986 Q3 to 1996 Q3) compared to the less-educated groups (see Figure 7). This is clear evidence of a relative demand shift favoring the highly-skilled group over the period.

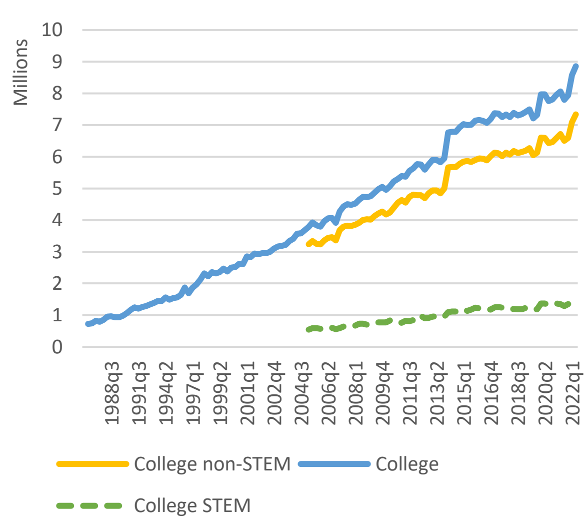
The decade following the 1997 crisis saw real wages for all education groups with less than bachelor's degree qualification declining substantially. The some-college- and secondary-educated groups suffered the most. College wages, on the other hand, recovered from 1999 to 2005 before declining rapidly thereafter until 2011 (Figure 8). Since then, college wage growth has remained stagnant until today. By contrast, wages for the less-educated groups began rising substantially from 2012. Two major factors were behind these increases: i) the 300 Baht daily minimum wage policy implemented over April 2012 to January 2013 saw average real minimum wage rising by more than 66 percent, and ii) slowdown or even decline in the supply of less-educated labor groups (see Figure 7).

Even more concerning for Thailand is the fall in wages for college graduates in Science, Technology, Engineering, and Mathematics (STEM) fields, even though these relatively high skilled individuals accounted for just over 3 percent of the adult population in 2022. As presented in Figure 8, the vast majority of college-educated adults have studied in the non-STEM fields. At the aggregate level, STEM college graduates accounted for just over 3 percent (1.5 from 47.6 million adult population) of the adult population in 2022, rising from a meager 1.2 percent in 2005. The fact that their wages have declined substantially over the entire 2005-2022 period provides another key evidence that there is insufficient demand for these highly skilled workers. This finding is extremely worrisome for Thailand's long-term growth prospects as it reflects the country's failure to sufficiently develop productive capabilities for upgrading to higher value-added activities within and across sectors. In advancing the next stage of structural transformation, Thailand sorely needs to develop new comparative advantages which can propel the economy to the next developmental stage.

Figure 8: Composition-adjusted real hourly wages for tertiary-educated (const 2019 THB)



College labor supplies (ages 15-64 years old)



Thailand's future growth will depend on its ability to re-ignite the structural transformation from low- to higher-productivity activities, both across and within sectors, and creating more and better jobs. Thailand needs to find a new engine that can deliver results like the locomotive that drove the boom in 1986-1996—an engine that sustainably and consistently creates opportunities for millions to improve their livelihoods (World Bank, 2016). Promoting investment and technological innovation will be crucial for raising the country's long-term growth prospects. As the labor force gets shrunk with ageing, sufficient capital accumulation and productivity gains will be needed to drive Thailand's potential growth, which will need to be driven by knowledge and innovation. This transformation stage is much more challenging than the previous one, given intense competition and rapidly moving goal post in the form of innovation and technological advancement. In order to realize the Thailand 4.0 ambition, the country will need to urgently address its skill bottlenecks which are constraining innovation and technology absorption capacity and limiting the country's future growth potential.

The importance of education and skills in economic development can be better analyzed within the broader context of the knowledge economy ecosystem. While education plays a crucial role in equipping individuals with the necessary knowledge and skills to participate in the economy, it is through the interaction of education with other elements of the innovation ecosystem that its full impact on economic development is realized. The following section evaluates the Thai economy within the context of the knowledge economy ecosystem framework.

Knowledge Economy Ecosystem

This section builds on the concept of the Knowledge Economy proposed by Chen and Dahlman (2006). The framework is based on the idea that the use and creation of knowledge is important for sustainable long-term economic growth and that growth due to rapid factor accumulation is subject to diminishing returns, and hence is not sustainable. In particular, successful transition to the Knowledge Economy involves "sustained investments in education, innovation, information and communication technologies (ICT), and a conducive economic and institutional environment." These elements have been termed by the World Bank as the 4 pillars of the Knowledge Economy.

Chen and Dahlman (2006) also introduced a knowledge economy benchmarking tool, the Knowledge Assessment Methodology (KAM), that provides a basic assessment of countries' readiness for the knowledge economy. The "Basic Scorecard" includes 12 knowledge variables, with 3 variables representing each of the 4 pillars.[1] These 12 variables were used to construct the KAM Knowledge Economy Index (KE

[1] The 12 selected variables in the basic scorecard for KAM are generally available for a larger time series and are regularly updated. They are assigned under the 4 pillars as follows: (I) *Economic incentive and institutional regime*: Tariff and non-tariff barriers; Regulatory quality; Rule of law; (II) *Education and human resources*: Adult literacy rate (% age 15 and above); Secondary enrolment; Tertiary enrolment; (III) *Innovation system*: Researchers in R&D, per million population; Patent applications granted by the USPTO, per million population; Scientific and technical journal articles, per million population; and (IV) *Information infrastructure*: Telephones per 1,000 persons (mainlines and mobile phones); Computers per 1,000 persons; Internet users per 10,000 persons. The KE Index is available for 128 countries from 1995 to 2014, but the series has been discontinued thereafter.

Index) by simply averaging the normalized values of the 12 indicators of the basic scorecard. However, the KE Index has not been updated since 2014 and has become less useful as a result.

Building on the original concept, this study develops a new set of the Knowledge Economy Ecosystem Indices consisting of 5 pillars: i) ICT infrastructure, ii) Innovation infrastructure, iii) Financial infrastructure, iv) Quality of institutions, and v) Educated and skilled workers. The subindices representing the first 4 pillars are used to construct a single ***Knowledge Economy Infrastructure Index***, while the 'Educated and skilled worker' pillar is represented by a measure called 'Average learning-adjusted years of schooling (LAYS) for adults aged 25 or more.' Box 1 briefly describes how these indices are constructed in this study.

Box 1: The Knowledge Economy Ecosystem Indices

To provide an overview of the performance of a country's knowledge economy ecosystem, 16 standard variables were selected, which can be grouped under the 5 pillars as shown in Table B1.

