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PRIORITY REGIONS FOR PREVENTION OF STUNTING

Ardi Adji, Priadi Asmanto, Hendratno Tuhiman

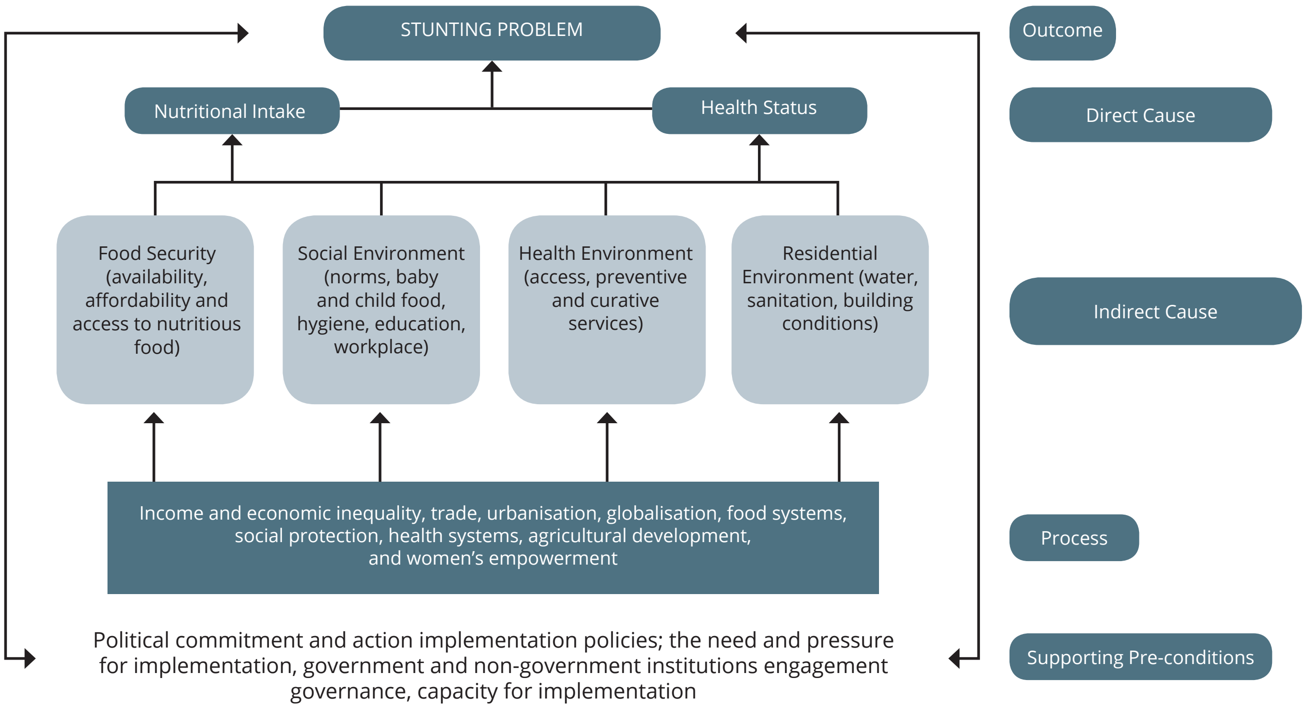
Abstract

One aspect of Indonesia's health profile that still needs improvement is stunting. In 2018 Indonesia had one of the highest prevalence rates for stunting in the world at 30.8 percent. To achieve the National Medium- Term Development Plan 2015-2019 (*Rencana Pembangunan Jangka Menengah Negara*: RPJMN) target of a 28 percent stunting rate, in 2018 the government set priority areas for stunting prevention in 100 districts/cities through a program that will be expanded gradually until 2021. This study is intended to provide a technical explanation for the selection of districts/cities and villages/*kelurahan* as priority areas for stunting prevention. The indicators used in determining priority areas for stunting prevention at the district/city level include: (i) the total number of poor people; (ii) prevalence of stunting in children under the age of five years; and (iii) total number of children under the age of five years with stunting. At the village and *kelurahan* level, priority areas are determined using indicators adjusted to those used in preparing the index at district and city level, namely: (i) total population; (ii) total poor population; (iii) poverty rate; and (iv) total occurrences of malnutrition. Determination of priority areas uses a weighted average index, at both the district/city level and village/*kelurahan* level.

