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Skills, Human Capital, and Economic Development

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Abstract

This paper presents a skills index for developing countries in Asia as a first step toward developing a Global Skills Index. The Asian Skills Index is roughly modeled on the European Skills Index for Organisation for Economic Co-operation and Development countries. However, the Asian Skills Index is substantially more complicated to develop. In addition to data limitations, the Asian Skills Index incorporates several structural and institutional features of labor markets in Asian countries, such as vulnerable employment and unemployment among the highly educated, which are specific to Asian countries. In addition, the newly developed learning-adjusted years of schooling indicator plays an integral role in the Asian Skills Index. Using the k-means clustering algorithm, the paper identifies a comparable group of Asian developing countries for which it develops an index of the country's skills system. While studies on human capital focus only on education, the Asian Skills Index is a more comprehensive construct since it goes beyond just education and skills development. By incorporating labor market conditions within which education and skills can thrive and be translated into productive output, a skills system provides crucial economic context for the human capital development process. Using the Asian Skills Index, the paper provides some economic estimates and policy recommendations.

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Skills, Human Capital, and Economic Development

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I. INTRODUCTION

The macroeconomics literature on the relationship between human capital and economic growth is extensive. The recognition that human capital is a primary driver of economic growth has impacted economic policy making at its most fundamental level. Improved schooling as a method of human capital enhancement has been a major goal of countries and international organizations. Nowhere is this more apparent than in the focus on primary schooling as a Millennium Development Goal (UN, 2015). To a large extent this focus on schooling has been successful as access to education in developing countries has rapidly expanded

A fundamental assumption in much of the literature is that human capital is synonymous with schooling. In cross-country studies this is necessitated not only by the availability of data but also by the notion that the difference between schooling levels in any given country is greater than intercountry differences between schooling levels. Over time, it has become increasingly obvious that wider access to schooling and the hoped-for enhancement in human capital that should have followed from greater schooling have not resulted in higher economic growth. In the literature, schooling is essentially equated with learning and skills acquisition. That this is a problematic assumption has become increasingly obvious. Hanushek (2013) points out that cognitive skills, rather than mere school attainment, is a better indicator of human capital and more intrinsically linked to economic growth. *"The importance of skills and conversely the unimportance of schooling that does not produce higher levels of skills has a direct bearing on human capital policies for developing countries"* (p.206). Economic models of growth that focus on years of schooling as a proxy for human capital enhancement may be misfocused.

The focus in economic models on years of schooling is easy to comprehend. Years of schooling is an easily measured metric; educational quality and "skills" on the other hand is a more amorphous attribute. Focusing on education quality rather than years of schooling has substantially complicated economic analysis. In recent years, however, internationally comparable student achievement tests such as the *Trends in International Mathematics and Science Study (TIMSS)* and *Program for International Student Achievement (PISA)* have become more widespread. Their growing coverage has led to increasingly reliable indicators of educational quality.

Cross-country scores on TIMSS and PISA provide one indicator of skills, However, the skills measured by such tests are primarily cognitive skills. Such skills are clearly valuable in technologically advanced economies. In developing countries, however, the situation is different. The requisite skills and returns to education in developing countries are markedly different due to a less advanced technological base and fundamentally different economic structures. Thus, cognitive skills as measured by international student achievement tests may not play as fundamental a role in human capital enhancement in developing countries.

The extant literature on human capital and economic growth has to a large extent focused on developed countries since data is more readily available for such countries. International student testing has been extended to all OECD countries and comparable data for OECD countries are now readily available (see Hanushek and Woessmann (2012)). However, research on the relationship between human capital, skills and economic growth in developing countries is considerably sparse since comparable test score data for such countries is not available. This may not, however, constitute a major disadvantage since the notion of skills in developing countries needs to be more expansive than focusing only on the cognitive, academic type skills measured by international tests.

The objective of our paper is threefold. Rather than focusing on cognitive academic skills alone, we focus on a more expanded notion of "skills." [3] Our first objective is to develop a composite indicator of skills for developing countries in Asia like the European Skills Index (ESI) developed by the European Centre for the Development of Vocational Training (CEDEFOP).[4] The Asian Skills Index (ASI) intends to measure the performance of a similar group of Asian countries in terms of how effectively labor market skills from post-secondary education level and beyond are being formed ("skills formation"), how effectively such skills are utilized in labor markets ("skills activation") and finally, how effectively labor market demand-supply mechanisms match skills to abilities ("skills matching").

The motivation to develop such an index is threefold. First, the ASI considers the *entire skills system* - ranging from how skills are formed, to how skills are activated, to how skills are ultimately deployed for economic growth. This is particularly important in the Asian context given that skills formation alone may not be the primary constraint since a significant pool of educated are unable to find productive employment. We also invoke the concept of deadweight loss for the education and skills development system due to a highly educated population with no jobs. It should be noted that a major difference between previous proxies for human capital such as "years of schooling" is that they essentially focus only on skills formation. But skills formation by itself is redundant if it is not activated through participation in the labor market and

[3] The term "Skills" is used in this paper to broadly define the acquisition of marketable competencies and attributes as applicable beyond secondary education and encompassing tertiary education (both technical vocational education and training and higher education at university level).
[4] https://www.cedefop.europa.eu/files/esi_-_technical_report_2020.pdf

if labor markets do not function effectively by matching skills sets. Both the ESI and ASI in this sense provide a more comprehensive picture of the process by which human capital is translated into economic output.

Second, measurements for each pillar in the process (Skills Formation, Skills Activation, Skills Matching) offer other insights. Skills formation, for instance, constitutes what is traditionally meant by human capital. By summarizing the 3 pillars built from several underlying indicators, the 3 pillars as well as the overall ASI, are easier to interpret than a battery of separate indicators. They offer a composite and succinct measure.

Third, the ASI like many composite indicators provides cross-country comparisons (both within and across pillars) that can illustrate complex issues. Such comparisons can often highlight why a particular policy followed by one country has led to superior results compared to another. The motivation for composite indicators is neatly summarized by Sharpe (2004, p.9): *"The aggregators believe for two major reasons there is value is combining indicators in some manner to produce a bottom line. First, they believe such a summary statistic can indeed capture reality and is meaningful. Second, they stress that bottom lines are extremely useful in garnering media interest and hence the attention of policy makers".*

Finally, the underlying motivation for the ASI is similar to the ESI. *"The ESI is intended to measure the performance of EU-27+4 countries' skills formation and matching systems to enable a comparative assessment across EU 27+4 countries. The concept of a skills system is a multifaceted and complex one, and there is no single all-encompassing measure of the system's performance"* (2020 European Skills Index, Technical Report).

There are several differences, however, between the ESI and ASI. In contrast to the ESI, we explicitly incorporate a metric of schooling quality and learning as measured by LAYS (*Learning Adjusted Years of Schooling*).[5] However, LAYS by itself means little if schooling, and the skills it engenders, does not translate into productive employment. A skills index takes into account not just learning but also skills activation and matching – that is, *the degree to which skills find productive expression in labor markets*. We incorporate within the skills index such measures as "unemployment among the highly educated" to provide some economic context. By embedding traditional measures of education and schooling quality within a broader skills system, crucial economic context is provided that is not present in other work in this area.[6]

Our second objective is to develop a skills index that accounts for certain idiosyncratic features of developing countries. An important issue in these countries relates to the nature of education itself and the relative emphasis between academic (at school and tertiary education levels) versus vocational education. Vocational education by focusing on job related skills is intended to provide an avenue for a speedier transition to some employment for youth who are not academically inclined, have the capacity and opportunity to pursue technical or vocational competencies, and/or need to enter the labor market faster due to household income constraints. In countries with high youth unemployment such a policy could make sense from both an economic and social perspective. In our skills index we incorporate structural and

[5] See Angrist et al. (2021).

[6] Other types of skills (social, emotional, computer, digital, etc.) would be a valuable addition to the broad notion of skills. However, data on these types of skills for broad populations is currently not available for developing countries. See Sackett et al (1977) for an early example of the development of an index that measures social, emotional, and physical well-being of populations. For an interesting example of a "digital inclusion index" see Thomas et al (2021) who develop such an index for Australia.

institutional features that are central to developing countries such as part-time employment, unemployment with advanced education and vulnerable employment.