Table B1: Five pillars under the Knowledge Economy Ecosystem

1. ICT infrastructure
   - Individuals using the internet (% of population)
   - Secured internet servers (per 1 million people)
2. Innovation infrastructure
   - Scientific and technical journal articles (per million people)
   - Patent applications (per million people)
   - Research and development spending to GDP
3. Financial infrastructure
   - Bank branches per 100,000 adults
   - ATMs per 100,000 adults
   - Bank credit to bank deposits (%)
4. Quality of institutions (Economist Intelligence Unit)
   - Voice and Accountability
   - Political Stability and Absence of Violence
   - Government Effectiveness
   - Regulatory Quality
   - Rule of Law
   - Control of Corruption
5. Educated and skilled workers
   - Average years of schooling for adults aged 25 or more (EdStats)
   - Learning Outcome (Harmonized Learning Outcome Database)

These variables are generally available for a relatively long horizon (at least from 2000) and are regularly updated. All of the variables, except those grouped under the 'Quality of institutions' pillar, are extracted from the World Bank databases (World Development Indicators, EdStats, and Harmonized Learning Outcome).

The 6 variables representing the 'Quality of institutions' pillar are available from the Economist Intelligence Unit (EIU) Database. EIU constructed these 6 variables by averaging the sub indicators grouped under their respective domains as shown in Table B2 below. Only the averages of the sub indicators are publicly available. The full dataset, however, is commercially available from EIU.

Table B2: Quality of Institutions Sub-Indicators (Economist Intelligence Unit)

Voice and Accountability
- Democracy Index
- Vested interests
- Accountability of Public Officials
- Human Rights
- Freedom of association

Political Stability and Absence of Violence
- Orderly transfers
- Armed conflict
- Violent demonstrations
- Social Unrest
- International tensions / terrorist threat

Government Effectiveness
- Quality of bureaucracy / institutional effectiveness
- Excessive bureaucracy / red tape

Control of Corruption
- Corruption among public officials

Regulatory Quality
- Unfair competitive practices
- Price controls
- Discriminatory tariffs
- Excessive protections
- Discriminatory taxes

Rule of Law
- Violent crime
- Organized crime
- Fairness of judicial process
- Enforceability of contracts
- Speediness of judicial process
- Confiscation/expropriation
- Intellectual property rights protection
- Private property protection

The Knowledge Economy Infrastructure Indices

Four indices are constructed to represent the level of development for each of the first 4 pillars. Specifically, an index is typically interpreted as a single value that captures the information from several variables into one composite measure and can be represented as:

$$Index = a_1x_1 + a_2x_2 + a_3x_3 + \cdots + a_nx_n$$

where the a_i's are weights to be determined and the x_i's are an appropriate set of n variables measuring various facets of development level of the pillar under investigation. The important question here is how to determine the weights, which are generally supposed to indicate the relative importance of a variable to explain a particular dependent variable (i.e., the final index). This study avoids using arbitrary approaches such as the assigning of weights based on value judgment or simply averaging the variables. Instead, the method of Principal Component Analysis (PCA) is used to determine the weights and the principle is based on the degree of variability of the individual items. The greater the variability, the more will be the assigned weight. Specifically, in PCA, the weights are determined from the principal component loadings and this particular linear combination is one that retains the maximum amount of information (variation) in the original variables.

Consider pillar 2 for example. This pillar consists of 3 variables measuring different aspects of the effectiveness of innovation system of businesses, research centers, universities, and other related organizations that keep up with, and make use of the global stock of knowledge. Each of the 3 variables is first 'normalized' by subtracting the mean for OECD countries in 2006 from it and then dividing the result by the corresponding OECD standard deviation.

Table B3: Variables under the Innovation infrastructure domain

OECD in 2006

Original Variables	Obs	Mean	Std. Dev.
Scientific and technical journal articles (per million people)	37	999.52	533.98
Patent applications (per million people)	36	575.67	833.62
Research and development spending to GDP	36	0.0170	0.0097

Thailand in 2006

Normalized variables	Obs	Mean	Std. Dev.
Scientific and technical journal articles (per million people)	1	-1.749	-
Patent applications (per million people)	1	-0.577	-
Research and development spending to GDP	1	-1.508	-

Under this normalization, Table B3 shows that in 2006 Thailand performed 1.749 SD below the OECD average on this particular indicator. Given that an average OECD country produced 999.52 scientific and technical journal articles per million people in 2006, it is straight forward to figure out that Thailand produced just 65.55 articles per million people in that year (999.52-(1.749x533.98)).

PCA is performed on the covariance matrix of these 3 normalized variables to obtain the Eigenvalues for all principal components, which are reported below:

	Eigenvalues	Difference	Proportion	Cumulative
Component 1	**2.245**	**1.881**	**0.818**	**0.818**
Component 2	0.364	0.228	0.133	0.951
Component 3	0.136	.	0.050	1.000

According to the Kaiser criterion, we can see that the underlying variables are 'unidimensional' and that the first principal component (Component 1) explains as much as 81.8 percent of the total variation of the original variables. In other words, the 3 variables do measure the same construct and could be combined into an overall score. The corresponding Eigenvector for the first principal component is reported in the table below under the 'Loadings' column:

Variables	Loadings
Scientific and technical journal articles (per million people)	0.705
Patent applications (per million people)	0.342
Research and development spending to GDP	0.621

Each element of the Eigenvector represents the component loading on each of the 3 variables. These principal component loadings are employed as weights to construct our new variable, the 'Innovation infrastructure Index,' which is again normalized so that OECD countries in 2006 have an average index value of zero and a unit variance. The remaining three indices representing 'ICT infrastructure,' 'Financial Infrastructure,' and 'Quality of Institutions' are similarly constructed.

These four subindices are in turn used to construct our single 'Knowledge Economy Infrastructure Index.' Applying PCA once again, we find that the underlying subindices are unidimensional and that the first principal component explains as much as 84.1 percent of the total variation of the original subindices. The resulting principal component loadings (shown in Table B4 below) are used as weights to construct the new ***Knowledge Economy Infrastructure (KEI) Index,*** which is again normalized so that the OECD countries in 2006 have an average index value of zero and a unit variance.

