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The Geography of Human Capital: Insights from the Subnational Human Capital Index in Indonesia

Virgi Agita Sari[1] · **Sailesh Tiwari**[2]

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Abstract

This paper explores the spatial heterogeneity in the human capital potential of Indonesia's next generation by constructing and analyzing sub-national human capital indices (HCI) for 34 provinces and 514 districts in Indonesia. The paper identifies data and methodological constraints in the construction of these sub-national indices and proposes and implements strategies to overcome these challenges. Several interesting findings emerge from the analysis. First, Indonesian's young generation can only achieve 53% of their future productivity relative to the full benchmark of health and education. Second, the variation in aggregate human capital potential across space in Indonesia is staggering: some parts of country are almost at par with countries like Vietnam and China while others have human capital levels that are comparable to Chad, Niger, and Sierra Leone. Third, differences in learning outcomes as measured by harmonized test scores account for the largest share of the variation in human capital across Indonesia, suggesting that the challenge of providing quality education remains one of the most important obstacles to equalizing opportunities for the next generation of Indonesians. And fourth, the correlation between government spending and performance on HCI at the district level appears rather weak, reinforcing conclusions reached by other recent studies that have highlighted the importance of focusing on the quality of spending. Finally, this paper also shows that Indonesia's human capital registered a modest improvement from 0.50 in 2013 to 0.53 in 2018 with stronger progress observed among the already top performing provinces.

Keywords Human Capital · Education · Inequality · Poverty · Indonesia

JEL Code · I24 · J24 · P36

✉ Virgi Agita Sari
v.a.sari@lse.ac.uk

Sailesh Tiwari
stiwari@worldbank.org

[1] London School of Economics and Political Science, London, UK

[2] The World Bank, Washington, DC, USA

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1 Background

Human capital accumulation among young people is a crucial component of the development process of any country. The current widespread consensus is that investments in human capital, especially for children, will yield future economic returns and propel countries into higher growth trajectories. However, the fact that the shorter-term benefits of investing in human capital are seldom distinct, while the costs are immediate, often leads growth-focused policymakers to place investing in human capital lower on their policy agendas. Recent efforts by the World Bank through the Human Capital Project (HCP) attempt to address this supposed inter-temporal trade-off by highlighting the future economic cost of failures to invest in human capital of the young generation today.[1] In particular, the country-specific Human Capital Indices (HCI) launched as part of the HCP quantify the future productivity of the next generation by measuring the amount of human capital a child born today in a particular country can expect to accumulate by the age of 18 (Kraay 2018). The index serves as a benchmark to track progress in human capital across countries globally.

There is a strong recognition within the government of Indonesia that investments in human capital are crucial to the country's future growth, productivity, and competitiveness. This is backed by a matching resolve to act as evidenced by, among others, the high-level commitment to tackling the challenges of chronic childhood malnutrition in the country and improving learning outcomes among schoolchildren. As one of the early adopters of HCP, the Government of Indonesia (GoI) made a strong commitment to redouble its efforts to address human capital challenges. However, this is a difficult task. PISA 2022 shows that Indonesian students scored lower than the OECD country average in all subjects and that their performance in reading and math has declined since 2018 (OECD, 2022, pp. 1–2). In 2018, more than one in three Indonesian children suffered from chronic malnutrition. The share of stunted children is so high that it is comparable to that of low-income countries such as Guinea and Liberia and well below the 31.1% and 25% average of lower-middle-income countries and neighbouring Southeast Asian countries respectively (UNICEF et al., 2019, p. 12). Progress in reducing child stunting has only been moderate; it was stagnant at 37% from 2007 to 2013 and then fell by roughly 1.2 percentage points per year from 2013 to 2018 (Riskesdas, 2007, 2013, 2018).

In the first edition of the HCI launched in October 2018, Indonesia scored 0.53 which implies that with the current level of quality of service delivery in critical human development sectors such as education, health, and social protection, the next generation of Indonesians will be half as productive as they would have been if health and education conditions had allowed them to realize their full potential during childhood and adolescence. In 2020, at 0.54, Indonesia's HCI had barely changed, highlighting the persistent challenge of improving human capital among the country's young generation (World Bank, 2020a). While Indonesia does outperform its lower-middle-income country peers on the overall index (0.48), its score is well below that of its regional East Asia Pacific neighbours (0.61) and below the average of the nine ASEAN countries included in the index (0.59).[2]

[1] The Human Capital Project is a global effort that aims to "accelerate more and better investments in people to improve equity and economic growth." Whilst development of the Human Capital Index is among HCP's efforts to benchmark cross-country progress in human capital, HCP also has a medium-term program of data and analytical work to improve measurement of a wide range of human capital outcomes. More detailed information is available in World Bank (2018).

[2] World Bank Human Capital Index (https://www.worldbank.org/en/publication/human-capital).

This international benchmarking is a useful starting point, but operationalizing the agenda as Indonesia intends to do will require examining human capital challenges with more granularity, especially given the spatial heterogeneity of the country. Most of the human capital investments in Indonesia are made by subnational governments, with intergovernmental transfers received from the central government being the primary source of revenue. Decentralization provides enough autonomy to local governments for them to customize and tailor solutions based on specific needs in their localities. Understanding the challenges at the local level is an essential pre-requisite to customizing local solutions. For the central government, being able to monitor and track progress on human capital outcomes at the subnational level opens the possibility of incentivizing progress by tying fund flows to performance whilst also complementing resources with other investments (e.g., capacity building) for needy locations.

Against this backdrop, this paper investigates the patterns of spatial heterogeneity in human capital outcomes in Indonesia. It does so by constructing a novel dataset on the subnational measures of the human capital index for 34 provinces and 514 districts in Indonesia at two different points in time and separately for boys and girls. It investigates the human capital outcomes across different geographies. In particular, the paper examines the extent to which the quantity and quality of spending on sectors such as education and heath are aligned with demonstrated needs. This paper also proposes several innovative solutions in operationalizing the human capital measurement at the subnational level using household and intercensal surveys data. Indonesia is one of the first countries to undertake human capital measures at the subnational level.[3]

The key findings suggest several key features of the geography of human capital in Indonesia. First, Indonesia scores 0.53 of future productivity relative to the full benchmark. Moreover, there is huge disparity in the generating of future productivity among children across Indonesian districts. The human capital index of the lowest-performing districts is similar to those of low-income countries such as Chad and Nigeria, whilst top-performing districts score as highly as China and Vietnam. In other words, the results suggest that where in the country children are born is a crucial factor in determining their opportunities to realize their full potential. Second, in almost all provinces in Indonesia, girls consistently perform better in accumulating human capital. This echoes existing studies that show that boys perform poorly in school as compared to their female counterparts; this is associated with their lower motivation, lack of orientation toward the future, and more frequent absences from school. Third, the chance of reaching full human capital potential is higher when we invest in quality of education. The data show that districts with higher scores in human capital tend to have higher average learning outcomes. This indicates that the quality of learning experiences explains the heterogeneity in the subnational HCI.

Fourth, progress in improving human capital is higher when investments are made in the quality of education vis-à-vis quantity of learning. Districts with higher HCIs tend to have substantially higher learning outcomes than districts with lower HCIs. Over time, Indonesia has made only moderate progress in improving the human capital of its youth. Between 2013 and 2018, Indonesia's HCI increased by merely three percentage points. Almost all provinces in Indonesia improved their HCIs, but at minimal rates. Urban areas performed better than rural areas, with differences in human capital of up to nearly 12% between rural peripheries and core-metro urban areas (i.e. the most urban and developed regions in the country).

[3] Other countries with subnational application of HCI include Pakistan, Peru, and Sierra Leone.

The results reveal a large disparity in HCIs at the subnational level in Indonesia. In particular, within-province inequality in human capital is higher than between-province inequality. The differences in HCI are largely explained by differences in child stunting and test scores between districts. This result resonates with the notion of inequality of opportunities. As such, the question of whether Indonesia's children can reach their potential largely depends on where they are born. This further highlights the importance of levelling access to and quality of basic services and infrastructure that are fundamental to improving human capital, including those of health and education.

The remainder of this paper is organized as follows. Section 2 summarizes the global HCI methodology and discusses the data-related challenges in constructing subnational HCIs for Indonesia and the strategies applied to overcome these challenges. Section 3 presents the main findings and describes the subnational and socio-economic and gender disaggregation of the HCI. Section 4 analyses the proximate correlates of district-level HCIs, focusing on linkages with monetary welfare and variations in subnational government spending. The final section summarizes and concludes with some recommendations for policy directions.

2 Data and Methods

2.1 The Human Capital Index

HCI measures the future productivity of the next generation of workers (Kraay, 2018, 2019). It is a forward-looking measure that estimates the human capital a child born today can attain by the age of 18 in any given country. The index uses information on health and education outcomes at various key stages in life (i.e., from when a child is born until the productive age of 18) and quantifies their consequences in terms of the generating of worker productivity in the future. It relies on the development accounting literature framework, which quantifies the contribution of physical and human capital to different levels of outputs (e.g., Caselli, 2005; Rossi, 2018; Weil, 2014). Health and education outcomes are assumed to stay the same throughout the 18 years of an individual's childhood and translate into different levels of productivity in the future. For instance, where a child is born and survives, if s/he grows up with good health and nutrition, s/he will be better prepared to learn at school and accumulate positive health and education outcomes, which later translate into higher productivity in the future, e.g., higher wages and better quality of employment.