Our final objective is to use our Skills Index to analyze the relationship between human capital, skills and economic growth and to provide estimates of what skills enhancement can mean for economic growth. Many studies have explored the relative contribution of human capital to cross-country income differences, but the results have been inconclusive. Angrist et al (2021, p. 407) point out that *"The challenges in measuring quality have contributed to substantial variation in estimates of the role of human capital in cross-country differences in income,* ***ranging from nearly all to potentially none****" (our emphasis).* Part of the reason for this is due to the significant heterogeneity of the countries considered. Estimates indicate that while human capital accounts for 54% of cross-country income differences in advanced economies, human capital accounts for only 4% in Sub-Saharan Africa.

In our paper, we focus on a similar group of developing countries in Asia. We develop a composite Asian Skills Index (ASI) for this group and then use the ASI as a proxy for human capital to study the link between skills development and economic growth. The ASI represents an extension of the effort initiated by the ESI to Asian countries. An important motivation for this effort is the concern that COVID may have on skills acquisition and the risk of large cohorts of children leaving school with few work-related skills. The index also may highlight the deleterious effects of COVID on the current operation of labor markets and the worsening imbalances of supply-demand mechanics in labor markets.

We apply a clustering algorithm using "K-means" to identify a similar group of Asian developing countries. For this group, which includes countries like Sri Lanka and Pakistan, we analyze secondary education completion rates, LAYS, vocational education, unemployment among the educated, vulnerable employment, etc. to analyze how countries fare on these different indicators.

II. LITERATURE REVIEW

The literature on human capital and economic growth has a long history in macroeconomics stretching all the way to Solow (1956), Becker (1962) and Mincer (1970, 1974). Mincer (1974) is among the earliest attempts at a systematic study of earning differentials based on human capital. Using schooling as the primary driver of human capital, Mincer applied his model to a random group of white, male urban workers and found that schooling accounts for only 7% of earnings differentials. Schooling, however, had more explanatory power for groups with similar levels of experience than for groups of similar age suggesting that experience mattered more than age.

The standard model in the literature is by Mincer (1974) who posits individual earnings (E) as a function of individual skills where skills are generally equated with human capital (H).[7] Thus:

$$E = \beta H + \varepsilon \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where ε is a stochastic term representing random earnings differentials. Human capital, H, is affected by a range of factors including quantity and quality of schooling, family inputs, individual abilities, and other factors such as health. Human capital, H, is however a latent variable. In

[7] The empirical explanation here closely follows Hanushek and Woesmann (2008).

empirical work, H, is essentially equated with the quantity of schooling. Given that cross country data on school attainment is readily available, there is a large empirical literature on explaining earnings differentials and returns to schooling. The Mincer earnings function takes the general form:

$$E = \beta_0 + \beta_1 S + \beta_2 Z + \beta_3 Z^2 + \beta_4 W + e \text{..............................} (2)$$

where E is earnings typically measured in logarithms, S is school attainment, Z is labor market experience and W is a vector of other factors affecting earnings. Barro and Lee (1993, 2001) developed internationally comparable data on years of schooling using a combination of census data, literacy data and enrollment data. Using Barro-Lee data, the estimated return to schooling in (2) is measured by β_1. However, this estimate is biased since school attainment, S, is correlated with factors like ability and family inputs. In fact, test scores have been added to the Mincer model above to control for such ability differences. If the definition of human capital is expanded to include non-cognitive skills (interpersonal skills, communication ability, ability to work with teams, etc.) estimating E becomes even more complicated.[8]

Over the last 30 years, a substantial amount of attention has focused on estimating the economic returns to schooling worldwide as depicted in (2). A fundamental econometric issue in many of these studies relates to causal effects; if people with more ability also tend to obtain more schooling, separating returns to schooling as distinct from returns to ability is not

[8] See Lemieux (2006) for a retrospective article on the performance of the Mincer equation 30 years after its publication. Lemieux concludes that the Mincer equation has held up remarkably well in estimating wage determination provided some adjustments are made such as including a quadratic term to account for the convex relationship between schooling and earnings.

straightforward. Most research including studies that employ estimation techniques specifically designed to control for endogeneity, find that increased schooling leads to higher returns, with returns to education being higher in lower income countries (see Psacharopoulos and Patrinos (2018, 2020)). Psacharopoulos and Patrinos estimate that the average private returns to a year of schooling is about 9% with social returns to education even higher.

Until recently, cross country data on skills (as measured by standardized tests) that was also linked to subsequent labor market performance was not available. The increasing availability of such longitudinal data has allowed researchers to document that higher achievement on standardized tests translates into substantial earnings advantages. The basic approach is to estimate a standard Mincer earnings function as in (2) and then add a measure of individual cognitive skills. Several studies document that students who perform better on standardized tests subsequently earn more. Lazear (2003), for instance, found that a one-point standard deviation improvement in test performance results in 12 percent higher annual earnings. In fact, these are lower bound estimates given that the economic value of skills and schooling has grown over time and increasing productivity over time is likely to lead to even larger returns.

While the empirical evidence suggests that there is broad positive correlation between schooling and earnings, it is not evident that increased schooling automatically translates to greater learning, better skills or enhanced human capital. *"Several studies have suggested that when human capital is measured by schooling, it does not deliver the returns predicted by growth models. However, when measured by learning, human capital is more strongly associated with growth"* (Angrist et al (2021), p.403). Essentially, international differences in years of schooling cannot explain cross country differences in per capita GDP growth. However, once cognitive skills are included in growth models, the ability of such models to explain economic growth is substantially enhanced (see Hanushek and Kimko (2000), Hanushek and Woessmann (2020, 2012)). From a macroeconomic perspective, there are several mechanisms through which education affects economic growth. In neoclassical growth theory, education increases human capital and labor productivity moving countries towards a higher equilibrium level of output. In endogenous growth theory, education increases innovation, new technologies, products and processes.

The next section develops a "Skills Index" that ties together many of the underlying concepts in this literature. Our objective is to use this Skills Index to analyze the relationship between human capital, skills and economic growth and to provide estimates of what skills enhancement can mean for economic growth.

III. THE CONCEPT OF A SKILLS INDEX

An index combines several variables into a single metric. The objective of a well-constructed index is to combine variables into a single metric such that the multidimensional nature of the data is preserved while highlighting the general directional movement of the whole. A well-constructed index can summarize complex, multi-dimensional realities to provide a useful guide for policy making, facilitate communication and promote accountability. Greco et al. (2019) point to the U.N.'s Human Development Index (HDI) as an example. The HDI was initially criticized for its methodology. However, Nobel laureate Amartya Sen, one of its early critics, changed his mind and deemed the HDI a success after noting the attention the index attracted and the subsequent debates it fostered.[9]

The European Skills Index (ESI) was first released in 2016 under the title "Making Skills Work Index" and recently updated in 2020. The ESI developed by CEDEFOP measures the performance of EU skills systems. The ESI consists of three pillars - *skills development; skills activation; skills matching* - each of which measures a different aspect of a skills system. The ESI is based on 15 individual indicators and then averaged to arrive at a composite score. The scores range from 0 (lowest) to 100 (highest). A score of 75, for instance, indicates that a country has reached 75% of the ideal performance leaving a 25% margin for improvement.

Our objective in this paper is to develop a skills index for developing countries in Asia. Consequently, our focus is on developing an "Asian Skills Index" (ASI) roughly modeled on the ESI. An Asian Skills Index is, however, substantially more complicated to develop. Most obviously, consistent, comparable data series for many Asian countries is not as widely available as OECD data. In addition, several structural and institutional features of labor markets in Asian countries such as part-time employment, vulnerable employment, and unemployment among the highly educated means that the ASI cannot simply replicate the ESI. Recent work by Angrist et al (2021, p.403) point out that *"For decades, studies used schooling as a proxy for human capital. This applies even to the most prominent index of human capital to date, the United Nation's human development index (HDI). However, using schooling as a proxy for human capital assumes that being in school translates to learning. Evidence suggests that this is often not the case".* In

[9] Most recently, the Economist (June 3-9, 2021, page. 84-85) developed a "Normalcy Index" based on indicators like sports and cinema attendance, air and road travel, office attendance, retail store visits, etc. to track lifestyle changes since COVID-19.

contrast to the ESI, we incorporate LAYS in the ASI.