Table B4: Principal Component Loadings for the KEI Index

Variable	Loadings
ICT infrastructure	0.468
Innovation infrastructure	0.386
Financial infrastructure	0.157
Quality of institutions	0.779

Learning-Adjusted Years of Schooling (LAYS)

Following Glawe and Wagner (2022), this study constructs an updated database on the learning-adjusted years of schooling (LAYS) for adults aged 25 or more over the period 2000 to 2020 by applying the World Bank (2020) and Filmer, Rogers, and Sabarwal (2019) methodology. Specifically, the purely quantitative measure of countries' mean years of schooling for the relevant cohort, obtained from the Barro and Lee (2013) dataset (up to 2010) and augmented by the Wittgenstein Centre for Demography and Global Human Capital data (to the year 2020), is adjusted to reflect differences in the quality of education across countries. The qualitative measure of education was obtained from the World Bank's Harmonized Learning Outcome (HLO) database. The following formula is used to construct our measure of LAYS:

$$LAYS_c = S_c \times R_c$$

where S_c is the average years of schooling of the cohort of interest for country *c* and R_c is a measure of learning in country *c* relative to a benchmark. As in the 2020 update of the Global Dataset on Education Quality, this study uses a benchmark score of 625 to compute $R_c = HLO/625$.

Estimation Strategy

To establish empirical support to the new Knowledge Economy Ecosystem framework, this study formally evaluates the importance of the 5 pillars as determinants of long-term economic growth. As with the KAM framework, we hypothesize that sustained investments in the 5 pillars will enhance countries' stock of knowledge capital, which, if utilized effectively in economic production, will lead to sustained increase in the growth rate of Total Factor Productivity (TFP), and consequently result in sustained economic growth.

This study employs the same estimation strategy as Glawe and Wagner (2022), which was the first study to analyze the impact of the LAYS on growth within a dynamic panel data setting. A dynamic panel data instrumental variable regression framework is employed to assess the effects of human capital (LAYS or HLO) and the new ***Knowledge Economy Infrastructure Index*** on growth rates of GDP per capita and total factor productivity (TFP). The dynamic specification for GDP per capita growth rate is given by the following equation: [2]

$$\Delta \ln GDPPC_{it} = \rho \ln GDPPC_{it-1} + \beta HC_{it} + \delta KE_{it} + \sum_j \gamma_j \ln Z_{j,it} + \emptyset_i + \emptyset_t + u_{it}$$

where $\ln GDPPC_{it-1}$ is the previous period's log GDP per capita, whose regression coefficient measures the growth convergence rate; Z is a vector of control variables, including trade openness, employment to population ratio, log of population aged 15 or more, and investment ratio (gross fixed capital formation/GDP); *HC* is the human capital variable (HLO or LAYS) and *KE* is the Knowledge Economy Infrastructure Index. We estimate the parameters using first-differenced specification to eliminate the country fixed effects and use deeper lags of $\ln GDPPC$ as instruments for $\Delta \ln GDPPC_{it-1}$ as per Anderson and Hsiao (1981):

$$\Delta^2 \ln GDPPC_{it} = \rho \Delta \ln GDPPC_{it-1} + \beta \Delta HC_{it} + \delta \Delta KE_{it} + \sum_j \gamma_j \Delta \ln Z_{j,it} + \Lambda_t + \Delta u_{it}$$

Similarly, for total factor productivity (*TFP*) we specify the following dynamic growth rate equation and its first-difference:

$$\Delta \ln TFP_{it} = \rho \ln \left(\frac{TFP_F}{TFP_i}\right)_{t-1} + \beta HC_{it} + \delta KE_{it} + \sum_j \gamma_j \ln X_{j,it} + \emptyset_i + \emptyset_t + u_{it}$$

$$\Delta^2 \ln TFP_{it} = \rho \Delta \ln \left(\frac{TFP_F}{TFP_i}\right)_{t-1} + \beta \Delta HC_{it} + \delta \Delta KE_{it} + \sum_j \gamma_j \Delta \ln X_{j,it} + \Lambda_i + \Lambda_t + \Delta u_{it}$$

where he term (TFP_F/TFP_i) captures the TFP gap of country i to the global technological frontier in year t (e.g. technology transfer as a source of productivity growth is captured by this variable); X is a vector of control variables, including trade openness, employment to population ratio, and log of population aged

[2] This specification enables us to take advantage of the time series variation in the data and to control for problems such as endogeneity, omitted variable bias, unobserved country heterogeneity, and measurement error, which likely affected earlier studies that mainly relied on a cross-sectional framework (see for example Hanushek and Woessmann (2012)).

15 or more; HC is the human capital variable (HLO or LAYS), and KE is the Knowledge Economy Infrastructure Index. Again, deeper lags of $\ln{(TFP_F/TFP_i)}$ are used as instruments for $\Delta\ln{(TFP_F/TFP_i)_{t-1}}$.

Estimation Results

Both the Average Learning-Adjusted Years of Schooling (LAYS) for adults aged 25 or more and the quality of the Knowledge Economy Infrastructure (KEI) have statistically significant positive impacts on economic growth. The main estimation results are reported in Table 1. Columns (1) and (2) of Table 1 present the estimation results for the per capita GDP growth models. The learning-adjusted years of schooling coefficient in column (1) shows that each year increase in LAYS is associated with a statistically significant 0.47 percentage point higher average annual growth rate in GDP per capita. The estimated effect of LAYS is very similar to the 0.49 percentage point reported in Glawe and Wagner (2022) for their preferred model. Another main variable of interest, the Knowledge Economy Infrastructure Index, also has a positive and highly statistically significant effect on per capita income growth. The coefficient estimate indicates that a one standard deviation increase in the KEI index is associated with 1.96 percentage points higher average growth rate. The model in column (2) repeats the analysis, but uses Harmonized learning outcome (HLO) as a measure of human capital. The coefficient estimate indicates that a 100-point increase in test scores (measured on the PISA scale) is associated with 1.3 percentage points[3] higher average growth rate and the estimate is statistically significant at conventional levels.

Similarly, we also find that both the LAYS for adults aged 25 or more and the KEI index have highly significant positive impacts on total factor productivity growth. The regression model from column (3) indicates that each year increase in LAYS is associated with a statistically significant 0.54 percentage point higher average TFP growth rate. The KEI index also has a positive and statistically significant effect on TFP growth rate. The coefficient estimate indicates that a one standard deviation increase in the KEI index is associated with 1.3 percentage points higher average TFP growth rate. Furthermore, the positive coefficient of the (Log) TFP gap to the global technological frontier supports the hypothesis of productivity (and income) convergence postulated by neoclassical growth theory. For instance, the effect of technology transfer on receiver country's productivity growth is captured by this important variable, which measures the technological 'catch up' rate. The model in column (4) repeats the analysis, but uses HLO as a measure of human capital. The coefficient estimate indicates that a 100-point increase in learning outcome is associated with 1.09

[3] The estimated effect is towards the lower end of the 1.24-2.02 percentage point range estimated in Hanushek and Woessmann (2012). As noted earlier, their estimates are likely biased due to the reliance on the problematic cross-sectional specification. Furthermore, their estimates are likely affected by reverse causality resulting from the way their cognitive skill variable was constructed. That is, by averaging all the observed math and science scores between 1964 and 2003 for each country. By regressing average GDP per capita growth rate over the 1960-2000 period on the cognitive skill measure, it can be expected that the potential reverse causality would cause the coefficient estimate to be biased upwards (specifically, additional resources arising from higher economic growth rate could plausibly have been invested in improving the educational outcomes of students).

percentage points higher average TFP growth rate. However, the estimate has a p-value of 0.137, which is not statistically significant at conventional levels.