Formally, the global human capital index is captured in the equation below.

$$HCI = Survival \times School \times Health \tag{1}$$

whereby HCI is the Human Capital Index measured at the country level. For each country, the HCI takes under-five mortality as a measure of *Survival*, quality-adjusted years of schooling by age 18 as a measure of education (i.e., *School*), and a combination of stunting rates and adult survival rates as measures of *Health*. The three components of survival, schooling, and health are captured below.

$$Survival \equiv \frac{p}{p^*} = \frac{1 - Under - 5Mortality\ Rate}{1} \tag{2}$$

$$School \equiv e^{\phi(S_{NG}-S^*)} = e^{\phi\left(Expected\ Years\ of\ School \times \frac{Harmonized\ Test\ Score}{625} - 14\right)} \tag{3}$$

$$Health \equiv e^{\gamma(z_{NG}-z^*)} = e^{\left(\gamma_{ASR} \times (Adult\ Survival\ Rate - 1) + \gamma_{Stunting} \times (Not\ Stunted\ Rate - 1)\right)/2} \tag{4}$$

As illustrated in Eqs. (2)–(4), HCI uses measures of 'returns' to education and health in the labour market from the literature and using the best-performing country as a benchmark to generate a Human Capital Index for every country. The index uses a scale between 0 and 1, whereby a full score of 1 means that, by the age of 18, a child born today can expect to reach the full productivity s/he could have if s/he is in full health and can enjoy the full 14 years of education stipulated. An HCI score of 0.5 means that a child born today can only achieve half of his/her future productivity given the current health and education circumstances where they live. The index provides a means to benchmark differences in the human capital of the next generation across countries. Currently, the index covers information on 2020 HCI data on 172 of the World Bank member countries (World Bank, 2020b).[4]

2.2 Constructing Subnational Indicators

Retaining the above global methodology for measuring HCI, the effort to calculate HCIs for subnational units in Indonesia proceeds with the following steps. First, all the required indicators for the subcomponents are constructed for each subnational unit. Second, each of the subcomponents is scaled appropriately to make the subnational calculations consistent with the global HCI exercise to enable international benchmarking of subnational HCIs. In addition, a special treatment is required for the test score information we use to quality-adjust expected years of schooling. This section summarizes some of these steps.

2.2.1 Data and Indicators

To construct the three components, we use several health and education outcomes that are representative at the district level to construct the five indicators of HCI. Appendix A lists all definitions of variables along with the data sources. Below is a brief overview of the indicators.

First, the *survival* component in HCI measures the probability of a child to survive to the age of 5. It is calculated by subtracting the under-5 mortality rate from 1. This paper constructs the under-5 child mortality rate at the district level by developing a lifetable from the intercensal survey (SUPAS 2015) to trace individual death histories.[5] SUPAS collected data from selected households on various topics on demography, ranging from fertility and disability to migration and mortality. It is the main data source that records mortality rates by age group in Indonesia. For the analysis, we use information on under-5 child mortality from the mortality module and follow the standard lifetable approach to construct the survival rate of children under 5.[6]

[4] Further detail on the construction of the Human Capital Index is available in Kraay (2018, 2019).

[5] Ideally, this would come from an administrative dataset that is not currently available to the public. The most recent census was in 2010, hence SUPAS data provide the best alternative to create child and adult survival rates that are representative up to the district level.

[6] The life table approach to construct survival rate using census data is widely applied as in WHO (2020) and UNESCO (2023). The methodology is discussed in Shryock et al. (1980).

The *school* component refers to quality-adjusted years of schooling and requires two key pieces of information: district-level representative data on the total net enrolment rates and student learning outcomes. This paper uses nationally representative household survey data (SUSENAS) to construct the expected years of schooling, as measured by the total net enrolment rate (TNER) at the district level.[7] TNER refers to the share of children in the theoretical age range for a given level of school who attend school at any level. For instance, the TNER for lower secondary school with a (theoretical) age range between 12 and 14 years measures the number of children aged 12–14 who are enrolled in any level of school as a fraction of all children belonging to that age group. As such, TNER represents the enrolment status of all 12- to 14-year-olds, regardless of the level of school they currently attend. Retaining the same measure used in global HCI, TNER in this paper refers to the sum of age-specific enrolment rates that approximates the net enrolment status of children aged 4–18, covering four levels of education: preschool, elementary, lower secondary, and upper secondary. We used data from the SUSENAS household roster to obtain the ages of children and data from the education module to obtain information on school enrolment. For the analysis, we used SUSENAS 2013 and 2018 to construct HCI for those years.

The expected years of schooling (EYS) then needed to be adjusted for quality of learning as measured by student learning outcomes. This was accomplished by using Ministry of Education administrative data on the Indonesian national examination test scores (referred to as the UN test score) as a proxy for the years 2013 and 2018. In particular, the school-level UN test scores of lower secondary schools are used as a proxy for quality of learning at the subnational level.[8] Data from other levels are also available, but the lower secondary level is considered more appropriate for this analysis. This is because lower secondary schools in Indonesia are under the direct supervision and authority of district governments, which is not the case for upper secondary schools. Focusing on the lower secondary level also facilitates international benchmarking as district test scores later need to be rescaled into PISA equivalents, which we discuss in the next subsection.

Lastly, the two indicators required for the *health* component are adult survival rate and child stunting. The adult survival rate measures the proportion of 15-year-olds who survive to the age of 60. It is calculated by subtracting the adult mortality rate from 1. Similar to the construction of the under-5 survival rate as discussed above, we used SUPAS 2015 and applied the life table approach to calculate the adult survival rate at the district level. Second, the subnational indicator for under-5 child stunting is based on 2013 and 2018 National Health Survey (Riskesdas), representative at the district level, and obtained from official statistics from the Indonesia National Statistics Agency (BPS).

2.2.2 Harmonizing Subnational Data for International Benchmarking

One important consideration as the district-level HCIs are created using these newly constructed district-level indicators is ensuring that the implied national-level HCI score is anchored to Indonesia's score in the global HCI exercise. This is desirable not only for the sake of consistency and ease of communication but also for the ability to compare subnational units within Indonesia to other countries. In order to do so, we essentially shifted the

[7] TNER is the ideal measure of expected years of schooling, as it measures the enrolment status of age-specific children regardless of the level of education in which they enrol (see Kraay 2019; D'Souza 2018).

[8] The data come from a census of school-level UN test scores for the years 2013 and 2018. These are official administrative data obtained from the Indonesian Ministry of Education.

Table 1 Indonesia's national HCI estimated using subnational data

HCI component	Indicators	I calculations for Indonesia in the global exercise (2018)	Subnational calculation (2018)
Survival	Probability of survival to age 5	0.97	0.97
School	Expected years of schooling	12.3	12.3
	Harmonized learning outcomes	403	403
Health	Adult survival rate	0.828	0.828
	Proportion of children under 5 not stunted	0.664	0.664
Human Capital Index		0.53	0.53

Source Authors' calculations

distribution of each of the indicators at the district level to align the means with the country averages used at the district level.

Once all required indicators were rescaled into global HCI units, constructing the subnational HCIs was straightforward. Retaining the global methodology, we then converted all indicators into units of productivity, yielding the subnational HCI as a product of three components, as defined below:

$$HCI_j = \frac{p_j}{p*} \times e^{\emptyset(s_j - s^*)} \times e^{\gamma(z_j - z^*)} \tag{5}$$

where $\frac{p_j}{p*}$ captures the child survival rate; where p_j is the average probability of a child to survive to the age of 5 in district j, expressed relative to the full benchmark of $p *= 1$. The school component is annotated as returns of education to future productivity. The school component is measured by s_j—the expected quality-adjusted years of schooling at the district level relative to the benchmark of full education ($s^* = 14$). This paper applies the same parameter for the return on education and health as does the global estimate.

Table 1 shows Indonesia's national values on HCI indicators from two sources: the reported values in the global HCI exercise and our own estimates built from various subnational data. As shown, after appropriate rescaling of some of the indicators to align the means, the national averages of the subnational indices are consistent with the national scores for Indonesia produced in the global exercise.

2.2.3 Linking Subnational UN Test Scores for International Benchmarking

One key component of the exercise that merits additional discussion is the treatment of test scores. There are two parts to this discussion. The first is the quality of the data and the steps taken to ensure it; the second is the translation of the scores into a usable form.

The national exams data, or UN test score data, are available for every school in Indonesia. However, to reduce the high rate of cheating that has been reported in these examinations, GoI has been rolling out computer-based testing (CBT) in all schools. The data on test scores do appear to corroborate the possibility of a high degree of cheating in some schools. In comparison to schools that have fully adopted CBT, schools that still rely on paper-based testing (PBT) appear to have a distinct bimodal distribution of test scores (as shown in Fig. 1a). As the CBT rollout increased from 2017 to 2018, shifting a greater

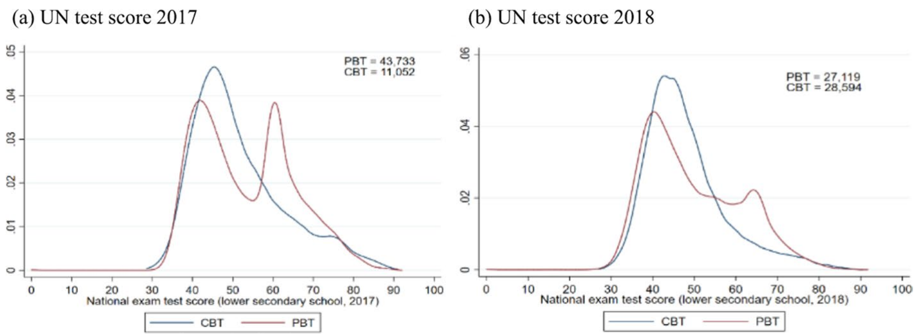


Fig. 1 The bimodal distribution among the PBT test scores, indicating a higher cheating occurrence among PBT test-takers in 2017. *Source* Authors' construction based on administrative data on 2017 and 2018 test scores from Ministry of Education

mass of PBT schools into the CBT category, the bimodality was muted, though it remained noticeable (Fig. 1b). This indicates that the second peak is likely driven by a higher rate of cheating among PBT test-takers. Looking at the same distribution separately by test subject reveals that the pattern is driven mostly by the math and science exams; the bimodal distribution is not observed in the language test (Indonesian language).