In developing the ASI we followed a few guiding principles. First, we chose data series all of which were derived from a specific source such as WDI, ED Stats or Penn World Tables. The intent was to preserve data comparability across countries as much as possible. Second, comparable series for which data for all countries were available were few. Therefore, we ignored some series we deemed useful in preference to others with fewer missing observations. Third, the data used in constructing the index represent average values of the available data over the period from 2016 to 2020. In some cases, a single observation over this period served as representative of the average. Fourth, while there are many methods to handle missing values, we replaced missing values with mean values so that the overall behavior of the index reflected the average values of the available data.

The ASI, like the ESI, is based on 3 broad pillars representing different aspects of a skills system. However, the ASI allows for modifications based on the structural and institutional features of labor markets in developing countries. The 3 pillars are:

i) **SKILLS DEVELOPMENT**: This pillar represents the quality of education and training available in a country and educational attainment of the population. In addition to variables such as pupil-to-teacher ratios and population with at least a secondary education (which are part of the ESI), the ASI includes other variables such as the share of population with advanced education and the recently developed LAYS which provides a composite metric of learning adjusted years of schooling.

ii) **SKILLS ACTIVATION**: Most studies of human capital focus on the first pillar, skills development. However, the economic productivity of a workforce is determined not only by skills developed through educational training but also by the degree to which these skills can be activated through greater participation in the labor market. This pillar is measured by variables such as the labor force participation rate among all adults and share of youth currently not in education, employment, or training.

iii) **SKILLS MATCHING**: This pillar captures the degree to which labor force skills are effectively utilized and the extent of labor market imbalances in the form of unemployment, under-employment and part-time employment.

These 3 pillars represent various aspects of a skills system and serve to conceptualize our understanding of the process by which human capital is developed (Pillar 1), activated through productive employment (Pillar 2) and finally, the extent to which these skills are effectively utilized through demand-supply mechanics of labor markets (Pillar 3). Clearly, interrelationships exist between all 3 pillars.[10]

It should be noted that a major difference between previous proxies for human capital such as "years of schooling" or LAYS is that they essentially terminate at Pillar 1 (Skills Development). But "Skills Development" by itself is redundant if it is not activated through participation in the labor market and if labor markets do not function effectively by matching

[10] This is evident in many indices. The Human Development Index (HDI), for instance, includes both expected years of schooling and mean years of schooling.

skills sets. In many Asian countries, skills development may not be the primary constraint since a significant pool of educated are unable to find productive employment. The ESI and ASI in this sense provide a more comprehensive picture of the process by which human capital is translated into economic output. The variables used in constructing the ESI and ASI are reported in Tables 1A and 1B.

The ASI tries to preserve the underlying logic of the ESI as is evident in comparing Tables 1A and 1B. Some variables are essentially similar. Preprimary pupil-teacher ratios; percentage enrolled in vocational education; youth not in education, employment, and training; labor force participation rate; etc. are in both indexes. There are, however, some significant differences. The inclusion of LAYS in the ASI in place of PISA scores in the ESI is one major difference. Another has to do with substituting 'Low Wage Workers' in the ESI with 'Vulnerable Employment' in the ASI. In addition, to Vulnerable Employment, the ASI also includes 'Unemployed with Advanced Education'. Labor market characteristics such as 'Vulnerable Employment' and 'Unemployed with Advanced Education' are distinctive features of many Asian labor markets and should be part of any index that purports to capture labor market conditions in such countries. In addition to the inclusion of some variables that are distinctively Asian, the exclusion of other variables in the ESI (Recent Training, High Computer Skills, for instance) were driven by the lack of consistent, uniform data for Asian countries.[11]

[11] We looked at almost all the series in WDI and Ed Stats to home in on the indicators that were most relevant. This was not a straightforward task. One of the cardinal principles we followed in the paper was that each variable used in the index needed to be from *the same source with precisely the same series code*. There are, in fact, numerous series that have similar names reported by different organizations using different collection methodologies and, in some cases, quite dissimilar values. In addition, not surprisingly, many series had missing values. Balancing out all these considerations to create a reasonably cohesive, comparable data set was the most challenging aspect of creating the index.

IV. AN ASIAN SKILLS INDEX (ASI)

Constructing a composite index involves several choices in terms of methodology. We describe below some of the major methodological choices in constructing the ASI.[12]

a) ***SELECTING COUNTRIES USING k-MEANS CLUSTERING****:* The constituent elements in any index clearly affect the behavior of the index. If an index is to serve its role as a tool for comparative measurement, the constituents in the index must be reasonably comparable. There are two important reasons for this comparability requirement. When there are missing values in the data set, replacing missing observations with mean values requires a similar grouping of countries. *"Cluster analysis serves as a method for selecting groups of countries for the imputation of missing data with a view to decreasing the variance of the imputed values.* (*Handbook on Constructing Composite Indicators*, p. 26). A second reason for comparability has to do empirical estimation. In the macroeconomics literature, empirical estimates of the role of human capital in real output range from nearly all to potentially none. Part of the reason for this is inclusion of economies at completely disparate levels of economic development.[13]

We began with a list of 30 Asian countries[14] and then used GDP per capita to cluster the countries using "k-means". k-means is an unsupervised machine learning algorithm for partitioning datasets into a set of k clusters such that objects within the same cluster are as

[12] See *"Handbook on Constructing Composite Indicators – Methodology and User Guide"* by the Joint Research Centre (JRC) of the OECD. https://www.oecd.org/sdd/42495745.pdf See also Greco et al (2019) for a comprehensive review of the methodological choices in composite indicators construction.

[13] The Dow Jones Industrial Average (DJIA) is, by far, the best-known index of U.S. stock market performance. However, the DJIA has an inherent methodological flaw. The smallest stock in the index is Walgreens Boots Alliance (WBA) with a market capitalization value of $46.2 billion. The largest is Apple (AAPL) with $2,100 billion or $2.1 trillion - 45 times larger than WBA (values as of June 2021). However, a $1 movement in the stock price of both companies is treated exactly alike in the DJIA even though AAPL has a market capitalization that is 45 times larger than WBA. For comparative performance, conflating large and small companies leads to methodological problems. The Standard & Poor's (S&P) 500 Index addresses this issue by weighting stock prices by market capitalization.

[14] By Asian countries we mean all countries classified as being in either South Asia, East Asia, or Central Asia.

similar as possible (i.e. high intra-class similarity) whereas objects from other clusters are as dissimilar as possible (i.e. high inter-class dissimilarity). The clustering algorithm uses Euclidean distance $D(x,y)$ to measure the degree of similarity between two variables, x and y over N dimensions such that:

$$D(x,y) = \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{N}} \quad \text{……………………………………}(3)$$

This resulted in a list of 3 clusters which are reported in Table 2.[15]

Even a cursory examination of Table 2 is sufficient to establish that the clusters, whether based on GDP per capita or HCI ranking, are essentially similar. Cluster 1 countries have HCI scores around .80, Cluster 2 countries generally have scores above .60 and Cluster 3 countries have scores below .60. There are, however, some anomalies. Vietnam is clearly a striking anomaly. Vietnam's per capita GDP places it in Cluster 3 but its HCI score of .69 should easily place it in Cluster 2. The reason for Vietnam's high HCI score has to do with its superior performance on harmonized test scores and LAYS. Vietnam's harmonized test score of 519 and LAYS score of 10.70 places it just below Cluster 1 countries. Uzbekistan also has a HCI score of .62 due to its test scores but its per capita GDP places it among lower middle-income countries.

Among the clusters, Cluster 3 contains the largest sample of similar countries. In the remainder of the paper, we focus on this cluster.