Table 1: The Effects of LAYS and KEI on GDP per Capita and TFP Growth

Dependent variable	ΔLog GDP per capita		ΔLog TFP	
Model	(1)	(2)	(3)	(4)
Log GDP per capita (t-5)	-0.1904***	-0.2445***		
	(0.032)	(0.032)		
Log distance to TFP frontier (t-5)			0.2572***	0.2809***
			(0.061)	(0.063)
Learning-adjusted years of schooling (age 25 plus)	***0.0047****		***0.0054*****	
	(0.003)		***(0.002)***	
Harmonized learning outcome		***0.0130****		***0.0109***
		(0.007)		***(0.007)***
Knowledge Economy Infrastructure Index	***0.0196******	***0.0197******	***0.0130*****	***0.0120*****
	(0.006)	***(0.006)***	***(0.006)***	***(0.006)***
Trade openness	0.0222**	0.0181*	0.0088	0.0056
	(0.010)	(0.010)	(0.008)	(0.008)
Employment to population ratio	0.2385***	0.2670***	0.0534	0.0592
	(0.055)	(0.057)	(0.043)	(0.044)
Log population age 15 plus	-0.1073***	-0.1159***	-0.0768***	-0.0728***
	(0.029)	(0.031)	(0.024)	(0.025)
Investment ratio	0.4449***	0.4800***		
	(0.045)	(0.043)		
Overall R-squared	0.641	0.653	0.437	0.427
Observations	581	592	567	568
Number of countries	64	65	61	61

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

There is also some evidence which indicates greater relative importance of the highly skilled for growth. Detailed country-specific distributional dimension of the PISA test scores enables our analysis to go beyond simple mean difference in scores and to estimate how per capita income or TFP growth is affected by the distribution of skills within countries. Regression model in column (1) of Table 2 shows that raising the share of students reaching basic proficiency (level 2 or higher in PISA) by 10 percentage points could be expected to increase average GDP per capita growth rate by around 0.69 percentage point. The greater relative importance of top performers can be seen from comparing column (2) to column (1), where it is estimated that a 10 percentage point increase in the share of top performers is expected to lead to a massive and statistically significant 1.94 percentage points higher per capita income growth rate. Similar conclusions are also reached when TFP growth is considered, as can be seen from regression models in columns (3) and (4) of Table 2.

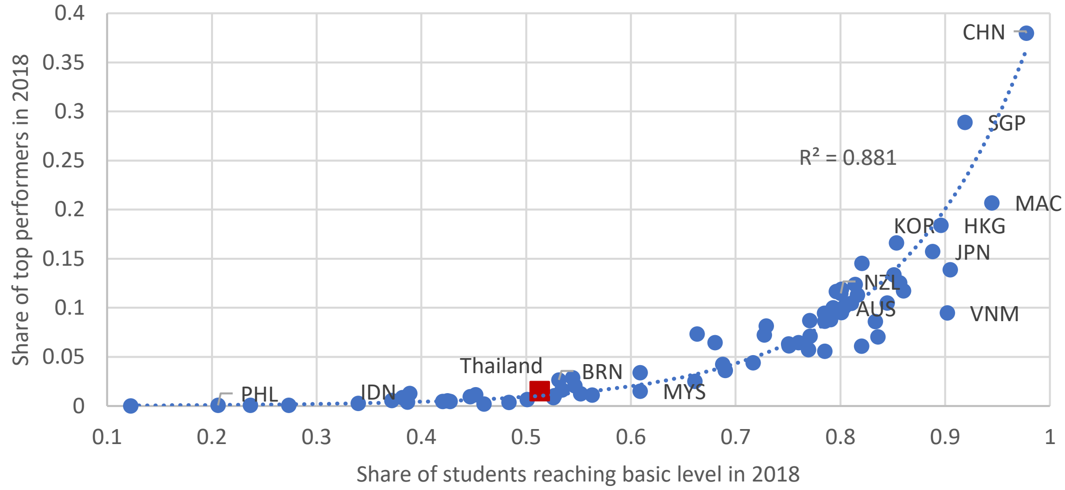
Table 2: The Importance of Highly-Skilled Labor relative to Labor with Basic Skills on GDP per Capita and TFP Growth

Dependent variable	ΔLog GDP per capita		ΔLog TFP	
Model	(1)	(2)	(3)	(4)
Log GDP per capita (t-5)	-0.2398***	-0.2366***		
	(0.039)	(0.038)		
Log distance to TFP frontier (t-5)			0.3322***	0.3105***
			(0.097)	(0.093)
Share of students reaching basic level	***0.0694****		***0.0556***	
	(0.039)		***(0.037)***	
Share of top-performing students		***0.1943*****		***0.1453****
		(0.088)		***(0.083)***
Knowledge Economy Infrastructure Index	0.0122*	0.0112	0.0018	0.0005
	(0.007)	(0.007)	(0.007)	(0.007)
Trade openness	0.0366***	0.0362***	0.0212**	0.0209**
	(0.012)	(0.012)	(0.010)	(0.010)
Employment to population ratio	0.3707***	0.3605***	0.1336**	0.1225**
	(0.063)	(0.062)	(0.057)	(0.055)
Log population age 15 plus	-0.1277***	-0.1251***	-0.0570*	-0.0538*
	(0.037)	(0.037)	(0.033)	(0.033)
Investment ratio	0.3795***	0.3834***		
	(0.054)	(0.054)		
Overall R-squared	0.619	0.620	0.364	0.376
Observations	441	441	431	431
Number of countries	57	57	55	55

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The results from Table 2 could mislead one to conclude that countries should focus more on nurturing only the high performers. However, as noted in Hanushek and Woessmann (2012), achieving basic literacy for all may well be a precondition for identifying the future high-performing engineers, scientists, and entrepreneurs and that competition among a large pool of students reaching basic skills may be an efficient way to obtain a greater share of high-performers. The relationship between the share of students reaching basic proficiency and the share of top performers shown in Figure 9 clearly supports this conjecture. The two variables exhibit an exponential relationship with a very high R-squared of 0.88.