This suggests that CBT test scores are more reliable, raising concerns about the quality of PBT test score data. For this reason, we choose to rely only on scores from schools with CBT. However, even in 2018, only slightly more than 50% of all schools had CBT. Furthermore, for about 126 out of a total of 514 districts, fewer than 3% of all lower secondary schools were CBT schools. We would be unable to construct measures of learning for these schools if we were to rely on the CBT scores alone.

We address this challenge by modelling cheating—defined as the difference between the average scores in PBT schools and CBT schools—and using that to infer CBT scores in districts that only had paper-based testing in 2018. The district-level variables used to model this include geographic characteristics (e.g., urban–rural status and province dummies), demographic characteristics (i.e., school-aged population and share of agricultural workers), school characteristics (e.g., student-to-teacher ratio, teachers' education and years of experience, number of schools with facilities such as internet and electricity), and other measures of the level of development of the district (e.g., proportion of households with clean water and sanitation). Appendix B provides more details on the methodology, indicators, and data sources.

The main objective is to devise a model that would best predict the learning outcomes for the 126 districts that have no CBT scores. In order to test the model's performance, we carry out within-sample predictions: (i) randomly use information from only 75% of the districts for which we have CBT scores to perform the estimation; (ii) make predictions for the remaining 25%; and (iii) compare the actual CBT scores with the predicted scores. The results of the correlation between the actual and predicted scores from 100 replications of this exercise are quite high, suggesting that the model is reasonably robust (see Table 4 in Appendix B for the correlations).

Next, the UN test score data at the district level needed to be rescaled to conform to the common unit of measurement with the global HCI exercise. Learning outcomes in the global HCI are measured in Harmonized Learning Outcome (HLO) units, that is, the

PISA-TIIMMS equivalent measure.[9] This required us to first convert our data into a scale comparable to PISA before converting into HLO units. However, PISA test scores are measured at the individual or student level, while the UN test score data for Indonesia are available at the school level. Linking UN test scores to PISA data requires information on the overall variation in student test scores to account for within-school variations. As such, we propose the following adjustment:

$$X_i^* = \frac{X_i - \mu_{UN,i}}{\sigma_{UN,i}} \times \sigma_{PISA,i} + \mu_{PISA,i} \tag{6}$$

Essentially, the UN-PISA equivalent test score on subject *i*, X_i^*, is simply a transformation of the distribution of the UN test scores using the average PISA score for the same subject combined with the variation in test scores on both UN and PISA tests as measured by their standard deviations. Because the UN test score data are available only at the school level, we do not observe within-school variation of student performance, which is a component that needs to be accounted for in the overall standard deviation of UN test score (σ_{UN}), which measures the dispersion of test scores across all students in Indonesia. To overcome this issue, we use the subgroup decomposability of variance to obtain student-level variation on UN test scores as:

$$\sigma_i^2 = \sum_{s=1}^{s} \frac{n_s}{n} \sigma_{s,i}^2 + \sum_{s=1}^{s} \frac{n_s}{n} \left(\overline{X}_{s,i} - \overline{X}_i \right)^2 \tag{7}$$

where, σ_i^2 represents the overall variance of scores across students and is estimated for each subject i. The first component of overall covariance is the sum of all school-level variance (σ_s^2) as weighted by the share of test-takers in school s (n_s) among all test-takers in the country (n). The latter component represents the weighted average of the squared difference between school-level test score and overall UN test score $\left(\overline{X}_s - \overline{X} \right)^2$.

In the final step, conversion of the UN-PISA equivalent test score into HLO units was performed using the exchange rate published by the Global Human Capital Project.[10]

3 The Geography of Human Capital in Indonesia

Previewing the results, four findings stand out. First, the subnational variation in human capital across space in Indonesia is large, with the poorly performing districts having HCIs comparable to low-income countries. Second, the gender-disaggregated measure of the subnational HCI in the country shows that girls consistently outperform boys, consistent with findings from the global HCI exercise. Third, HCI across districts in Indonesia also appears to be positively associated with several measures of economic development, indicating persistent inequality of opportunity in health and education outcomes between children from poor vis-à-vis better-off localities. Finally, the results show that Indonesia's

[9] As mentioned above, harmonized learning outcomes were measured using the international and regional student achievement examination (PISA) and later converted to TIIMMS scaling with scores ranging from 300 to 625 (see Kraay, 2018, 2019).

[10] To convert PISA-equivalent UN test scores to HLO units, we applied the exchange rate obtained from the World Bank Global Human Capital Project team, where Reading = 1, Science = 1.051088, and Maths = 1.049667.

human capital registered a modest improvement from 0.50 in 2013 to 0.53 in 2018 with stronger progress observed among the already top-performing districts/provinces. This section discusses these observations in detail.

3.1 The Disparity in Human Capital Outcomes Across Space and Time in Indonesia

The first thing that emerges from the analysis of subnational HCIs is that the gap in the aggregate human capital potential across space in Indonesia is staggering; some parts of the country are almost on par with Vietnam and China while others have human capital levels comparable to those of Chad, Niger, and Sierra Leone. Figure 2 benchmarks the performance of Indonesia's districts in human capital potential relative to other countries. Poorly performing districts in Indonesia have HCIs similar to those of the lowest among the 157 countries surveyed in the HCI global exercise.

As shown, the gap in HCI between the best- and worst-performing districts in Indonesia is wide, suggesting high levels of inequality in education and health outcomes among youth across space. In 2018, the district-level HCI estimates show that children born in the lowest-performing districts in the country are being prepared to achieve a mere 30% of their future productivity potential (0.3 HCI). In contrast, children born in the best-performing districts can achieve as much as 70% of their future productivity.

The lowest-performing provinces and districts are concentrated in the eastern regions and remote areas of Indonesia. Figure 3a shows the variation of human capital potential across provinces and island regions. The best-performing provinces are in western

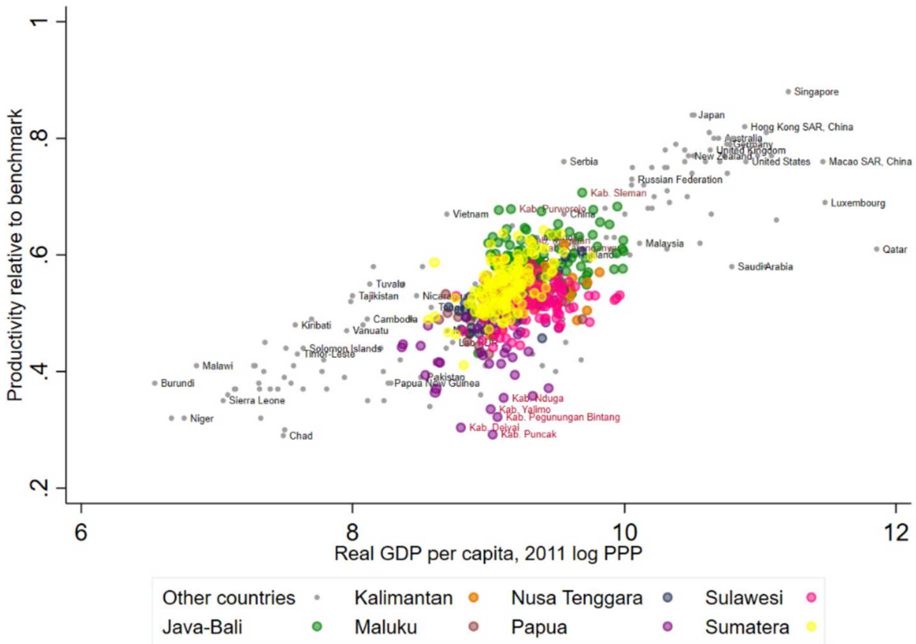


Fig. 2 Indonesia's district-level HCI relative to other countries globally (2018). *Source* Authors' calculations. Note: HCI score for other countries are from Kraay et al. (2018) and for the year 2017, while HCI scores for Indonesia's districts are for the year 2018

Indonesia (e.g., Java and Sumatera) while those with poorer performance are in the eastern part of the country (e.g., Maluku and Papua). Human capital potential in the worst-performing province is nearly 20% below the national HCI and 36% below the best-performing province (i.e., DI Yogyakarta). Additionally, district-level HCI estimates show that the worst-performing districts are mainly in the Papua provinces (Fig. 4b). This includes the districts of Deiyai, Puncak, and Pegunungan Bintang, which are characterized by geographical challenges (remote and mountainous) and frequent local social conflicts.

Disaggregating HCI by location type reveals that non-metro rural areas are significantly behind. A child born in a non-metro rural area is likely to achieve 52% of her future productivity relative to the benchmark of full health and education. This is 7% points below the metropolitan cores (Fig. 3b). At the district level, cities dominate places with the highest human capital potential. The top-performing districts are mainly in Central Java and Bali and districts in the special region of Yogyakarta (Fig. 4a). The majority of the top ten performing districts are located in or near the special region of Yogyakarta, which is well known for its quality of education and home to some of the best universities in the country. Denpasar is the second-highest performing district, located in Bali province, with a relatively high socio-economic profile. Nevertheless, it is interesting to note that the better-performing regions are not necessarily the wealthiest and most developed, suggesting a more nuanced story than matching poverty levels with development progress. For instance, Sleman district, located in the special region of Yogyakarta, scored the highest at 0.7 points. However, the district is not the largest in terms of population size and has a relatively high level of economic inequality at 39 (slightly lower than the 2016 national level).