Background

Improving the quality of life of the Indonesian people is one of the priority targets on the national development agenda. These targets will be achieved through improving the quality of education, public health services, community welfare, social security, and developing Indonesia from the periphery by strengthening regions and villages within the national development framework. Improving the quality of life is intended to improve the quality of human capital and welfare of every citizen. A measure of the quality of human capital is the Human Development Index (*Indeks Pembangunan Manusia:* IPM), while public welfare can be measured from poverty level and nutrition status.

Figure 1: Thinking Framework of Causes for Nutritional Problem



Source: UNICEF 1997; IFPRI, 2016; BAPPENAS 2018; adapted to the Indonesian context

One of the national development challenges is poverty reduction. In the decade to 2019, poverty has decreased significantly–from around 16.58 percent to 9.82 percent. Although the fall has been quite significant, poverty is still relatively higher than the government's targets in the National Medium-Term Development Plan 2015-2019 (*Rencana Pembangunan Jangka Menengah Negara:* RPJMN).

The annual rate of poverty reduction has tended to slow down–both in absolute and percentage terms. The number of poor between 2007 and 2018 decreased by an average of 963,000 persons or 0.595 percentage points/year. The largest drop occurred in 2009 with a decrease of 2.43 million people, equivalent to 0.84 percent. Poverty reduction slowed in 2013-2015 and again experienced quite a progressive decline up to early 2018, however, despite this acceleration, the poverty rate has still not reached the RPJMN target.

Poverty is a factor that disrupts food availability in households, preventing them from meeting nutritional requirements for adequate quality and quantity which, in turn, results in stunted growth and nutritional status.[1] The government has undertaken various poverty alleviation programs that target individuals, households, and community groups as beneficiaries, however, there are indications that these programs have not achieved the optimal targets set by the government. The complexity of poverty requires an integrated and coordinated policy intervention (integrated solution). Poverty reduction efforts have, to date, tended to be partial, not properly measured, and some are even unsustainable.

Various short-term shocks affect the dynamics of the poverty rate in Indonesia. Poverty reduction efforts have, therefore, aimed at improving access to basic services, such as education and health. Improving both is expected to have an effect on long-term poverty reduction trends by severing inter-generational poverty.

One of the health factors that needs to be improved is stunting. Children under three years of age who are stunted will not achieve their intellectual potential, making them more vulnerable to illnesses in the future and at risk of reduced productivity and income. International experience shows that stunted children could potentially lose up to 20 percent of their income as adults, resulting in an increase in poverty and a widening of income disparity in the future.

The results of the *Riskesdas* 2018 study published in November 2018 show an improvement in indicators for nutritional status of children under five years of age, especially in relation to status of stunted children. The stunting prevalence among children under the age of five years declined from 37.2 percent in 2013 to 30.8 percent in 2018. The proportion of malnourished and undernourished children in this age group also declined from 19.6 percent to 17.7 percent while the prevalence of severely underweight and underweight children under the age of five years has improved from 12.1 percent to 10.2 percent. While these improvements are encouraging, there is a need for more robust interventions to accelerate the rates of reduction in these key indicators.

Objectives

To achieve the RPJMN 2015-2019 stunting target of 28 percent, in 2018 the government established priority regions for stunting prevention in 100 districts/cities through a program that will be gradually expanded until 2021. This document aims to explain for stakeholders the technical reasons behind the selection of priority districts/cities and villages/*kelurahan* for stunting prevention. Stunting prevention efforts using an intensity approach are not new. During the New Order period, a poverty reduction approach–known as the *Inpres Desa Tertinggal* (Presidential Instruction for Underdeveloped Villages) program–was implemented to target pockets of poverty. Area-based poverty targeting approaches have not only been applied in Indonesia, but also in several other developing countries, such in China, Burkina Faso, India, Turkey, and the Slovak Republic.