Figure 9: Share of Students Reaching Basic Proficiency vs. Share of Top Performers in PISA 2018



The empirical evidence established in this section, therefore, lends support to the hypothesis that sustained investments in the 5 pillars of Knowledge Economy Ecosystem will result in sustained TFP and income growth. In order for countries to make the transition to the knowledge economy, where knowledge is the main engine of economic growth, it is essential that they continually invest in the 5 pillars of knowledge economy to enhance their stock of knowledge capital, which, if used effectively in economic production, will lead to sustained increase in the growth rate of Total Factor Productivity (TFP), and consequently result in sustained economic growth.

Benchmarking Thailand's Knowledge Economy Ecosystem

Thailand has made good progress in improving the country's knowledge economy infrastructure over the last 15 years, narrowing the gaps to OECD and high income-countries. As can be seen from the KEI Index chart of Figure 10, Thailand's KEI index was around 3 standard deviations (SD) below the average for OECD country and HIC countries in 2006. By 2020, the gap has narrowed to around 2 SD, which is roughly on par with the average observed for UMC countries. Closer investigation of the subindices representing the 4 pillars for KEI presented in Figure 10 reveals that Thailand has surpassed the average for UMC countries in all pillars (ICT, Innovation, and Financial Infrastructure) except in the Quality of Institutions domain, which the country has performed consistently poorly since early 2000's.

However, Thailand has not done so well with regards to the all-important Human Capital domain (5th pillar of the Knowledge Economy Ecosystem). As can be seen from the left-hand chart of Figure 11, Thailand's average years of schooling completed for adults aged 25 or more in 2020 was only 8.6 years, which was 3.4 years below the average for the OECD. Adjusted for learning outcomes, the gap to the OECD and HIC countries in 2020 becomes even wider (3.7 years). Moreover, Thailand has consistently underperformed the averages for UMC countries on both the raw and the learning-adjusted years of schooling measures since data became available in 2000.

Figure 11: Quantitative and Quality-Adjusted Measures of the Average Years of Schooling for Adults Aged 25 or more

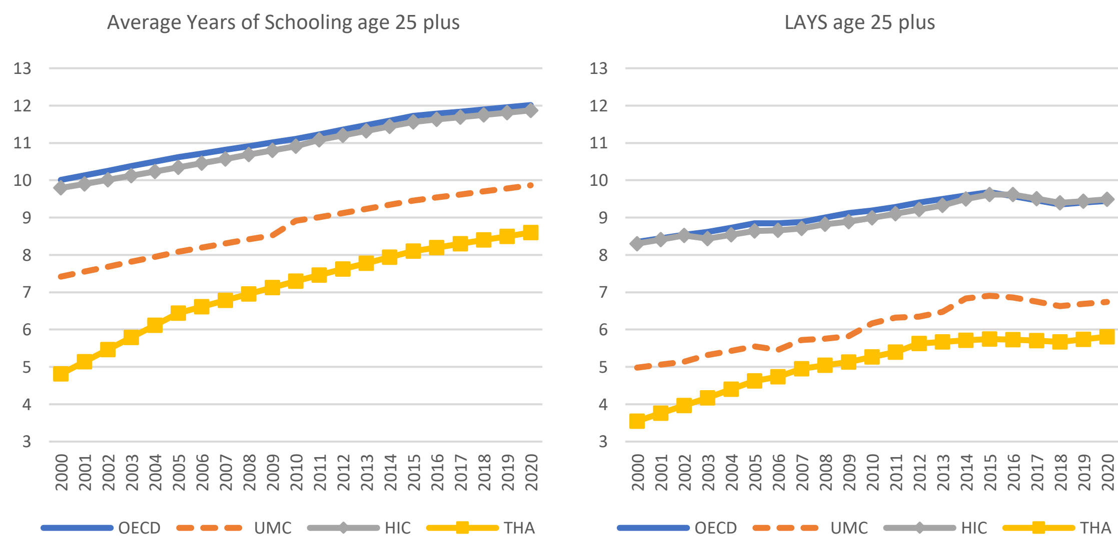
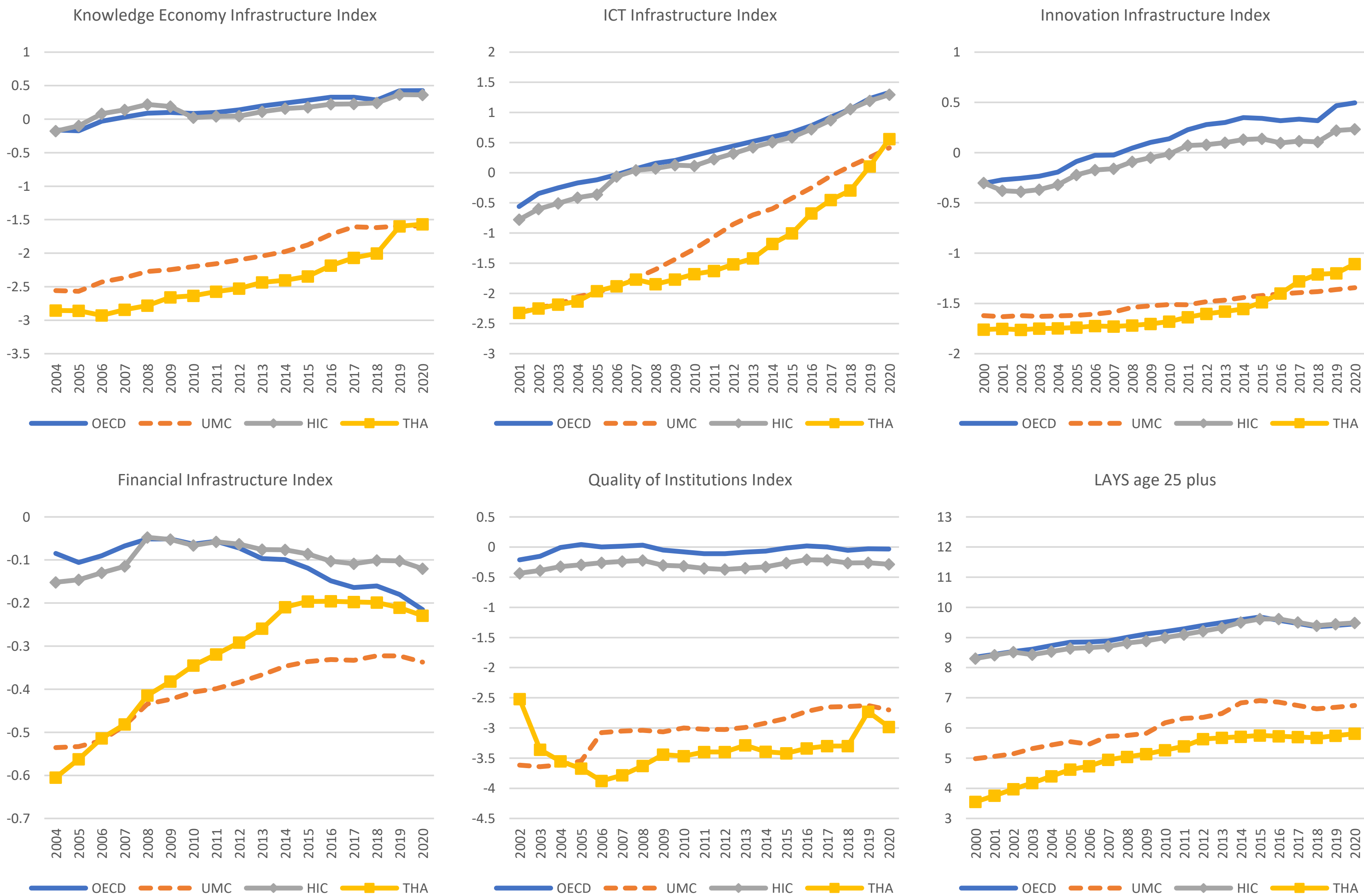