Indonesia's overall increase in HCI from 0.5 in 2013 to 0.53 in 2018 is a result of improvements in human capital in almost all provinces (Fig. 5). Improvements were greater in provinces with initial top-performing human capital potential, such as DI Yogyakarta and Central and West Java. Exceptions include East Kalimantan and South Sumatera, where there was a slight decline in the HCI score. High-performing districts appear to be less geographically challenged and better connected to health and education infrastructure. DI Yogyakarta, for example, is home to a large population of students and high-quality education at all levels, attracting talents from all over the country. Nevertheless, this implies a widening gap in human capital potential across space over time. The bottom-performing provinces with the least improvement in HCI include geographically challenged areas such

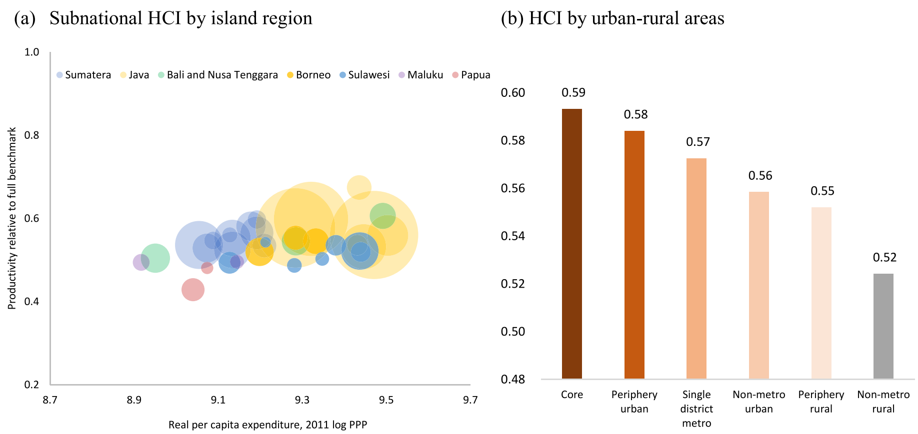


Fig. 3 Human capital gaps between different regions and areas in Indonesia (2018). *Source* Authors' calculations

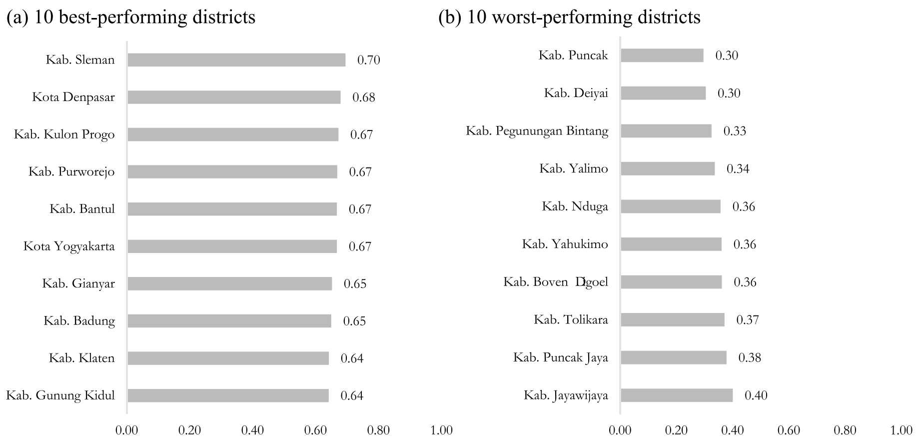


Fig. 4 Best- and worst-performing Indonesian districts in Human Capital Index (2018). *Source* Authors' calculations

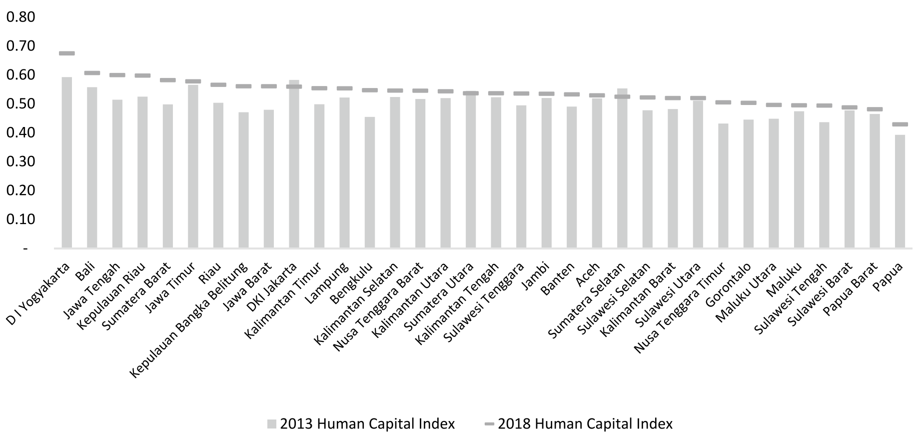


Fig. 5 Between 2013 and 2018, HCI improved in almost all provinces in Indonesia and declined in only a few. *Source* Authors' calculations

as West Papua and West Sulawesi, which also have the least access to health and education infrastructure. This is reflected in learning outcomes; for example, in West Papua, only one-fifth passed the minimum national exam benchmark for reading; in mathematics, the figure was 16% (UNICEF, 2019). Progress in improving human capital across space in Indonesia in the past five years has also been moderate. It reflects the persistent low quality of learning as well as disparities in learning outcomes, despite notable advancements in the past decades. According to a World Bank report (2019) on 'The Promise of Education in Indonesia', enrolments are up by more than ten million since 2000, yet learning poverty and learning inequality across schools in Indonesia persist.

3.2 Gender-Disaggregated Subnational HCI

The second characteristic of subnational HCIs in Indonesia is that girls consistently achieve higher human capital potential than boys. Examining human capital by gender in Indonesia is necessary to fully inform and target health and education policies to reduce gender-based imbalances and discrimination. Abundant research has documented the persistent gender differences in the country. A recent study examined earnings differences in Indonesia using 2007 IFLS data and found that women earned 30% less than men. Half of that difference is explained by the self-employed status of many women (Sohn, 2015). Another study, using data from Sakernas 2010, found that the gender wage gap in the country is mostly due to gender discrimination, with the process of urbanization favouring male workers with higher wages (Taniguchi & Tuwo, 2014). This indicates that most women are in relatively low-quality jobs with less access to economic security than male workers.

This section describes the gender-disaggregated human capital index for provinces and districts in Indonesia. Gender-disaggregated HCI relies on the availability of gender-disaggregated information on the five indicators of HCI.[11] The results show that girls perform better in all provinces in Indonesia (Fig. 6). A girl born in 2018 in Indonesia is expected to achieve 55% of her future productivity relative to the full benchmark; this is three percent higher than that of a boy. Girls also outperform boys in all components of human capital. The gender difference in human capital potential is driven by the large gap in learning outcomes. Boys scored 398 in harmonized learning outcomes –10 points lower than girls' average. Female students outperform male students continuously over the years. PISA 2018 data show that girls scored 25 and 10 points higher in reading and mathematics, respectively, than their male counterparts. This trend also holds over time. The finding is not entirely surprising; various countries observe the same pattern. PISA 2018 shows that girls perform better in reading by an average of 30 score points across all economies (OECD, 2019).[12] The gender difference in performance seems to be driven by differences in learning attitudes and growth mindsets. A study by Muller and Perova (2018) based on primary data collected on growth mindset and socio-economic skills from 56,000 Indonesian students in grade eight found that boys had lower attendance rates, lower aspirations for learning, and lower engagement in learning. This explains boys' underperformance in school compared to girls.

3.3 Indonesia's HCI Rises Along with Socio-Economic Status

Consistent with results for other countries (D'Souza et al., 2019), there is a positive association between HCI and socio-economic status in Indonesia. Following closely the methodology proposed by D'Souza et al. (2019), this paper disaggregates Indonesia's HCI by socio-economic status (hereinafter SES-HCI). Formally,

[11] All indicators of HCI are readily disaggregated by gender except child stunting. District-level data on child stunting are not readily disaggregated by gender as gender-based data are only released at the national level. We thus used the information on the share of stunted boys and girls and applied it as a weighted average in generating girls' and boys' stunting at the district level. The inevitable drawback is that we assume equivalent gender gaps in stunting across districts.

[12] OECD (2018). PISA Country Note for Indonesia. *Programme for International Student Assessment (PISA) Results from PISA 2018.*

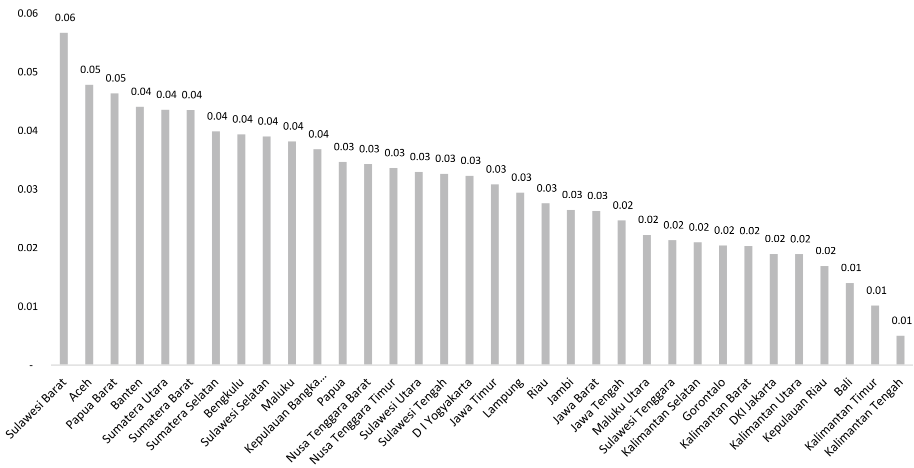


Fig. 6 Female-male differences in human capital index by province (2018). *Source* Authors' calculations. Note: Gender gap is measured as the average girl's human capital minus the average boy's human capital at the province level

$$SES - HCI_q = Survival_q \times School_q \times Health_q \tag{8}$$

where $SES - HCI_q$ represents the aggregate human capital index estimated for each quantile q, and is a product of the three components: $Survival_q$, $School_q$, and $Health_q$, each estimated by quantile q.