[15] It is interesting to note that countries in Cluster 1 held the top positions in the HCI 2020 index. Singapore (1), Korea, Rep. (2), Japan (3) and Hong Kong SAR, China (4).

b) ***NORMALIZATION****:* When variables are measured in different units (millions for GDP and decimals for unemployment rates, for instance), variables measured in larger units exert a greater effect when employing machine learning methods like cluster analysis. We chose to use Min-Max normalization i.e., $\frac{x-Min(x)}{Max\,(x)-Min(x)}$ where x is the series under consideration. The min-max normalization constrains values to the [0,1] range with 0 and 1 representing the lowest and highest values in the chosen series. In some cases, variable values and index criteria move in opposite directions.[16] For example, a high preprimary pupil teacher ratio decreases the quality of education. In this case, the country with the highest preprimary pupil teacher ratio has a value of 0. Similarly, a high proportion of the youth population not in education, employment or training lowers the quality of the skills system.[17] In these cases, an alternative normalization can be used: $\frac{Max\,(x)-x}{Max\,(x)-Min\,(x)}$.

c***) WEIGHTING & AGGREGATION*****:** The impact of the constituent series on their respective pillars (i.e. weights) is not immediately obvious. Ravallion (2010) offers a critical assessment of the strengths and weaknesses of development indices…. "*One theme of the paper is the importance of assessing the (rarely explicit) tradeoffs embodied in these indices – for those tradeoffs have great bearing on both their internal validity and their policy relevance." (p.4).* Ravallion goes on to point out that *…."The reality is that no consensus exists on what dimensions to include and how they should be weighted in any of the mashup indices of development in use today" (p.17).*

[16] For some variables it is unclear whether a high or low value is favorable for economic growth. For instance, a high percentage of the population in vocational education is set to 1 on the assumption that this is favorable for economic growth in developing countries.
[17] In addition to "preprimary pupil teacher ratio" and "youth population not in education" other variables also move in directions opposite to the index such as unemployment, part-time employment, unemployment with advanced education, and vulnerable employment. In all these cases, the country with the highest values of these variables has the lowest index value of 0.

While there exists no clear consensus, several methods have been used for allocating weights. The most common method is to assume equal weights which implies that each constituent series, X_i, has the same impact on their respective pillars. (This is equivalent to assuming that each of the series are perfectly substitutable). The index value of each pillar, I_{Pillar}, is then the arithmetic mean of the constituent series thus:

$$I_{Pillar} = \frac{\sum_i^n x_i}{n} \quad \text{..............................(4)}$$

The ESI uses a mix of weighted arithmetic and geometric means at different levels of the index. The constituents within each pillar have varying weights usually around .35 but could have a weight as much as .70 ("Early Leavers from Training") or as low as .10 ("Low waged Workers"). The weighted arithmetic average of the sub-pillars yield a pillar score. The three pillars have weights of .30, .30 and .40. The basis for these weights is, however, not very explicit. The overall ESI score is then computed as the weighted geometric average of the 3 pillar scores.

We followed a similar procedure for the ASI. However, rather than using varying weights within and across pillars as in the ESI, we used equally weighted arithmetic averages for sub-pillars. The overall Asian Skills Index (ASI) is, computed as the geometric mean of the 3 pillars.[18] Thus:

$$ASI = (I_{Pillar\ 1} \, . I_{Pillar\ 2} . I_{Pillar\ 3})^{1/3} \quad \text{............................(5)}$$

[18] The Human Development Index (HDI) is constructed in a similar manner. The HDI is the geometric mean of 3 dimensional indices: HDI = $(I_{Health} . I_{Education} . I_{Income})^{1/3}$. See Technical Notes, Human Development Report /2020.

d.) DETERMINING WEIGHTS ENDOGENOUSLY USING PCA: Most composite indicators use equal weighting which implicitly assumes that all variables have the same effect on the composite index. An alternative is to use a statistical criterion such as Principal Component Analysis (PCA) to determine the weights of each series and then aggregate it into a composite index. PCA generated weights are reported in the final section of the paper.

The raw data used in constructing all the indices, as well as the index values for each constituent pillar, is shown in Tables 3A, 3B, 4A, 4B, 5A and 5B. The composite Asian Skills Index is shown in Table 6 using the equal weights method. Table 7 reports HCI and HDI scores to provide a contrast to the ASI. Note that a larger value for the ASI indicates a higher skills level.

V. APPLYING THE ASIAN SKILLS INDEX (ASI)

The ASI provides a composite picture of the skills system of Asian developing countries with each pillar capturing different aspects of the system. Among the pillars, Pillar 1 (Skills Development) is most directly linked to both HCI and HDI since HCI includes LAYS and expected years of schooling while HDI includes expected years of schooling. Table 8 reports correlation coefficients between LAYS, HCI, HDI, ASI and all 3 pillars.

The LAYS, HCI and HDI are all highly correlated as expected. HCI and LAYS, in particular, exhibit a correlation of +.98. Pillar 1 is positively correlated with LAYS, HCI and HDI with correlations around +.65. This is not surprising given that LAYS, HCI, HDI and Pillar 1 have varying emphasis on skills development. Pillars 2 and 3 on the other hand exhibit low positive or even negative correlations with HCI and HDI. This is not surprising given that these pillars capture labor market conditions rather than human capital formation per se.

Table 8 also shows that the correlation of the composite ASI to individual pillars is generally much higher than the correlation of the pillars to each other indicating that the pillars are not replicating the same information.[19] Additionally, the negative correlations between Pillar 3 and LAYS and HDI is not surprising given that Pillar 3 captures frictions in the labor market (i.e., part time employment; vulnerable employment; unemployment among the highly educated), conditions that would depreciate skills development. The same notion is reinforced by the negative correlations between Pillar 1 and Pillar 2 (-.24) and between Pillar 1 and Pillar 3 (-.10). These correlations provide some evidence that individual pillars in the ASI are capturing different aspects of an economy's skills system.

In addition to the correlation between HCI, HDI and individual pillars as reported in Table 8, correlation between the overall ASI index and individual components of the ASI constitute another straightforward method of assessing the validity of the index (see Table 9).

The first three rows report correlations between the ASI and 3 major metrics – GDP per capita, HCI and HDI. All three correlation coefficients are in accordance with economic intuition. A higher ASI is positively correlated with all three metrics; higher ASI values led to higher per capita GDP, HCI and HDI. In addition, the correlation between ASI and GDP per capita, as well as the correlation between the ASI and HCI, is statistically significant. The correlation between ASI and HDI is positive but not statistically significant. This is not surprising given that the HDI

[19] It could be argued that since the ASI includes LAYS it is not surprising that ASI is positively correlated with LAYS, HCI and HDI. This, however, ignores that fact that LAYS is only one of 5 components in Pillar 1 and only one of 11 components in the overall ASI composite index. The positive correlation between ASI, LAYS, HCI and HDI provides some assurance that the ASI is capturing crucial aspects of human capital development.

captures overall human development including aspects like health and income which are not specifically focused on human capital.

Table 9 indicates that the ASI is positively correlated with LAYS, educational attainment, proportion enrolled in vocational education, percent of population with bachelors and the labor force participation rate. ASI is negatively correlated with preprimary pupil teacher ratios, proportion of youth not in education, employment, or training; total unemployment; part time employment; unemployment with advanced education and vulnerable employment. Several of these variables are statistically significant. Most strikingly of all, ASI and "Unemployment with advanced education" has not only a high negative correlation of -.70 but the correlation is also statistically very significant.

VI. POLICY IMPLICATIONS

The analysis in the previous section highlights aspects of skills systems that can illuminate broad policy questions. The first point to note is that all variables used to construct the ASI have correlations that are in accordance with economic intuition. This provides some reassurance on the general directional validity of the overall index. The 3 pillars in the ASI each focus on one specific aspect of a skills system and can thus be considered policy levers.