Figure 10: Trends of Knowledge Economy Ecosystem Indices for Thailand and Selected International Comparators



Thailand has recently ramped up investments in the Innovation Infrastructure domain relative to other UMC countries, but measured outputs from R&D have remained subdued. As can be seen from the 'Innovation Infrastructure Index' chart in Figure 10, Thailand has rapidly increased investment in its innovation infrastructure since 2009. The index value for Thailand, which has been consistently below the UMC average since 2000, has surpassed that for the UMC for the first time in 2016. The left-most chart in Figure 12 reveals that Thailand's R&D spending increased massively from a mere 0.2 percent of GDP in 2008 to 1.33 percent of GDP in 2020. Scientific and technical journal articles produced also increased from 88.6 to 183.5 per million people over the same period. Likewise, Patent applications also increased from 86.4 to 105.3 per million people. Nevertheless, the mentioned improvements in measured R&D outputs were achieved from very low baselines. It should be mentioned that even though Thailand's R&D expenditure as a share of GDP has clearly surpassed that of the UMC countries, the quantities of measured research outputs have not. Furthermore, the gaps to the OECD and HIC countries remain very large. The lack of a large enough pool of highly skilled personnel who can conduct quality research and innovative activities could be a main reason behind the perceived low returns to R&D investments in Thailand.

A more informative approach to benchmarking Thailand's knowledge economy ecosystem performance is to compare the country's index values across the 5 pillars against international peers at similar level of technological development. Results from this benchmarking exercise are presented below in Figure 13. Consider first the 'Knowledge Economy Infrastructure Index' chart. We can see from the chart that Thailand's index value of -2 SD is almost 0.7 SD below the international benchmark (fitted world regression line). In other words, countries at similar distance away from the global technological frontier (measure using the log TFP gap), on average, scored 0.7 SD higher than Thailand in the KEI index. Among EAP countries, Thailand scored slightly higher than Indonesia, Vietnam, and the Philippines, even though it is substantially closer to the world frontier.

In fact, this benchmarking exercise reveals that Thailand scored below comparable peers in all pillars, except in the domain of Financial Infrastructure. Even though we have seen from Figure 10 that Thailand has improved its ICT and Innovation Infrastructure indices significantly in the last decade, the observed improvements were still inadequate for Thailand to reach the international benchmark. Moreover, Thailand scored especially poorly in the Quality of Institutions domain and is ahead of only Vietnam, Cambodia, Myanmar, and Lao PDR in the EAP region. Similar benchmarking of the 6 sub-indices within the Quality of Institutions domain shown in Figure 14 sheds further light on Thailand's perceived weaknesses.

Thailand's lack of highly skilled workforce is a major cause for concern when viewed under this benchmarking exercise. We can see from the LAYS chart in Figure 13 that Thai workforce's average LAYS is around 1.5 years below the international benchmark. Among EAP countries with available data, Thailand is ahead of only the Philippines and Indonesia. Furthermore, these are the only 3 countries in the region which performed below the international benchmark. It should be noted that fast-growing economies in the last decade (such as Vietnam and China) as well as advanced economies (such as Singapore, Japan, Korea, and New Zealand) all performed well above the international regression line in this, as well as in ICT and Innovation Infrastructure domains.

Figure 12: Indicators Representing the Innovation Infrastructure Index

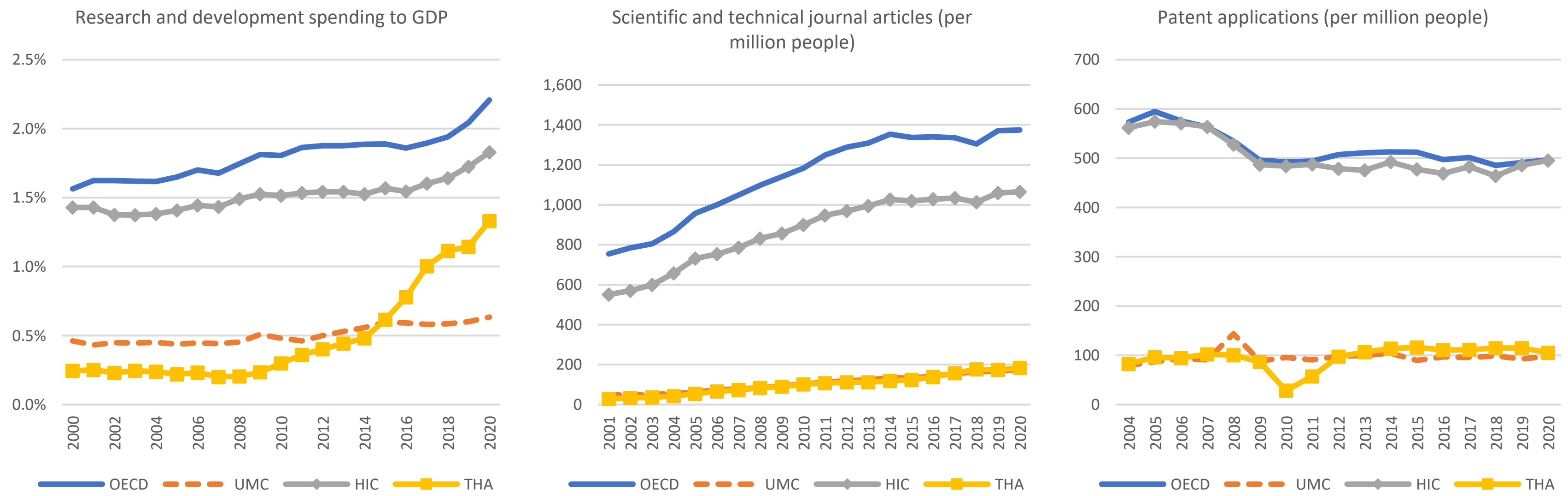


Figure 13: Benchmarking Thailand’s 5 Pillars of Knowledge Economy Ecosystem against International Peers (2018)