The first step in constructing SES-HCI is to disaggregate the five indicators by quintiles of expenditure, using the same datasets used to construct subnational HCI whenever possible. National household survey data (SUSENAS 2018) were used to calculate the expected years of schooling by quintiles of expenditure. The calculation was straightforward given the availability of expenditure information, and we used the same dataset to calculate the EYS, perhaps the most reliable measure in this exercise. For under-5 child stunting, we used the 2013 published information on child stunting by quantiles.[13] PISA 2018 was used to calculate SES-learning outcomes, as illustrated for several other countries in Kraay (2018).[14] For the child and adult survival indicators constructed from the intercensal survey, survey-to-survey imputation methodology is used to generate survival rates by quintiles of socio-economic status. Appendix C provides details on the methodology, indicators, and data sources.

Results show that children born into poorer families (1st quintile of consumption distribution) in Indonesia achieve 17% lower HCI than children born into wealthier families (5th quintile) (Fig. 7a). This finding is consistent with existing evidence from a study documenting correlations between human capital outcomes and household incomes across 51 countries (D'Souza et al., 2019). In Indonesia, the HCI of children in the lowest two

[13] No more recent data is available. It was not feasible to calculate the SES-child stunting rate using the 2018 data, given the absence of expenditure-related information in the datasets.

[14] Information on the wealth index in PISA 2018 data for Indonesia is used to construct SES-disaggregated test score. This method implies the unavoidable yet fundamental assumption that PISA has the same income distribution as the household survey.

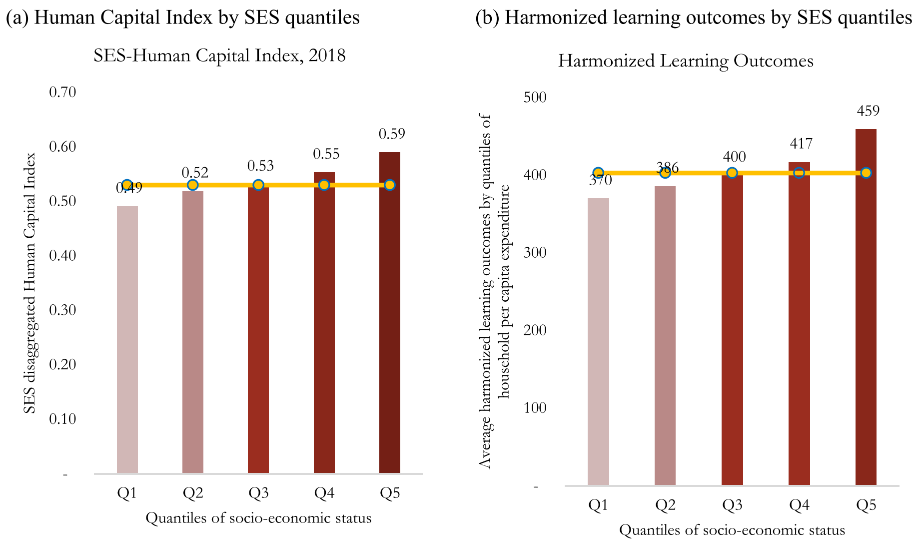


Fig. 7 Indonesia's human capital index rises with higher socio-economic status. *Source* Authors' calculations

quantile is below the 2018 national HCI of 0.53. The gap in the next generation's future productivity by SES is larger at the tails of the distribution and has widened over the years.

Third, the gap between the human capital of Indonesia's poorer and wealthier households is largely accounted for by the lower quality of learning experienced by children in poorer families. In 2018, the average harmonized learning outcomes of lower secondary students belonging to the poorest families (bottom quantile of the household per capita expenditure distribution) is 370 (Fig. 7b). This is 20% lower than that of children from the wealthiest families (top quantile of the distribution). This again reinforces the point on inequality in the quality of education, particularly in the learning experiences of school-aged children across varying socio-economic statuses. Moreover, the gap has been increasing in the last five years, owing to the improved average learning outcomes among children in the top quantiles. The test scores of children from the poorest families (1st quantile of the distribution) fell slightly by two points from 369 to 367, while those of children in the rest of the distribution improved.

4 Determinants of Subnational HCI

This section explores associations between the subnational HCIs and some relevant district-level characteristics. Key findings suggest that: (i) district-/province-level HCIs are positively associated with income levels and negatively correlated with poverty, (ii) sectoral government spending is only weakly correlated with human capital outcome, and (iii) better access to health and education facilities is associated with higher HCI. Detailed discussions follow.

First, the results show that variations in subnational HCI are positively associated with income. This finding is in line with evidence from the global exercise (D'Souza et al., 2019). Figure 8a plots subnational measures of the index and GDP per capita for

Indonesia and selected other countries. As shown, Indonesia's human capital potential is generally higher in provinces with higher GDP per capita. This trend resembles those of other countries such as the Philippines, Niger, and Romania, suggesting that a higher level of economic development is associated with higher human capital potential among youth. The disparities between regions in Indonesia appear to be greater than in other countries (Fig. 8a). However, the variations in Indonesia's regional HCIs are smaller than the variations in regional income (Fig. 8b), suggesting that income gaps are wider than human capital gaps.

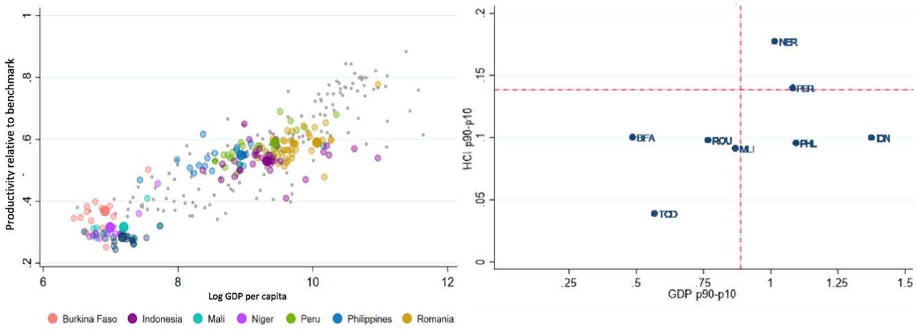
Second, the finding suggests a negative correlation between subnational HCI and poverty rates: the subnational HCI is higher in places with lower poverty rates. Figure 9 plots Indonesian poverty rates and HCI at the province and district levels. As observed in the preceding section, the poorest provinces in Indonesia (i.e. Papua, Nusa Tenggara, and Maluku) also tend to score the lowest in human capital.[15] The relationship between poverty and human capital flattens at the district level and the distribution of HCI is skewed to the left, indicating high variations in human capital in districts with similar poverty levels. The overall results suggest that a child born in a poorer region tends to have a lower level of future potential productivity than a child born in wealthier region.

This result, too, conforms with existing cross-country evidence, in which the gradient between HCI and poverty rates is steeper in middle-income countries than in low-income countries (Kraay, 2018). However, it is also important to note that there are several outliers, particularly at the tails of the subnational HCI distribution. For instance, the special region of Yogyakarta has the highest HCI score, yet also has high levels of poverty and inequality. By contrast, districts in Papua are among the weakest performers in terms of HCI regardless of their poverty levels (Fig. 9b). Overall, this signals the importance of geographically based, targeted policies in health and education to better guide regional governments.

Third, sectoral government spending is only weakly correlated with variations in subnational HCI. Figure 10a shows that overall district-level government spending accounts for less than one percent of variations in human capital across space. This could be expected given that overall government spending covers multiple sectors beyond health, education, and human capital. However, there is also no strong correlation between sector-specific district-level government spending and health and education outcomes. For instance, education spending at the district level accounts for less than six percent of variations in subnational learning outcomes (Fig. 10b). Nduga district in Papua province spent nearly the same amount per capita on education as Magetan district in Central Java, yet Nduga has one of the poorest learning outcomes in the country whilst Magetan district is among the top performers. This indicates a mismatch between quantity and quality of spending across geographies, with many districts struggling to increase the quality of spending. Figure 10c also captures a high level of inequality in the quality of learning across different districts. The 2019 World Bank report shows that many of Indonesia's regions remain challenged by learning poverty and learning inequality.

This result indicates very low returns to public education expenditures despite increases in allotments. Indonesia's educational spending has tripled since 2000, and its allocations of education spending are among the highest in the world, reaching up to 20% of the total government budget. Efforts to increase access to education for children from poor families are also substantial; educational assistance accounts for the largest share of government

[15] Based on authors' calculations using SUSENAS March 2018, island-/region-based poverty levels are highest in Papua, Nusa Tenggara, and Maluku.