[1] BAPPENAS 2018, Pedoman Pelaksanaan Intervensi Penurunan *Stunting* Terintegrasi di Kabupaten/Kota.

Joint Action and Breakthroughs for Stunting Prevention

The vice president of Indonesia, Jusuf Kalla, as head of TNP2K (National Team for the Acceleration of Poverty Reduction) led a limited meeting on preventing stunting on Wednesday, 12 July 2017. On this occasion he also invited ministers and heads of relevant institutions who implement policies and programs to prevent stunting.

The meeting produced a range of action plan recommendations to prevent stunting (Figure 2). It also aimed to map stunting and formulate an action plan process that would, in turn, be reported to the president. The president is very concerned about finding breakthroughs to address stunting.

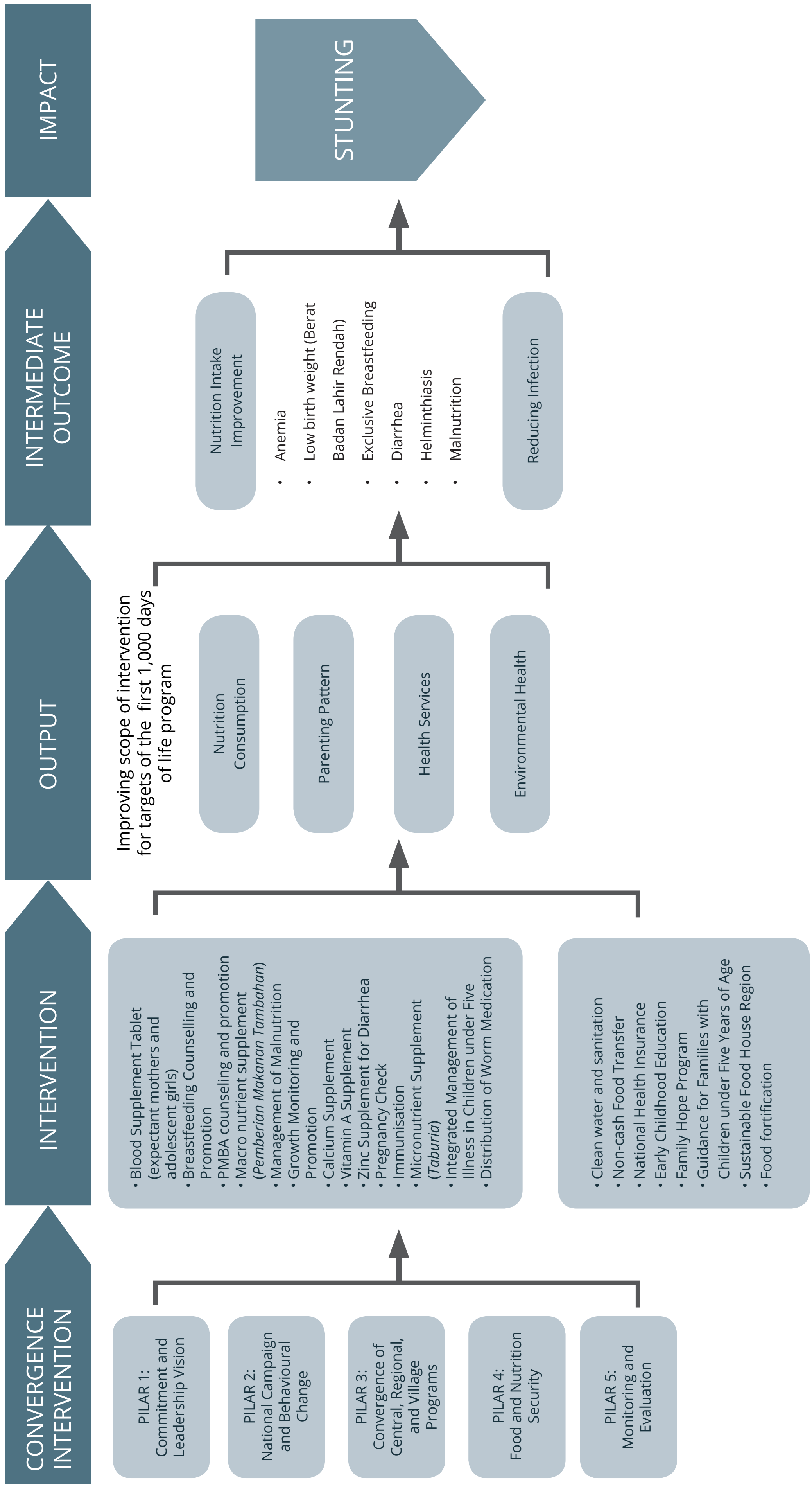
Figure 2: Proposed Time Frame for Action Plan in Stunting Prevention