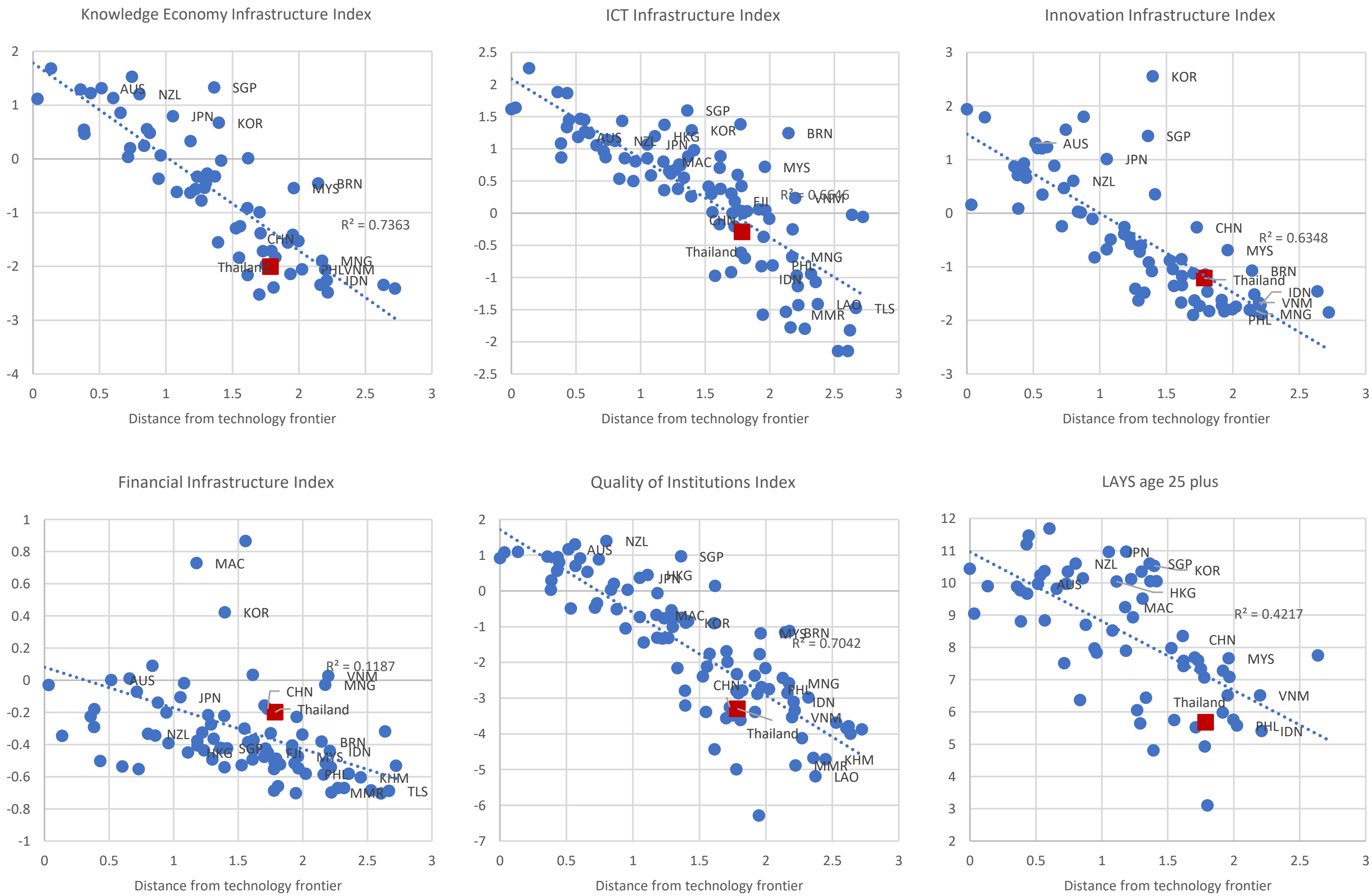
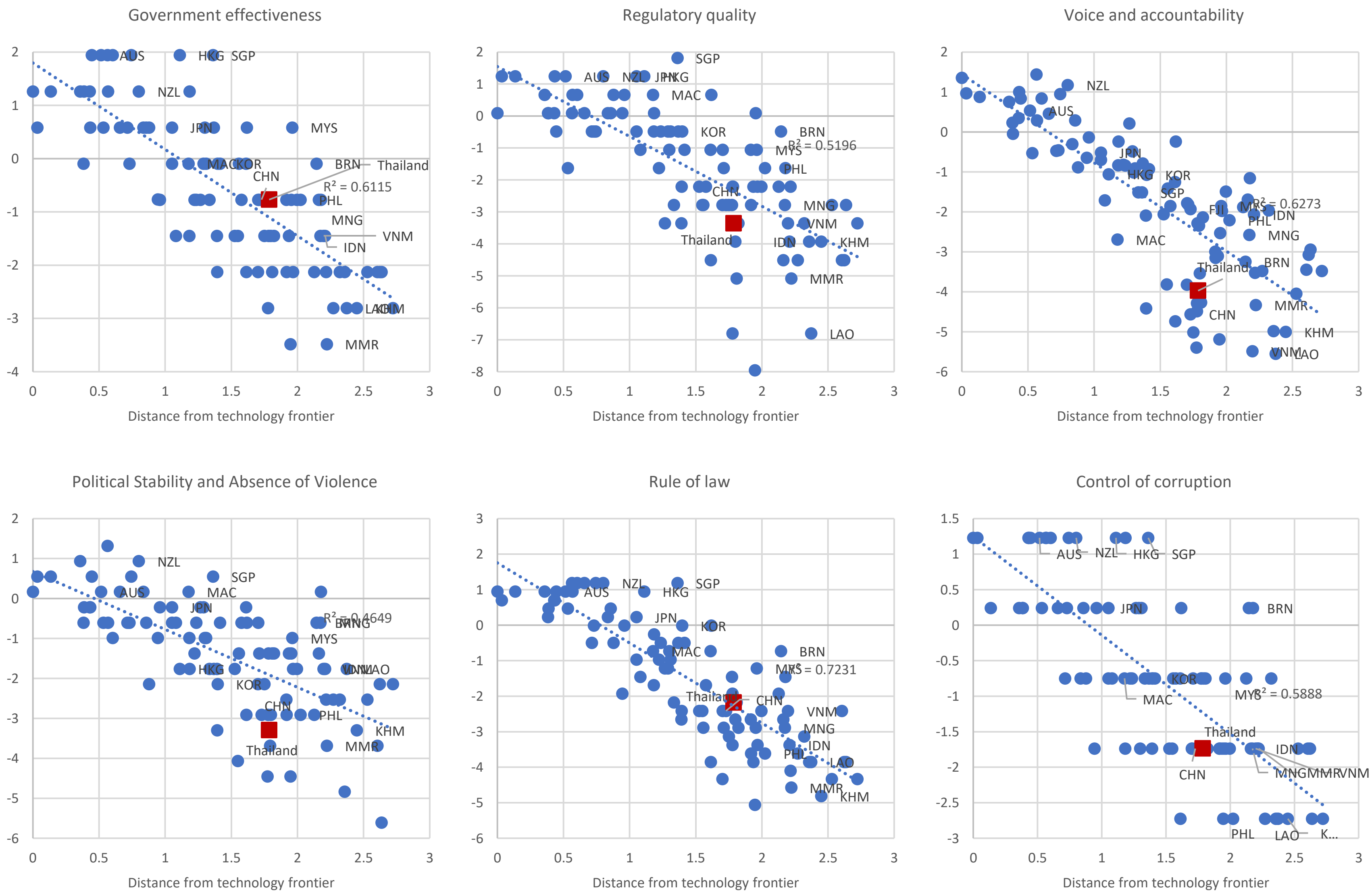