The first question we examine is if low pupil-to-teacher ratios at the preprimary level improve LAYS scores. If low preprimary ratios translate to high LAYS, we would expect a high negative correlation. However, the correlation between preprimary ratios and LAYS in Table 3A is positive (+.09) rather than negative. This is reinforced by examining Table 3A more closely. Bhutan, for instance, has the second lowest preprimary pupil-teacher ratio at 11.44. However, its LAYS score of 6.30 places it below the average of 7.18. (Bhutan's educational attainment at the lower secondary level is also among the lowest in the sample). On the other hand, Mongolia has the second highest pupil teacher ratio at 33.16 but its LAYS score of 9.20 is the highest in the sample. The fact that preprimary ratios do not seem to substantially affect learning (at least in the Asian context) is an interesting finding that contradicts the central role of this variable in economic growth studies.

Pillar 2 captures the extent to which skills are activated in labor markets. The higher the proportion of youth not in education, employment, or training, the lower the value of Pillar 2 and the overall ASI. Similarly, a high labor participation rate increases the value of Pillar 2[20] and the overall ASI. Pillar 3 captures the extent to which skills are matched in labor markets. All 4 variables used to construct Pillar 3 (total unemployment, part time unemployment, unemployment with advanced education, and vulnerable employment) exhibit strong negative correlations with the ASI indicating that as unemployment of any type increases, the ASI worsens. Table 9 indicates that of all the 11 variables used to construct the ASI, the correlation coefficient between ASI and "Unemployment with advanced education" exhibits not only high negative correlation (-.70) but also statistical significance. A possible explanation for why this variable seems to have such a significant influence is related to the incentive effect. A situation in which even those with advanced degrees have difficulty finding productive employment is bound to create a significant disincentive effect that infects the entire skills system. Also note that "youth not in education" has a statistically significant negative effect on the ASI. Taken together, these results imply that

[20] This should be interpreted carefully. If we are looking at the correlation between the raw series for youth not in education, employment, or training (Table 4A) and Pillar 2, the correlation is -.66. However, if we are looking at the correlation between the transformed series for youth not in education, etc. in Table 4B (where the scale is inverted so that the highest value is set to 0 and lowest value to 1) and Pillar 2, the correlation is +.66.

labor market policy in Asian countries should focus on creating more productive employment opportunities for both youth and the highly educated.

An analysis of the individual pillars highlights several other interesting aspects of skills systems of Asian developing countries. Tables 3A and 3B report results for Skills Development. Here, the country that stands out is Uzbekistan which scores high on every aspect of skills development including low pupil teacher ratios, high educational attainment and a high proportion enrolled in vocational education resulting in the top ranking on Pillar 1. As a check on the reasonableness of this result, we also examined Uzbekistan's standing in the HCI ranking. Even though Uzbekistan is classified as a lower middle-income country, it has high expected years of schooling, high harmonized scores and LAYS. Uzbekistan's also does well on the HDI (which like the HCI incudes "expected years of schooling") with its HDI score placing it alongside "high human development" countries. Uzbekistan's standing on Pillars 2 and 3 are, however, much more mixed. The proportion of Uzbekistan youth that are not in education, employment, or training is 25%, its labor force participation rate at 65% is not as high as Cambodia's (85%) and it has a high unemployment rate at 5.67%. The utility of a skills index lies in insights such as this. Uzbekistan's education system seems to be doing a creditable job of creating human capital, but its labor markets are less effective in transforming that capital into productive economic output.

Sri Lanka's skills system is in many ways typical of Asian developing countries. Sri Lanka's pupil-teacher ratio is relatively low at 13.46 compared to other South Asian countries such as India, Pakistan, and Nepal, all of which have higher ratios of around 20. A high proportion of Sri Lanka's population (82%) has at least a secondary education and its LAYS score of 8.50 is the third highest in its cluster. The proportion of Sri Lankan youth not in education, employment or training is 25%. This is typical for this cluster of countries.[21] Sri Lanka's labor force participation rate of 59% is lower than average and substantially lower than East Asian countries like Cambodia (85%) and the Lao People's Democratic Republic (81%). On the Pillar 3 indicators of total unemployment, part-time unemployment and unemployment with advanced education, Sri Lanka is typical of this group of countries.

An examination of Pakistan's comparative ranking in Pillar 1 (Tables 3A and 3B) indicates that its educational attainment and percent of population with bachelor's degrees is lower than average as compared to its cluster. Most striking, however, is its LAYS score of 5.10 which is substantially lower than average and, in fact, almost a full point lower than the next lowest score in the sample (Bangladesh's LAYS score of 6.0). Given that the mean and standard deviation of LAYS scores in this cluster is 7.18 and 1.17, Pakistan's LAYS score places it in the lowest 4th percentile of this sample. Pakistan's labor force participation and unemployment rates are also worse than the average placing it among the second lowest country in the overall Asian Skills Index.

India's pupil-teacher ratio and LAYS score is about average for its cluster while the percentage of population with bachelor's degrees, given India's relative size, is quite impressive at 9.11%. These indicators rank India's performance on Pillar 1 at about average. However, India's relative standing on Pillars 2 and 3 is worse than average on every indicator. India's labor force participation rate is barely over 50%, 30% of Indian youth are not in education, employment or training, unemployment with advanced education is 15% (more than twice the average in this

[21] Myanmar's high position in the ASI is due to the fact that its total unemployment, as well as its unemployment among those with advanced education, is extremely low at 1.79% and .80%. The total unemployment rate in 2019 was even lower at .50%. (see https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?locations=MM)

group) and vulnerable employment at 75% is close to the worst in the sample. Thus, even though skills development in India is about average, skills activation and skills matching are close to the worst. On the overall Asian Skills Index, both India and Pakistan occupy the lowest spots. Not surprisingly, both India and Pakistan's HCI scores are also among the lowest in the sample.

VII. HUMAN CAPITAL, THE ASIAN SKILLS INDEX, AND ECONOMIC GROWTH

In the economic growth literature, the impact of human capital (proxied by earnings, years of schooling, cognitive scores, LAYS, HCI, etc.) is usually assessed by its impact on per capita GDP. A straightforward way of assessing this relationship is to regress measures of human capital on per capita GDP. Table 10 reports the results of estimating versions of this model using regressors like Mean Years of Schooling, LAYS, HCI, HDI and most significantly of all, a variable not so far considered in the literature, a metric of an economy's skills system such as the ASI.

What is immediately striking is that the coefficient estimates in all versions of the model are significant. These coefficient estimates vary from a low of 216 to a high of 14,981. The coefficients of these models allow us to approximate the impact of a change in each of these variables on per capita GDP. For instance, an additional year of schooling translates into a per capita GDP increase of $216 (constant 2010 US$) while an additional learning adjusted year of schooling (LAYS) translates to an effect that is three times larger at $675. Similarly, a .10 increase in HCI and HDI increases per capita GDP by about $1,244 (.10 x $12,442) and $1,498 (.10 x $14,981). The size of these estimates might seem surprising. However, a .10 increase in the HDI is an extremely large change – approximately, the difference between Singapore and Argentina. The impact of a .10 change in ASI is $565 (.10 x $5,650) lower than the HDI and HCI estimates.

This is not surprising given that the ASI is more narrowly focused while the HDI captures macro changes in an economy's overall human development.

VIII. ESTIMATES OF DEADWEIGHT LOSSES

The coefficient value of ASI indicates that a 1% (i.e., .01) increment in the value of the ASI changes per capita GDP by $5,650.2 (2010 U$) x .01 = $56.50. This value represents the average impact of a marginal change in ASI on per capita GDP. Given that the ASI has a mean value of .47 and standard deviation of .10, this implies that if a country can improve its ASI standing by one standard deviation, this would result, on average, in a per capita GDP increase of $565. Another way of conceptualizing this is to contrast the maximum value of the ASI with the existing value. Given that the ASI has a maximum value of .64, this value can be used as an aspirational or frontier value in estimating what is, in fact, achievable if the skills system was functioning in an optimal manner. The difference between the existing skills system and an optimal system represents a form of "dead weight loss" - opportunity losses stemming from the underutilization of human capital. Table 11 reports these losses.

The losses range from a low of 11% (Indonesia) to a high of 171% (Nepal). The magnitude of these losses may seem surprising, but it should be noted that skills systems represent the entire economic and social framework within which real output is generated. A smooth functioning skills system generates economic output; a poorly functioning one substantially hinders it. The losses estimated here, in fact, probably underestimate actual deadweight losses. These losses would be substantially higher if the countries analyzed here were compared to a higher performing cluster.