(a) HCI-GDP correlations (b) HCI vs GDP dispersion

Fig. 8 Variation in HCI with dispersion of regional income relative to other countries. *Source* D'Souza et al. (2019), Chapter 3 on geographic disaggregation of HCI, The World Bank

(a) Province-level estimates (b) District-level estimates

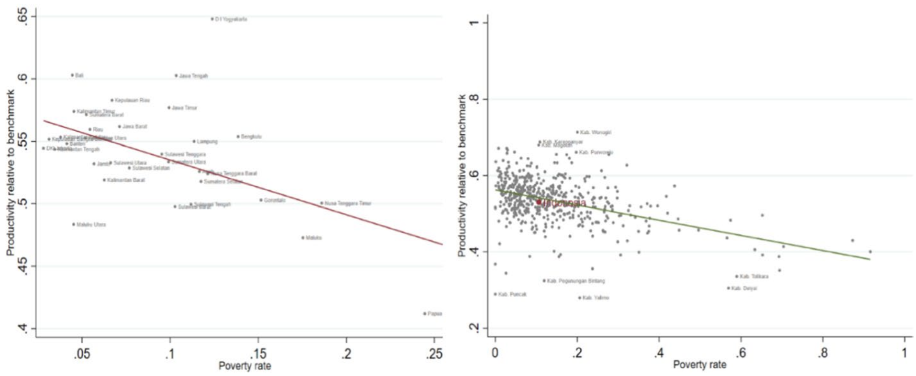


Fig. 9 Provinces with higher HCI scores tend to have lower poverty rates (2018). *Source* Authors' calculations

expenditures on social programs, surpassing those on health and community programs. Regardless, progress in improving the quality of learning in Indonesia remains limited. The most recent cross-country PISA data (2018) show that the academic performance of Indonesia's 15-year-olds has remained below the OECD average since 2000. Indonesia's performance is also lower than that of neighbouring countries such as Thailand and Malaysia. The average score declined from 2015 to 2018 in all subjects – reading, science, and maths—although this could be a result of the increased coverage of the PISA sample in 2018.

Similarly, health spending accounts for less than 0.5% of the variation in the health component of human capital across districts in Indonesia. This reflects Indonesia's challenges in achieving its full health potential, given the low level of health spending. Despite increases in the past decade, Indonesia's total health spending, at 1.4% of GDP, remains among the lowest in the world (World Bank, 2020c).

Fourth, better access to basic infrastructure, health services, and education is linked to higher subnational HCI. Variations in the subnational human capital result from

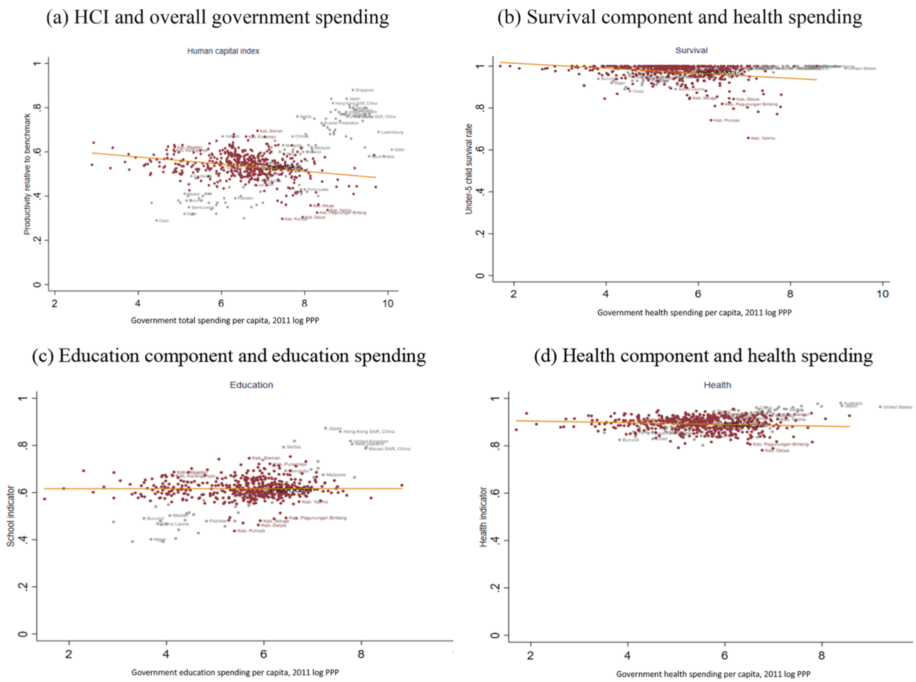


Fig. 10 Government spending is only weakly correlated with variations in HCI. *Source* Authors' calculations based on wbopendata, World Bank HCP, and SUSENAS

combinations of factors that shape future worker productivity. This includes health and education infrastructure, geographical diversity, socio-economic demographic characteristics, and government spending. To further examine the interaction between these various factors, we ran regressions of the following:

$$HCI_j = \alpha + \beta_1 Education_j + \beta_2 Health_j + \beta_3 GovernmentSpending_j + \beta_3 Demography_j + \varepsilon_{ij} \tag{9}$$

where, HCI_j is the human capital index of district j, for $j = 1, \ldots, 514$ districts. $Education_j$ represents school resources including student-to-class ratio, teacher-to-class ratio, and infrastructure such as internet and computer lab facilities in district j. $Health_j$ represents the average health conditions in district j related to children's and mothers' health and access to health infrastructure. Inclusion of children's and mothers' health is based on the hypothesis that these outcomes relate to the health component of human capital (i.e. under-5 child survival and stunting). $GovernmentSpending_j$ controls for district-level government expenditure in health and education. $Demography_j$ controls for geographical and demographic variations between districts, including poverty headcount and inequality, access to basic infrastructure, urban/rural area, and other factors.

Table 2 summarizes the results of a standard OLS estimation on the correlates of subnational HCI for the year 2018.[16] These results show that teacher quantity and experience are positively correlated with subnational human capital. Higher student-to-teacher ratios correlate with lower HCI in Indonesia. Indeed, quality of learning depends on the availability of teachers as well as their experience and qualification. This is particularly relevant for schools with more socio-economically disadvantaged students, where many have reported a lack of teaching staff (OECD, 2019).

Interestingly, this finding also suggests that school infrastructure such as access to ICT devices like internet and computers has no association with HCI. This is relatively consistent with other studies that suggest increasing students' access to ICT devices will increase their efficiency in usage but not necessarily improve their learning outcomes (JPAL, 2019). Only a purposely designed ICT intervention has the potential to generate desirable outcomes in improved learning outcomes, e.g. educational software designed for students learning at their own pace or combined online and offline means of teaching delivery.

Second, maternal and child health do not explain the variations in subnational human capital. As shown in Table 2, a one percent increase in completed child immunization is linked to a 0.67 percentage points increase in average future productivity in Indonesian districts. There is also no observed significant correlation between maternal health and human capital. Nevertheless, this is mainly due to persistent low-quality prenatal care and poor access to prenatal care in many areas of Indonesia. Many Indonesian mothers lack knowledge on healthy pregnancy and child health; only one in every three mothers in Indonesia takes the recommended 90+ iron tablets during pregnancy and only 26% of 1- to 4-year-old children had taken deworming tablets in the 12 months prior to survey (Riskesdas 2018).

Third, access to basic infrastructure and better household welfare are associated with higher human capital potential. Studies show that better access to sanitation and improved drinking water reduces infectious disease and supports child development (Cameron et al., 2019). Poverty also negatively correlates with variations in subnational human capital across space, although in a very limited way as it is associated with a one percent drop in the next generation's productivity. This result echoes the descriptive picture drawn earlier, in which poverty rate is negatively correlated with subnational HCI.

5 Conclusion

This paper provides insights into the future productivity of Indonesia's youth. First, there is a high level of inequality in human capital potential across districts in Indonesia. The disparity between districts is so great that children in the lowest-performing district can only achieve a share of their potential productivity comparable to low-income countries such as Chad, Niger, and Sierra Leone. Second, the geography of HCI in Indonesia reveals a story more complex than the conventional measure of monetary welfare. Our findings indicate that high-performing districts are not necessarily the wealthiest or those with the lowest levels of poverty and inequality. This suggests that, in addition to ensuring better

[16] The table shows results for subnational HCI using the corrected UN test scores. Given that the correction relies on imputation of test scores relying on district characteristics, there is a risk that the corrected test scores (hence overall HCI) may reflect some of these district characteristics. For robustness, we ran the same regression only for districts with CBT tests only and confirm that the results remain consistent. Table 6 in Appendix D provides the results.

Table 2 Correlates of subnational HCI (2018)

Indicators	Coefficient	s.e
Education infrastructure		
Student-to-teacher ratio	−0.002***	(0.000)
School with internet access (%)	−0.003	(0.013)
Teachers with experience > 25 years (%)	0.001***	(0.000)
Head of school years of experience (2015)	0.001	(0.001)
Head of school with 1–3 years of university (%)	−0.000	(0.000)
Head of school with bachelor's degree (%)	0.002	(0.003)
Head of school with post-graduate education (%)	−0.000	(0.001)
Health infrastructure		
Share of completed immunization (2017)	0.067***	(0.014)
Share of access to skilled birth attendant	0.000	(0.000)
Share of completed exclusive breastfeeding (2017)	0.006	(0.011)
Nearest physician location: Ease of reaching	−0.035***	(0.010)
Nearest village birth facility: Ease of reaching	−0.006	(0.006)
Demography		
Government education expenditure, 2016 log realization	−0.002	(0.003)
Government health expenditure, 2016 log realization	0.003	(0.003)
Head of village years of schooling	0.001	(0.002)
Poverty headcount rate	−0.001**	(0.000)
Access to good sanitation (%)	0.081***	(0.015)
Urban	−0.001	(0.005)
Constant	0.403***	(0.098)
Island-regions dummies	Yes	
Observations	496	
Adjusted_R^2	0.689	

Note The table shows selected covariates only. *, **, and *** indicate significance level at 10, 5, and 1%, respectively. Standard errors in parentheses

Source Authors' calculations

household welfare, improving health and education outcomes through better quality spending is important in narrowing the gap in human capital across areas. Third, variations in subnational human capital outcome also show distinctive characteristics that reveal the way development benefits unfold in different parts of the country. There is a clear gradual pattern; human capital outcomes are consistently higher in the western part of the country, reducing toward the eastern part of Indonesia with the least infrastructure and economic development. Girls are also consistently doing better in school in every province in Indonesia, suggesting that interventions are necessary to improve the learning experiences of boys in school and boost their performance. The gap between children from rich and poor families is also apparent, with children born in the poorest quantile of the distribution able to expect fully 20% lower future productivity than children from the wealthiest families.