Figure 14: Benchmarking Thailand's Quality of Institutions Sub-Indices against International Peers (2018)



Conclusion

This paper provides empirical insights into the role of the Knowledge Economy Ecosystem framework in determining long-term economic growth. The study employs a rigorous estimation strategy, building upon previous research, to assess the impact of the five pillars of the Knowledge Economy Ecosystem (human capital, ICT infrastructure, quality of institutions, innovation infrastructure, and financial infrastructure) on both GDP per capita and total factor productivity (TFP) growth.

The findings of this study highlight the significance of investments in human capital, as measured by both Learning-Adjusted Years of Schooling (LAYS) and Harmonized Learning Outcome (HLO), and the Knowledge Economy Infrastructure Index (KEI) in driving economic growth. These investments are associated with statistically significant positive effects on both GDP per capita and TFP growth rates. Moreover, the results emphasize the importance of bridging the gap in human capital and improving knowledge economy infrastructure to foster economic development.

Furthermore, the research indicates that while there is evidence of the positive impact of high performers on growth, achieving basic literacy and skills among the entire population remains a crucial foundation for identifying and nurturing future high-performing individuals. The study's analysis demonstrates that countries should aim to create a competitive environment among a broad pool of students reaching basic skills as a means to cultivate a greater share of high-performers.

The benchmarking exercise, focusing on Thailand's progress in enhancing its Knowledge Economy Ecosystem, reveals important insights. Thailand has made substantial strides in improving its infrastructure, particularly in the domains of ICT and innovation. However, significant challenges remain, especially in terms of human capital development. Thailand's average years of schooling and learning-adjusted years of schooling lag behind international benchmarks, indicating the need for continued investments in education and skills development. Additionally, the country faces challenges in the quality of its institutions, which is a critical pillar for a thriving knowledge economy.

In light of these findings, it is evident that sustained investments in the five pillars of the Knowledge Economy Ecosystem are essential for achieving and maintaining economic growth. To transition successfully to a knowledge-based economy, countries must prioritize the development of human capital, infrastructure, and institutions. Bridging the gap in education and skills, fostering innovation, and strengthening the quality of institutions are paramount to ensuring long-term economic prosperity.

Thailand's experience serves as a valuable case study, highlighting both progress and areas that require further attention. This research contributes to our understanding of the dynamics between knowledge capital and economic growth, offering policymakers insights into the strategic investments necessary to foster a thriving knowledge economy and sustain economic development.

References

Anderson, T.W. and Hsiao, C. (1981). Estimation of Dynamic Models with Error Components. Journal of the American Statistical Association, Vol. 76, No. 375 (Sep., 1981), pp. 598-606

Barro, R.J. and Lee, J.W. (2013). **A new data set of educational attainment in the world, 1950–2010.** Journal of development economics, Elsevier.

Chen, D.H. and Dahlman, C.J. (2006). The Knowledge Economy, the Kam Methodology and World Bank Operations. *Policy Research Working Paper*. 37256.

Glawe, L. and Wagner, H. (2022). Is schooling the same as learning? – The impact of the learning-adjusted years of schooling on growth in a dynamic panel data framework. *World Development*, 151(C).

Filmer, D., Rogers, H., Angrist, N. and Sabarwal, S. (2020). Learning-adjusted years of schooling (LAYS): Defining a new macro measure of education. *Economics of Education Review*, 77(C).

Hanushek, E.A. (2013). Economic growth in developing countries: The role of human capital. *Economics of Education Review*, 37, 204-212.

Hanushek, E.A. and Kimko, D.D. (2000). Schooling, Labor-Force Quality, and the Growth of Nations. *American Economic Review*, 90(5), 1184-1208.

Hanushek, E.A. and Woessmann, L. (2012). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. *J Econ Growth* **17**, 267–321 (2012).

Lathapipat, D. and Chucherd, T. (2013). **Labour Market Functioning and Thailand's Competitiveness**. Working Papers 2013-03, Monetary Policy Group, Bank of Thailand.

World Bank (2016). Thailand - Systematic Country Diagnostic: Getting back on track - Reviving growth and securing prosperity for all (English). Washington, D.C.: World Bank Group.

World Bank (2020). The Human Capital Index 2020 Update: Human Capital in the time of COVID-19. Washington, D.C.: World Bank Group.

World Bank (2022). Adult Skills Assessment in Thailand, 2022. Washington, D.C.: World Bank Group. (forthcoming)