2018	2019	2020	2021
Maximising the implementation of programs related to stunting in **50 municipalities/ cities** to coordinate and implement the pillars of stunting prevention	Maximising the implementation of programs related to stunting in **160 municipalities/ cities** to coordinate and implement the pillars of stunting prevention	Maximising the implementation of programs related to stunting in **390 municipalities/ cities** to coordinate and implement the pillars of stunting prevention	Maximising the implementation of programs related to stunting in **514 municipalities/ cities** to coordinate and implement the pillars of stunting prevention

Source: TNP2K Plenary Meeting, 12 July 2017.

It was proposed to divide the action plan recommendations for preventing stunting into five main pillars (Figure 3).

Figure 3: Conceptual Framework for Integrated Stunting Reduction Intervention



Pillar 1: Commitment and vision of the top leadership of the country. In this pillar, the president/vice president's commitment is needed to direct relevant ministries/agencies to manage stunting at both the national and sub-national levels by establishing a policy and strategy as well as targets at national and sub-national (both provincial and district/city) levels. It is also necessary to leverage the Secretariat of Sustainable Development Goals and the Secretariat of TNP2K as coordination and control institutions for relevant stunting prevention programs.

Pillar 2: Conduct a national campaign focusing on understanding, behavioural changes, political commitment, and accountability. Based on international experience and evidence regarding programs that could effectively reduce the prevalence of stunting, the main strategy that needs to be immediately implemented is a national campaign through the mass media and targeted communication to households and ongoing advocacy (Figure 4).

Figure 4: Scheme for Division of National Socialisation and Campaign

Source: TNP2K Plenary Meeting, July 12, 2017.

Pillar 3: Convergence, coordination, and consolidation of national, regional and community programs. This pillar aims to reinforce convergence, coordination, and consolidation, as well as expand program coverage conducted by relevant ministries/agencies. There need to be improvements in the service quality of existing programs (*puskesmas*, *posyandu*, PAUD, BPPSPAM, and PKH),[2] especially in assisting pregnant women, nursing mothers, and toddlers during the first 1,000 days of life by providing incentives for programs that have successfully reduced stunting in their regions. Lastly, this pillar could also be implemented by leveraging the use of Special Allocation Funds and Village Funds to direct regional expenditures for intervention in stunting priorities.

Pillar 4: Encourage "Food Nutritional Security" Policy. The focus of this pillar is to: (i) encourage policies that ensure access to nutritious foods, especially in regions with the highest prevalence of stunting; (ii) implement a comprehensive plan for fortification of bio-energy, food, and fertilizers; (iii) reduce food contamination; (iv) implement supplemental food programs; and (v) seek investment through private partnerships, Village Funds, and other sources within food market infrastructure–both at urban and rural levels.