Our findings also shed light on the binding factors limiting human capital potential across different spaces in Indonesia. First, the disparity in human capital across different places begins in early life, stemming from limited access to good nutrition and health services for mothers and infants. Indonesia has one of the highest shares of stunted children in the world and is well below the 25% average among the neighbouring countries in Southeast Asia (UNICEF et al., 2019, p. 12). Access to immunization is limited (only 36% of children ages 0–2 complete their immunizations), as is exclusive breastfeeding practice (only 58% breastfeed exclusively) (INDO-DAPOER, 2017). Second, regions lagging in human capital also lag in learning outcomes, indicating the limited quality of education in less developed parts of the country. Indonesia's PISA score is well below the OECD average and has a hump-shaped distribution over the years, particularly in reading, indicating no significant average change in students' performance in the nearly two decades from 2000 to 2018 (OECD, 2022). Third, the overall health environment from childhood to adolescence remains a challenge, with limited access to healthcare in many parts of the country. Inequality between villages in accessing public health care (PHCs) is high, and PHCs in urban Indonesia tend to serve almost double the populations than those in rural areas (Rajan et al., 2018). A high prevalence of smoking among Indonesians and increasing obesity incidence among both children and adults are among the other risk factors putting Indonesians at risk of NCDs, estimated to be responsible for 76% of deaths in the country (WHO, 2016).

Improving the future productivity of Indonesia's next generation will require significant efforts to address the determinant factors of human capital accumulation. A multisector approach and data-informed interventions are crucial to address the nutrition crisis in Indonesia. This would include improving upon GoI's ambitious agenda to reduce stunting (StraNas program) via regular data collection for progress monitoring, conducting behavioural interventions to promote maternal and infant health, and promoting capacity-building for village-level care providers. Also, improving learning experiences early on is critical to increasing the quality of education in Indonesia. This would entail enhancing the quality of early childhood education (ECED) provision, performance management for teachers to increase their skills, as well as aligning curricula to match future demand to better prepare the next generation of workers as they enter the labour market. Third, efficient allocation of limited resources towards targeted health interventions and increasing budget allocations is key to ensuring improved overall health outcomes for Indonesians. Prioritizing the provision of health services, particularly in eastern Indonesia, is necessary. GoI could also increase health spending, as Indonesia has one of the lowest health budgets among its peers; in 2016, health accounted for a mere 1.4% of total GDP.

Finally, our paper points to important areas for further research. First, it is crucial to further examine the role of quality of public spending and institutional capacities at the subnational level. With subnational governments having more control over local resources and allocation as a result of decentralization, it is only natural that improving human capital potential relies on strong institutions with geographically based policies. The current HCI largely focuses on the role of public services (health and education) in shaping the human capital of the next generation. Accounting for the process of children's education beyond the formal (school) setting (e.g., the role of parents in children's learning experiences), could further highlight disparities in human capital, particularly in developing country settings. Monitoring longer-term changes in subnational HCI and performing in-depth analysis of its driving factors as well as of the contribution of between- and within-district changes in HCI would help inform both subnational and national policies to narrow the gap in human capital accumulation across the country.

Appendix A: Data Sources for Measuring Indonesia's Subnational HCI

The human capital index (HCI) quantifies the future productivity of the next generation. It measures the amount of human capital that a child born today can expect to accumulate by the age of 18, given the current conditions of health and education prevailing in the country in which they live. The subnational measure of HCI provides a way to measure the differences in the human capital accumulation across space within a country. This paper constructs HCIs for 34 provinces and 514 districts in Indonesia for the years 2013 and 2018, retaining the methodology used for the global exercise of the World Bank Human Capital Project as illustrated in Kraay (2019) and D'Souza (2018). In constructing the subnational index, this paper uses data representative at the intended levels of measurement: the district and province levels. Table 3 summarizes the indicators and data sources used to construct subnational HCIs for 2013 and 2018.

Appendix B: Methodology to Correct UN Test Scores

As discussed in Sect. 2.2.3, it is important to correct for the test scores in PBT-only districts and in districts with high levels of PBT test-takers. We did so by imputing test scores in the relevant districts with several steps as follows. Let y be $\overline{UN_{ij}} - \overline{CBT_{ij}}$, that is the difference between the overall UN test score and CBT score subject j in district i. The first step is to model the extent of cheating, that is, to predict the y, which is estimated as a function of demography, school facilities, community infrastructure, and geographical characteristics as captured below:

$$Y_{ij} = \alpha + \beta_1 PBT_{ij} + \beta_2 Region_i + \beta_3 Demo_i + \beta_4 School_i + \beta_5 HH_i + \beta_6 MoRA_i + \varepsilon_{ij} \tag{10}$$

where, PBT_{ij} is the average (PBT) score for subject j in district i; $Region_i$ is geographical characteristics including urban–rural status, province dummies, poverty rate, logs of government education and health expenditure; $Demo_i$ captures the school-age population and share of agricultural workers in district i; $School_i$ captures the variation in school characteristics, including student-to-teacher ratio, teachers' and head of school educational levels and their years of working experience, and school facilities including number of schools with access to computers and internet (data obtained from DAPODIK 2013, 2018); HH_i accounts for household characteristics including share of households with access to clean water and sanitation facilities as well as household dependency ratio; and $MoRA_i$ controls for the total number of religious schools in each district.

In essence, $\overline{UN_{ij}} - \overline{CBT_{ij}}$ provides us with the extent of cheating in districts where the proportion of CBT test-takers is high. Once we estimated the difference, we took the predicted value of the difference between the overall and CBT test score, or formally:

$$PredictedCBT_{ij} = \overline{UN_{ij}} - \widehat{Y_{ij}} \tag{11}$$

We then used the predicted test score to interpolate the test scores in the districts where the percentage of CBT test-takers was under three percent.

Our results show that using the predicted test scores for the relevant districts helps refine the UN test score distribution in two ways. First, it reduces test scores

Table 3 List of indicators and data for subnational HCI in Indonesia

HCI Components	Indicators	Variables	HCI (2013)	HCI (2018)
Survival	Under-5 survival rate	Survival rate of children aged 0–5 years	SUPAS 2015, child survival rate is calculated from information on child mortality using life table approach	SUPAS 2015, child survival rate is calculated from information on child mortality using life table approach
Education	School enrolment	TNER—sum of net enrolment in all levels of education until the age of 18	SUSENAS 2013	SUSENAS 2018
	Test scores	Lower-secondary national examination test scores	2013 National exam (UN) test scores from Ministry of Education	2018 National exam (UN) test scores from Ministry of Education
Health	Stunting	Proportion of children under five not stunted	Riskesdas (2013)	Riskesdas (2018)
	Adult survival rate	Proportion of 15-year-olds who survive to age 60	SUPAS 2015, survival rate is calculated from information on child mortality using life table approach	SUPAS 2015, survival rate is calculated from information on child mortality using life table approach

in non-metro rural areas and in a few provinces, including Maluku, Nusa Tenggara, Papua, and Sulawesi, as shown by the red bars in Fig. 11. These are areas with higher cheating prevalence or with a relatively low percentage of CBT test-takers. The modelling also increases test scores where the percentage of CBT test-takers is relatively high; these include urban peripheries, single-district metro areas, and the Java-Bali region.

Our model also performs relatively well. In order to test model performance, we carried out within-sample predictions in which we: (i) used information from 75%, chosen at random, of the districts for which we had CBT scores to perform the estimation; (ii) made predictions for the remaining 25%; and (iii) compared the actual CBT scores with the predicted scores. The results can be seen in Table 4.

Appendix C: Generating Socio-Economic Status Disaggregated HCI (SES-HCI)

Generating SES-HCI at the national level would require HCI indicators aggregated by monetary welfare measure: household per capita expenditure, household income or wealth. In Indonesia, monetary welfare is measured by the real household per capita expenditure. This paper follows an established methodology as outlined in D'Souza et al. (2019). As discussed in their paper, the key challenge in generating SES-HCI indicators is that some of the datasets are not readily disaggregated into quantiles of monetary measure. We faced similar challenges and propose several strategies to address some of them. This appendix details the steps to construct SES-HCI for Indonesia. Table 5 provides key indicators and data sources.

First, we constructed SES-disaggregated child and adult survival indicators, relying on the estimation model using household per capita expenditure. We arrived at child and adult survival rates using the intercensal census (SUPAS), which does not provide information on household expenditures. To solve this issue, this paper uses SUSENAS data to impute household per capita expenditure at the district level in SUPAS.[17] SUSENAS is Indonesia's socioeconomic household survey representative at the district level, containing information on both household per capita expenditure and household and regional characteristics. The strategy is to model household expenditures from SUPAS data using the covariates in SUPAS (that is, the household and regional characteristics) yet using the *coefficient* (i.e. the extent to which each of the covariates affects the level of household expenditure) estimated from the household expenditure model based on SUSENAS information. Formally, let y be the real household per capita expenditure. We modelled household expenditure at the district level as a function of household socio-economic characteristics and geographical variation. Equation (12) below shows the household expenditure model.

$$Y_{ij} = \alpha + \beta_1 HHhead_{ij} + \beta_2 HHchars_{ij} + \beta_3 HHassets_{ij} + \beta_4 Regions_j + \varepsilon_{ij} \tag{12}$$

[17] In this exercise, we used SUSENAS 2015 rather than SUSENAS 2018 for estimating the household expenditure in SUPAS 2015. This is to ensure the comparability of household characteristics between the two datasets. The drawback is that we assume that there are no significant changes in the distribution of household characteristics or in household expenditures from 2015 to 2018.