The losses estimated here seem outsized but they also represent economic opportunities. Even marginal improvements through a better skills development, activation or matching system can substantially increase GDP.

IX. ASI AND PRINCIPAL COMPONENTS ANALYSIS (PCA)

The ASI consists of 3 pillars with sub-components all of which are equally weighted. Clearly, these weights have an important impact on the structure and interpretation of the index. Equal weights imply that any given sub-component is no more important than any other sub-component. The designated weights also impact the structural time dynamics of the index. If the objective is to measure existing skills levels, one would weight Pillar 3 ("Skills Matching") higher than Pillar 1 ("Skills Development"). If the objective, however, is to measure the future stock of skills, one would weight Pillar 1 higher than Pillar 3.

A feasible alternative to equal weighting is to determine weights by applying *Principal Components Analysis (PCA)*. The major advantage of this method is that the underlying weights would be endogenously driven by the underlying data.[22] The fundamental notion behind PCA is to transform a large data set of correlated variables into a smaller set while preserving most of the information in the larger data set. PCA does this by capturing the highest variance possible in the original data set with as few components as possible. Noorbakhsh (1998, p. 593) in a reformulation of the Human Development Index (HDI provides the underlying rationale for PCA*: "An a priori determination of weights for various components implies the existence of a*

[22] See Greco et al (2019) for a comprehensive discussion of the methodological issues underlying composite index construction. See Noorbakhsh (1998), Ogwang and Abdou (2003) for a discussion on why PCA constitutes a better method than the weighting schemes used in human development indices like the Human Development Index, Gender-Related Development Index and Gender Empowerment Measure.

universally acceptable human welfare/development function which is not the case. An alternative way is to derive these weights from the data…… it would be possible to derive a set of weights from the latent roots (eigenvalues) and latent vectors (eigenvectors) of the data matrix. The application of principal components analysis (PCA) would reduce the data matrix to its latent vectors (factors) each accounting for a proportion of the total variance".

Given a data set of n variables, one can compute n principal components whereby each is a linear combination of the original variables with coefficients equal to the eigenvectors of the covariance matrix. The general form for computing the first principal component (PC) is given by:

$$PC_1 = \beta_{11}x_1 + \beta_{12}x_2 + \beta_{13}x_3 + \cdots \ldots \ldots .. \beta_{1n}x_n \text{..................(6)}$$

where β_i are "loadings" and $x_i \ldots x_n$ are standardized variables. PCA is useful in extracting information on the degree to which a set of correlated variables change relative to each other. The largest weights are assigned to the variables that have the largest variation across countries. This is a particularly desirable property for cross country comparisons since variables that are similar across countries have minor impact in explaining cross country variation.

Based on the standardized correlation matrix of all 11 variables used in the construction of the 3 pillars, the eigenvalues for the principal components are reported in Table 12 and the associated factor loadings in Table 13.

Table 12 implies that the first PC component explains 31% of the total variance, the second PC explains 22% of the total variance and so on. Standard practice is to choose PCs that have eigenvalues greater than 1 or individual PCs that explain more than 10% of cumulative variance. The first four PCs satisfy both conditions. Taken together these 4 components explain 78% of the cumulative variance of the skills index. Consequently, these 4 PCs are used as the basis for deriving weights for the ASI. The squared values of the principal components constitute the factor loadings and capture the proportion of the total explained variance by each PC. These 4 PCs can then be aggregated into a composite by assigning weights to each one equal to the proportion of their explained variance. (See Nicoletti et al (2000) for an example). These weights are reported in the final column of Table 13.

What is immediately striking regarding these PCA derived weights is that the range of weights is quite narrow, varying within a band between 7.60% and 10.89%. Essentially, the PCA weights could have been reasonably approximated by assuming equal weights on all variables. The fact that all variables are represented with almost equal weights is indicative of the fact that every variable contributes to the index. It is also interesting to contrast the PCA derived ranking of countries with the equal-weights method used earlier. The contrasting ranking of both these methods is shown in Table 14.

Ravallion (2010 p.19) notes that *"The most common method of testing robustness is to calculate the (Pearson and/or rank) correlation coefficients between alternative versions of the index mashup index, such as obtained by changing the weights".* The correlation coefficient of +.96 between both methods is indicative of the fact that both methods result in rankings that are very similar to each other.

X. CONCLUSION

This paper presents a skills index for developing countries in Asia as a first step towards developing a Global Skills Index. The Asian Skills Index presented here is roughly modeled on the European Skills Index but includes features specific to developing countries in Asia such as “vulnerable employment” and “unemployment among the highly educated”. In contrast to the ESI, we explicitly incorporate learning adjusted schooling as measured by LAYS.

Macroeconomic research on the relationship between human capital and economic growth has focused on several proxies for human capital over the years, including earnings, years of schooling, cognitive scores and most recently, LAYS. However, all these measures have some shortcomings. LAYS is based on internationally comparable tests, which primarily measure cognitive skills. Such skills are clearly valuable in developed countries. In developing countries, however, the requisite skills and economic requirements of labor markets are different. Metrics like LAYS are clearly valuable (as our own work here indicates) but LAYS by itself means little if schooling, and the skills it engenders, does not translate into productive employment. The Asian Skills Index developed here considers not just learning but also the process by which skills translate into economic output. By embedding traditional measures of education and schooling quality within a broader skills system, the paper provides crucial economic context to the human capital enhancement process.

There are several directions in which future research in this area can proceed. One of the most significant has to do with economic indicators that by their very nature can be intrinsically misleading. Nepal’s total unemployment rate, for instance, is lower than average. However, this masks the fact that many of the jobs are classified as “vulnerable employment”. Tajikistan, on the other hand, has the highest total unemployment in the sample but the lowest rate of vulnerable employment. Including one variable and excluding another does not seem a plausible solution. We use a weighted average of both variables, but this is still not an entirely satisfactory solution.

The inclusion of other types of skills (social, emotional, digital, computer skills, etc.) in addition to cognitive skills would be a valuable addition to the broad notion of skills. Such data is however currently not available. Many other interesting series could not be examined due to missing observations. Some series that are integral components of the ESI turned out to be of marginal significance in the ASI. This highlights the fact that skills indexes, unlike HCI and HDI, probably cannot have a one-size-fits-all template. Substantial regional variations mean that a "Global Skills Index" would probably have to be constructed region by region resulting in a Latin American Skills Index and an African Skills Index. Future work in this direction would be a valuable addition to the Asian Skills Index. The authors are currently working towards this goal.

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TABLE 1A
LIST OF VARIABLES FOR EUROPEAN SKILLS INDEX (ASI)

PILLAR 1: SKILLS DEVELOPMENT	PILLAR 2: SKILLS ACTIVATION	PILLAR 3: SKILLS MATCHING
Pupil-teacher ratio, preprimary	Early Leavers from training Share of population 18-64 “not in employment”	Long term unemployment (%) Unemployed for twelve months or more
Educational attainment, at least completed upper secondary, pop 15-64, total (%)	Recent graduates in employment Share of employed 20-34 who completed upper secondary education	Underemployed part timers (%) Underemployed part-time workers aged 15-74 as share of active population
PISA Score	Activity Rate (20-24) Employed persons as a share of same age total population	Overqualification Rate (%) Share of employed persons aged 15-34 with ISCED11, level 5 and 6 occupying jobs not corresponding to ISCO 1,2 or 3
Recent Training Share of population 15-64 who stated they received formal or non-formal training in the four weeks preceding survey	Activity Rate (25-54) Employed persons as a share of same age total population	Low Waged Workers Proportion of low wage earners out of all employees of ISCED 11, level 5-6 qualification level
VET Students (%) Share of the population at ISCED 11, level 3 attending vocational training		Qualification mismatch (%) Measures incidence of both overqualification and underqualification
High Computer Skills (%) Share of population 15-64 able to complete 5 out of 6 tasks described in the survey		