[2] *Puskesmas* (*pusat kesehatan masyarakat*: community health center); *posyandu* (*pos pelayanan terpadu*: integrated service post); PAUD (*pendidikan anak usia dini*: early childhood education); BPPSPAM (*Badan Peningkatan Penyelenggaraan Sistem Penyediaan Air Minum:* Potable Water Supply System Implementation Improvement Agency); and PKH (*Program Keluarga Harapan*: Family Hope Program).

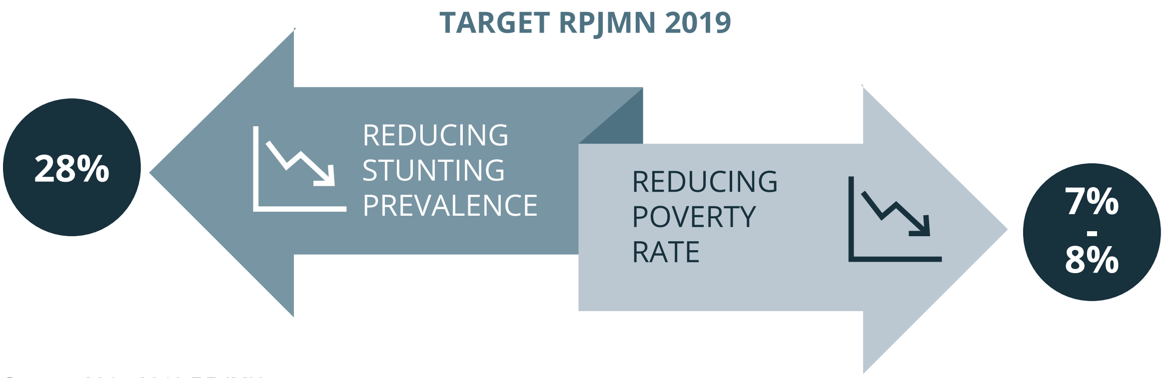
Pillar 5: Monitoring and Evaluation. This last pillar includes monitoring awareness and behavioural change as a result of the stunting national campaign; periodic monitoring and evaluation to ensure the provision and quality of program services in stunting prevention; periodic measurement and publication of results of stunting prevention and annual development of children for accountability; national and sub-national government programs with results-based planning and budgeting; and control of stunting prevention programs.

Selection of Priority Regions for Prevention of Stunting

Thinking Framework

The results of the stunting action plan should be seen over the medium to long term–more or less within six years. By implementing effective policies and programs in the right regions, it is expected that efforts to manage stunting will reduce its prevalence while also reducing the rate of poverty.

Figure 5: Target for Reducing Prevalence of Stunting and Poverty Rate in 2019



Source: 2015-2019 RPJMN.

Joint actions and breakthroughs to prevent stunting serve as the basis for determining priority regions. Based on the joint agreement, 100 districts/cities have been selected as priority regions in preventing and reducing stunting. It is hoped that the selection of appropriate regions will significantly reduce the prevalence of stunting. An important argument in determining the priority regions is government budget constraints. It is, therefore, necessary to determine the regions in a way to ensure that the allocated budget is effective and on target to achieve the objective of reducing the incidence of stunting. In addition to reducing the prevalence of stunting, selecting these priority regions is also expected to reduce poverty.

Method for Region Selection

Selection of priority regions for reducing poverty is through using an approach to determine the priority of region-based interventions, better known as geographical targeting. Priority regions for poverty reduction are selected following those with high rates of stunting, then compiled and determined using two main indicators, namely: (i) prevalence; and (ii) the number of children under the age of five years with stunting. Another indicator used to reflect poverty at the district/city level is the number of poor as a weighting factor.