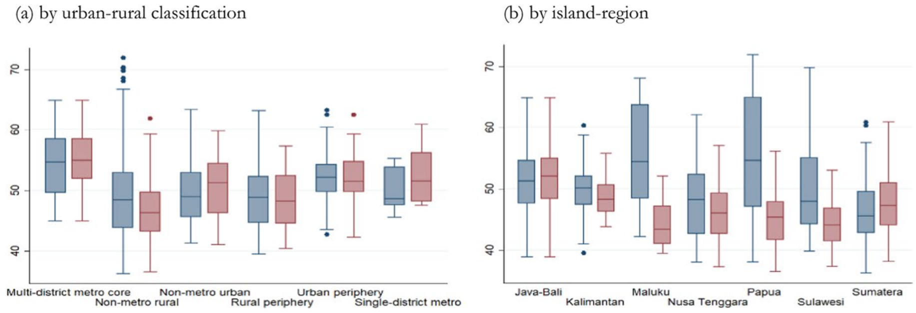


Fig. 11 Corrected UN test scores bring down the average test score in areas with high cheating prevalence. *Note* The blue bars indicate test scores prior to correction, whilst the red bars show test scores after the correction. *Source* Authors' calculations based on 2018 UN test score data by Ministry of Education

Table 4 Correlations between predicted average CBT scores and actual CBT scores from a randomized sample

Correlation	Rep	Mean	Std. Dev	Min	Max
Average	100	0.65	0.05	0.54	0.73
Bahasa language	100	0.94	0.01	0.91	0.97
Math	100	0.90	0.02	0.85	0.96
Science	100	0.92	0.02	0.85	0.96

Source Authors' calculations using 2018 UN test scores

where Y_{ij} is real household expenditure per capita of household i in district j, and is a function of household head characteristics ($HHhead_{ij}$) including age, gender, literacy, marital status, education level work sector, and employment type; household characteristics ($HHchars_{ij}$) including dependency ratio, number of employed household members, their education level, household size, housing conditions, and access to water and sanitation; household assets ($HHassets_{ij}$) including house ownership and car/motorcycle ownership; and regional characteristics ($Regions_j$) which include geographic variations.

The imputation of real per capita household expenditure implies a few steps. First, we used SUSENAS (socio-economic household survey in which a monetary variable is present) and estimated real household per capita expenditure. This is to retrieve a vector of β later used to input household real per capita expenditure (hereinafter HH rpcexp) in SUPAS from which the welfare variable is unavailable. We did so by running the household expenditure model using the vector of covariates from SUPAS and the vector of β retrieved earlier. Once we imputed the household per capita expenditure in SUPAS, we then disaggregated the child and adult survival rates by socio-economic status.

The estimated household expenditure based on the result is robust for several reasons. First, the reliability of the model in estimating household expenditure in intercensal survey data relies on the comparability of the two datasets used. We performed means testing on the key characteristics and covariates used in the model and found no statistically significant differences between the two datasets (results are available upon request). Second, our model comes with a relatively high predictive value at the district level. We ran the household expenditure model at the district, provincial, and national levels and found that the model has highest predictive value at the district level. The province-level model underestimates the household per capita expenditure, a natural result given that

Table 5 Indicators and data sources for SES-HCI

SES-HCI indicator	Data source (2013)	Data source (2018)
SES-child survival	Survey-to-survey imputation, using SUSENAS March 2013 and intermittent census (SUPAS) 2015	Survey-to-survey imputation, combining SUSENAS March 2015 and intermittent census (SUPAS) 2015
SES-expected years of schooling	SUSENAS March 2015	SUSENAS March 2015
SES-harmonised learning outcomes	PISA 2015	PISA 2018
SES-non-stunted children	Official statistics on SES-stunting based on Riskesdas 2013	Official statistics on SES-stunting based on Riskesdas 2018
SES-adult survival	Survey-to-survey imputation combining SUSENAS March 2015 and intermittent census (SUPAS) 2015	Survey-to-survey imputation combining SUSENAS March 2015 and intermittent census (SUPAS) 2015

the province-level variation fails to capture the more granular variations of expenditure at the district level (results are available upon request). Once we imputed the household per capita expenditure in SUPAS data, the child survival rate could be disaggregated by socio-economic group. For the SES-adult survival rate, we followed the same steps.

Next, we constructed the SES-harmonized learning outcomes (SES-HLO). Note that we were unable to use the UN test scores to calculate learning outcomes as the data included neither information on monetary welfare nor other information that could be used to predict socio-economic status. Instead, we used test score data from the OECD's Programme for International Student Assessment (PISA) for 2013 and 2018. We used the PISA index of economic, social, and cultural status (ESCS) to generate the test scores by quantiles of socio-economic status. The ESCS index is a composite index developed based on a series of indicators, including students' parental education, students' parental occupation, and their home possession status (as a proxy of students' family wealth) (OECD, 2015, pp. 339–340).

However, there are a few caveats. First, using PISA to generate the SES-HLO imposes the unavoidable yet necessary assumption that the distribution of households by socio-economic status in PISA is the same as the distribution in SUSENAS. The same assumption was applied by D'Souza and colleagues in the cross-country SES-HCI exercise (2019). We closely followed the steps as suggested in the global exercise. In addition, PISA collects information only on 15-year-old children attending school, whilst SUSENAS collects information from all 15-year-olds regardless of their school enrolment status. This is important to take into consideration when calculating the SES-HLO, given the high probability that the share of test scores rises with children's socio-economic status; poor children are more likely to drop out of school. To reflect this, we performed the following step, as illustrated in D'Souza et al. (2019, pp. 12–13), to "link" the PISA and SUSENAS data.

The purpose is to account for the actual test-takers in quantiles of socio-economic status in SUSENAS and apply this to PISA data as captured in the following steps:

i. Calculate the average test score by quantile of SES using PISA data.
ii. Let E_i be the total net enrolment of 15-year-old children for quantile i of household real per capita expenditure. Using SUSENAS data, calculate E_i.
iii. Then, calculate the share of 15-year-olds who took the test by quantile of SES. This is simply the ratio of enrolled 15-year-olds in each SES quantile to total enrolment of 15-year-olds, or formally:

$$S_j \equiv \frac{\sum_{i=1}^{j} E_i}{\sum_{i=1}^{5} E_i}$$

iv. Apply the actual share of test takers by SES in SUSENAS data to calculate the average HLO by quantile in PISA data. For instance, if the actual percentage of test-takers in quantile 1 is 15% in SUSENAS data, then the average HLO for quantile 1 in PISA data is the average HLO up to 15 percentile.

Lastly, we generated the SES-EYS using SUSENAS and official statistics on SES-disaggregated child stunting published by the Ministry of Health. Once we had constructed all SES-disaggregated indicators, constructing the SES-HCI index followed the same methodology described in the methodology section.

Appendix D: Regression Results of Subnational HCI Determinants

See Table 6.

Table 6 Correlates of subnational HCI (all districts and districts with CBT only)

Indicators	All districts		CBT-only districts	
	Coefficient	s.e	Coefficient	s.e
Education infrastructure				
Student-to-teacher ratio	−0.002***	(0.000)	−0.003**	(0.001)
School with internet access (%)	−0.003	(0.013)	−0.002	(0.033)
Teachers with > 25 years of experience (%)	0.001***	(0.000)	0.002***	(0.000)
Head of school years of experience (2015)	0.001	(0.001)	−0.001	(0.001)
Head of school with 1–3 years of university (%)	−0.000	(0.000)	0.000	(0.001)
Head of school with bachelor's degree (%)	0.002	(0.003)	−0.007	(0.005)
Head of school with post-graduate education (%)	−0.000	(0.001)	0.004	(0.003)
Health infrastructure				
Share of completed immunization (2017)	0.067***	(0.014)	0.083**	(0.037)
Share of access to skilled birth attendant	0.000	(0.000)	−0.002	(0.001)
Share of completed exclusive breastfeeding (2017)	0.006	(0.011)	0.085***	(0.024)
Nearest physician location: Ease of reaching	−0.035***	(0.010)	−0.040	(0.030)
Nearest village birth facility: Ease of reaching	−0.006	(0.006)	−0.011	(0.011)
Demography				
Government education expenditure, 2016 log realization	−0.002	(0.003)	0.001	(0.006)
Government health expenditure, 2016 log realization	0.003	(0.003)	0.002	(0.005)
Head of village years of schooling	0.001	(0.002)	0.001	(0.008)
Poverty rate	−0.001**	(0.000)	−0.001*	(0.001)
Access to good sanitation (%)	0.081***	(0.015)	0.002	(0.047)
Urban	−0.001	(0.005)	0.005	(0.011)
Constant	0.403***	(0.098)	0.453***	(0.143)
Island regions dummies	Yes		Yes	
Observations	496		101	
Adjusted_R^2	0.689		0.617	

Note The table shows linear regression result of district-level HCI 2018. The 'All districts' column shows regression results for all districts which include corrected UN test scores; the 'CBT-only districts' column shows results for districts in which only CBT tests are available

Source Authors' construction

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Declarations

Competing Interests Competing Interests The authors declare they have no competing interests related to this research.

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