See *2020 European Skills Index, Technical Report, pages 9-10.*

TABLE 1B LIST OF VARIABLES FOR ASIAN SKILLS INDEX (ASI)		
PILLAR 1: SKILLS DEVELOPMENT	**PILLAR 2: SKILLS ACTIVATION**	**PILLAR 3: SKILLS MATCHING**
Pupil-teacher ratio, preprimary Source: WDI	Share of youth not in education, employment, or training (% of youth population) Source: WDI	Unemployment, total (% of labor force) Source: WDI
Educational attainment, at least completed lower secondary, pop 25+, total (%) Source: WDI	Labor force participation rate for ages 15-64 (total %), ILO estimates Source: WDI	Part time employment, total (% of total employment) Source: WDI
Proportion of population 15 -24 years enrolled in vocational education, both sexes (%) Source: Ed Stats		Unemployment with advanced education (% of total labor force) Source: WDI
Percentage of population age 25+ whose highest level of education is bachelors Source: Ed Stats		Vulnerable employment, total (% of total employment) (modeled ILO estimate) Source: WDI
Learning Adjusted Years of Schooling: LAYS (HCI Data Sept 2020) Source: https://datacatalog.worldbank.org/dataset/human-capital-index		

OTHER DATA
HCI: https://www.worldbank.org/en/publication/human-capital#Index

HDI: http://hdr.undp.org/sites/default/files/2020_statistical_annex_table_1.pdf

TABLE 2 k-MEANS CLUSTERING		
CLUSTER 1	**CLUSTER 2**	**CLUSTER 3**
Singapore (.88)	Azerbaijan (.58)	Afghanistan (.40)
Hong Kong SAR, China (.81)	China (.65)	Bangladesh (.46)
Korea, Rep. (.80)	Kazakhstan (.63)	Bhutan (.48)
Japan (.80)	Malaysia (.61)	Cambodia (.49)
	Maldives (?)	India (.49)
	Thailand (.61)	Indonesia (.54)
	Turkey (.65)	Lao PDR (.46)
		Mongolia (.61)
		Myanmar (.48)
		Nepal (.50)
		Pakistan (.41)
		Philippines (.52)
		Sri Lanka (.60)
		Tajikistan (.50)
		Uzbekistan (.62)
		Vietnam (.69)

Note: HCI 2020 scores are in parentheses. The full dataset is available from: https://www.worldbank.org/en/publication/human-capital#Index

TABLE 3A DATA ON SKILLS DEVELOPMENT					
Country	**pupil_teacher_ratio_ preprimary**	**ed_attainment_lower_ secondary**	**proportion_enrolled_in _vocational_ed**	**percent_of_population_ bachelors**	**LAYS**
Bangladesh	19.37	43.11	2.19	5.26	6.0
Bhutan	11.44	28.22	7.14	7.87	6.3
Cambodia	33.29	12.34	7.14	4.83	6.8
India	20.10	37.57	7.14	9.11	7.1
Indonesia	12.68	47.44	12.80	8.50	7.8
Lao PDR	18.25	51.69	1.75	7.44	6.3
Mongolia	33.16	51.69	6.30	7.44	9.2
Myanmar	16.23	51.69	0.14	7.44	6.8
Nepal	19.91	26.94	7.14	3.20	7.2
Pakistan	19.37	36.83	7.14	6.85	5.1
Philippines	30.36	59.41	7.14	15.63	7.5
Sri Lanka	13.46	82.25	3.36	3.37	8.5
Tajikistan	12.18	94.53	7.14	0.90	6.8
Uzbekistan	11.34	99.90	23.42	16.31	9.1
AVERAGE	**19.37**	**51.69**	**7.14**	**7.44**	**7.18**
MAX	**33.29**	**99.90**	**23.42**	**16.31**	**9.20**
MIN	**11.34**	**12.34**	**0.14**	**0.90**	**5.10**

Note: Data for some countries was not available. Many of the series reported here were missing for Afghanistan and Vietnam. Consequently, these countries were not part of the final sample in the ASI computation.

TABLE 3B INDEX OF SKILLS DEVELOPMENT						
Country	**pupil_teacher_ratio_preprimary**	**ed_attainment_lower_secondary**	**proportion_enrolled_in_vocational_ed**	**percent_of_population_bachelors**	**LAYS**	**PILLAR 1**
Bangladesh	0.63	0.35	0.09	0.28	0.22	.32
Bhutan	1.00	0.18	0.30	0.45	0.29	.44
Cambodia	0.00	0.00	0.30	0.26	0.41	.19
India	0.60	0.29	0.30	0.53	0.49	.44
Indonesia	0.94	0.40	0.54	0.49	0.66	.61
Lao PDR	0.69	0.45	0.07	0.42	0.29	.38
Mongolia	0.01	0.45	0.26	0.42	1.00	.43
Myanmar	0.78	0.45	0.00	0.42	0.41	.41
Nepal	0.61	0.17	0.30	0.15	0.51	.35
Pakistan	0.63	0.28	0.30	0.39	0.00	.32
Philippines	0.13	0.54	0.30	0.96	0.59	.50
Sri Lanka	0.90	0.80	0.14	0.16	0.83	.57
Tajikistan	0.96	0.94	0.30	0.00	0.41	.52
Uzbekistan	1.00	1.00	1.00	1.00	0.98	1.00

TABLE 4A DATA ON SKILLS ACTIVATION		
Country	**youth_not_ in_education_employment_training**	**labor_force_participation_rate**
Bangladesh	28.13	60.68
Bhutan	25.01	69.52
Cambodia	6.09	84.89
India	29.97	52.43
Indonesia	21.53	69.30
Lao PDR	42.08	81.35
Mongolia	19.70	63.76
Myanmar	15.30	66.21
Nepal	35.35	85.39
Pakistan	30.96	54.60
Philippines	20.64	62.53
Sri Lanka	25.33	58.78
Tajikistan	25.01	42.51
Uzbekistan	25.01	65.22
AVERAGE	**25.01**	**65.53**
MAX	**42.08**	**85.39**
MIN	**6.09**	**42.51**

TABLE 4B INDEX OF SKILLS ACTIVATION			
Country	**youth_not_ in_education_employment_training**	**labor_force_participation_rate**	**PILLAR 2**
Bangladesh	0.39	0.42	.41
Bhutan	0.47	0.63	.55
Cambodia	1.00	0.99	.99
India	0.34	0.23	.28
Indonesia	0.57	0.62	.60
Lao PDR	0.00	0.91	.45
Mongolia	0.62	0.50	.56
Myanmar	0.74	0.55	.65
Nepal	0.19	1.00	.59
Pakistan	0.31	0.28	.30
Philippines	0.60	0.47	.53
Sri Lanka	0.47	0.38	.42
Tajikistan	0.47	0.00	.24
Uzbekistan	0.47	0.53	.50

TABLE 5A DATA ON SKILLS MATCHING				
Country	**unemployment_ total**	**part_time_employment**	**unemployment_with_advanced _education**	**vulnerable_employment**
Bangladesh	4.51	19.07	9.88	55.69
Bhutan	2.62	7.90	7.07	72.24
Cambodia	0.29	16.44	0.91	49.11
India	5.73	20.42	15.18	75.00
Indonesia	4.06	31.63	4.74	47.99
Lao PDR	0.71	25.84	6.90	75.75
Mongolia	5.72	13.35	6.86	47.62
Myanmar	1.17	13.99	1.93	61.26
Nepal	3.24	31.20	8.46	77.22
Pakistan	4.09	13.04	7.15	57.10
Philippines	2.64	26.34	7.51	33.88
Sri Lanka	4.34	21.33	7.28	39.28
Tajikistan	6.92	20.42	7.07	31.39
Uzbekistan	5.67	20.42	7.07	35.67
AVERAGE	**3.69**	**20.01**	**7.00**	**54.23**
MAX	**6.92**	**31.63**	**15.18**	**77.22**
MIN	**0.29**	**7.90**	**0.91**	**31.39**

TABLE 5B INDEX ON SKILLS MATCHING					
Country	unemployment_total	part_time_employment	unemployment_with_advanced_education	vulnerable_employment	PILLAR 3
Bangladesh	0.36	0.53	0.37	0.47	.43
Bhutan	0.65	1.00	0.57	0.11	.58
Cambodia	1.00	0.64	1.00	0.61	.81
India	0.18	0.47	0.00	0.05	.18
Indonesia	0.43	0.00	0.73	0.64	.45
Lao PDR	0.94	0.24	0.58	0.03	.45
Mongolia	0.18	0.77	0.58	0.65	.54
Myanmar	0.87	0.74	0.93	0.35	.72
Nepal	0.55	0.02	0.47	0.00	.26
Pakistan	0.43	0.78	0.56	0.44	.55
Philippines	0.65	0.22	0.54	0.95	.59
Sri Lanka	0.39	0.43	0.55	0.83	.55
Tajikistan	0.00	0.47	0.57	1.00	.51
Uzbekistan	0.19	0.47	0.57	0.91	.53

TABLE 6
ASIAN SKILLS INDEX

Country	PILLAR 1	PILLAR 2	PILLAR 3	ASIAN SKILLS INDEX
Bangladesh	.32	.41	.43	.38
Bhutan	.44	.55	.58	.52
Cambodia	.19	.99	.81	.54
India	.44	.28	.18	.28
Indonesia	.61	.60	.45	.55
Lao PDR	.38	.45	.45	.43
Mongolia	.42	.56	.54	.51
Myanmar	.41	.65	.72	.58
Nepal	.35	.59	.26	.38
Pakistan	.32	.30	.55	.37
Philippines	.50	.53	.59	.54
Sri Lanka	.57	.42	.55	.51
Tajikistan	.52	.24	.51	.40
Uzbekistan	1.0	.50	.53	.64

TABLE 7
HUMAN CAPITAL INDEX (HCI) & HUMAN DEVELOPMENT INDEX (HDI)

Country	**HCI**	**HDI**
Bangladesh	0.4640	0.632
Bhutan	0.4753	0.654
Cambodia	0.4916	0.594
India	0.4935	0.645
Indonesia	0.5400	0.718
Lao PDR	0.4567	0.613
Mongolia	0.6144	0.737
Myanmar	0.4777	0.583
Nepal	0.5046	0.602
Pakistan	0.4061	0.557
Philippines	0.5160	0.718
Sri Lanka	0.5983	0.782
Tajikistan	0.5041	0.668
Uzbekistan	0.6228	0.720

SOURCES :
HCI: https://www.worldbank.org/en/publication/human-capital#Index

HDI:
http://hdr.undp.org/sites/default/files/2020_statistical_annex_table_1.pdf

TABLE 8 CORRELATION MATRIX						
VARIABLE	**LAYS**	**HCI**	**HDI**	**PILLAR1**	**PILLAR2**	**PILLAR3**
LAYS						
HCI	.98**					
	[.95, 1.00]					
HDI	.82**	.85**				
	[.50, .94]	[.58, .95]				
PILLAR1	.65*	.68**	.64*			
	[.18, .88]	[.24, .89]	[.16, .87]			
PILLAR2	.17	.12	-.12	-.24		
	[-.40, .64]	[-.43, .61]	[-.61, .44]	[-.68, .33]		
PILLAR3	-.01	.02	-.05	-.10	.58*	
	[-.54, .52]	[-.52, .54]	[-.56, .50]	[-.60, .45]	[.08, .85]	
ASI	.53	.53*	.41	.50	.59*	.69**
	[-.00, .83]	[.00, .83]	[-.16, .77]	[-.04, .81]	[.08, .85]	[.26, .89]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation.
* indicates $p < .05$. ** indicates $p < .01$.

TABLE 9
CORRELATION MATRIX BETWEEN ASI AND LISTED VARIABLES

Variable	
GDP_per_capita	+.46*
HCI	+.53**
HDI	+.41
Pupil teacher ratio preprimary	-.02
Education attainment lower secondary	+.30
Proportion enrolled in vocational education	+.40
Percentage_of_population_ bachelors	+.47*
LAYS	+.53**
Youth_not_in_education_ employment_or_training	-.58**
Labor_force_participation_rate	+.28
Unemployment_total_rate	-.29
Part_time_employment	-.09
Unemployment_with_advanced _education	-.70***
Vulnerable_employment	-.49*

Significance levels: *p<.10; **p<.05; ***p<.01
NOTE: The variables here are in their raw form.

TABLE 10
GROWTH MODELS

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
Intercept	653.28 (904.10)	-2600.3 (1678)	-4126* (2239)	-7626*** (1967)	-432.8 (1500)
Mean Years of Schooling	215.58* (115.70)				
LAYS		674.7** (231)			
Human Capital Index (HCI)			12,442** (4345)		
Human Development Index (HDI)				14,981*** (2971)	
Asian Skills Index (ASI)					5650.2* (3103)
R^2	.22	.42	.41	.68	.22

NOTE: Dependent variable is average GDP per capita (2016-2019)
*p<.10; **p<.05; ***p<.01

TABLE 11 DEADWEIGHT LOSSES			
Country	**ASI**	**ESTIMATE OF DWL** GDP per capita (constant 2010 US$)	**Percentage of 2019 GDP**
Bangladesh	0.38	1,469	114
Bhutan	0.52	678	21
Cambodia	0.54	565	45
India	0.28	2,034	95
Indonesia	0.55	509	11
Lao PDR	0.43	1,187	64
Mongolia	0.51	735	17
Myanmar	0.58	339	21
Nepal	0.38	1,469	171
Pakistan	0.37	1,526	129
Philippines	0.54	565	17
Sri Lanka	0.51	735	18
Tajikistan	0.40	1,356	121

TABLE 12 EIGENVALUES & VARIANCES			
Principal Component	**Eigenvalue**	**Variance (%)**	**Cumulative Variance (%)**
1	1.85	31.07	31.07
2	1.55	21.92	53.01
3	1.29	15.18	68.19
4	1.06	10.12	78.31
5	.98	8.67	86.98
6	.77	5.39	92.37
7	.68	4.25	96.62
8	.50	2.26	98.88
9	.26	.64	99.52
10	.20	.36	99.88
11	.13	.12	100.00

TABLE 13 FACTOR LOADINGS OF PRINCIPAL COMPONENTS					
	FACTOR 1	**FACTOR 2**	**FACTOR 3**	**FACTOR 4**	**PCA DERIVED WEIGHTS**
pupil_teacher_ratio_preprimary	0.0381	0.0916	0.0004	0.3012	0.0801
ed_attainment_lower_secondary	0.2167	0.0001	0.0022	0.1055	0.1008
proportion_enrolled_in_vocational_ed	0.1146	0.0311	0.1213	0.0067	0.0784
percent_of_population_bachelors	0.0335	0.0440	0.1471	0.1776	0.0767
LAYS	0.1041	0.0843	0.0549	0.0027	0.0760
youth_not_in_education_employment_training	0.0002	0.2960	0.0898	0.0071	0.1010
labor_force_participation_rate	0.1261	0.0431	0.2164	0.0223	0.1065
unemployment_total	0.1967	0.0466	0.0239	0.0341	0.1007
part_time_employment	0.0057	0.0054	0.2860	0.1006	0.0712
unemployment_with_advanced_ed	0.0293	0.2349	0.0140	0.2212	0.1089
vulnerable_employment	0.1351	0.1230	0.0441	0.0211	0.0996
	1.00	**1.00**	**1.00**	**1.00**	**1.00**
EXPLAINED VARIANCE	3.42	2.41	1.67	1.11	
PROPORTION OF VARIANCE	40%	28%	19%	13%	

TABLE 14 CONTRASTING EQUAL WEIGHTS RANKING WITH PCA RANKING		
Country	**ASI USING EQUAL WEIGHTS**	**ASI USING PCA WEIGHTS**
Bangladesh	.38	.38
Bhutan	.52	.50
Cambodia	.54	.60
India	.28	.29
Indonesia	.55	.55
Lao PDR	.43	.43
Mongolia	.51	.49
Myanmar	.58	.58
Nepal	.38	.37
Pakistan	.37	.40
Philippines	.54	.55
Sri Lanka	.51	.54
Tajikistan	.40	.47
Uzbekistan	.64	.72