Districts and Cities

Indicators used in determining the priority regions for stunting prevention include the poverty rate, prevalence, and number of children under the age of five years who are stunted. Poverty rate is the number of people living under the poverty line at the district and city levels and is sourced from BPS (*Badan Pusat Statistik*: Statistics Indonesia). Prevalence of stunting is the prevalence of short and very short children in the 0-59 months age group sourced from *Riskesdas* (*Riset Kesehatan Dasar*: Basic Health Research) of the Ministry of Health in 2013. The number of stunted children under the age of five years is the number of children whose height is classified as short and very short according to the results of *Riskesdas* 2013.

$$Z1_i = \frac{x_{1i} * PP_i}{\sum_{i=1}^{n}(x_{1i} * PP_i)} \quad (1)$$

$$Z2_i = \frac{x_{2i} * PP_i}{\sum_{i=1}^{n}(x_{2i} * PP_i)} \quad (2)$$

$$IKS_i = 0.5 * Z1_i + 0.5 * Z2_i \quad (3)$$

Remarks: Where IKS = Stunting Coefficient Index (*Indeks Koefisien Stunting*); Z1 = Stunting Prevalence Index (*Indeks Prevalensi Stunting*); Z2 = Index of Stunted Children Under the Age of Five; x1 = Prevalence of Stunting; x2 = Number of Stunted Children Under the Age of Five; PP = Number of Poor Population; i = District/City.

The IKS has been developed to support determination of priority regions for prevention of stunting, however, priority regions for prevention of stunting are determined using a hybrid approach. Selection of priority regions for prevention of stunting at the district and city level does not purely use IKS. The approach is used with consideration of currently running government programs and aspects of inter-regional equal distribution, where each province has at least one priority region. As of budget year 2019, 160 priority district/city regions have been determined.

Selection of a priority district is done using two indexes (ratios) of prevalence and number of stunted children under the age of five years. The first step is the district/city ranking process through formation of an inverse ratio or share of stunting prevalence that is standardised with poor population size as the multiplier factor. The second step is to conduct a district/city ranking through formation of an inversed ratio or share of the number of stunted children under the age of five years standardised with the poor population size as the multiplier factor. Both indexes have the same weight, each at 50 percent, to determine the composite stunting index (3).

Villages and *Kelurahan*

At the village and *kelurahan* levels, priority regions are determined using an indicator that is adjusted to the one used in compiling the index at the district/city level:

- **Population**: the population in one village in 2015. The data is from BPS and the Ministry of Home Affairs (MoHA).

- **Poor Population Size**: the number of village poor, sourced from the BPS/TNP2K Integrated Database. The village poor population distribution is adjusted to the district/city poor population issued by BPS.
- **Poverty Rate**: the percentage of the village population who are poor. The data is produced from BPS and TNP2K calculation proportional to the poverty rate of district/city in 2014.
- **Malnutrition**: the incidence of malnourished people, both in marasmus and kwashiorkor forms in the past three years.[3] The data is from the Village Potential (*Podes*) Survey 2014. This indicator is a proxy of indicators of stunted children under the age of five years that is unavailable at the village/*kelurahan* level.

Those indicators are also indicators used by the Ministry of Finance (MoF) in allocating village funds. MoF and TNP2K refined the formula used as the basis for Village Fund allocations for the 2018 budget year.

$$Z1_{ij} = \frac{x_{1i}}{\sum x_{1j}} \quad (4)$$

$$Z2_{ij} = \frac{x_{2i}}{\sum x_{2j}} \quad (5)$$

$$Z3_{ij} = \frac{x_{3i}}{\sum x_{3j}} \quad (6)$$

$$\text{IKS}_{ij} = \left(\frac{1}{3} * Z1_{ij} + \frac{1}{3} * Z2_{ij} + \frac{1}{3} * Z3_{ij}\right) \quad (7)$$

Remarks: IKS = Village Poverty Score; Z1 = Share of Village Poor Population to Poor Population of District/City; Z2 = Share of Village Poverty Rate to Total Poverty Rate of District/City; Z3 = Share of Number of Malnourished Population to Total Malnutrition of District/City; x1 = Total Poor Population (*Direktorat Jenderal Perimbangan Keuangan*/DJPK, *Dana Desa*/DD 2017); x2 = Poverty Rate (DJPK, DD 2017); x3 = Number of Malnourished Population (*Podes* 2014); i = Village; j = District/City.

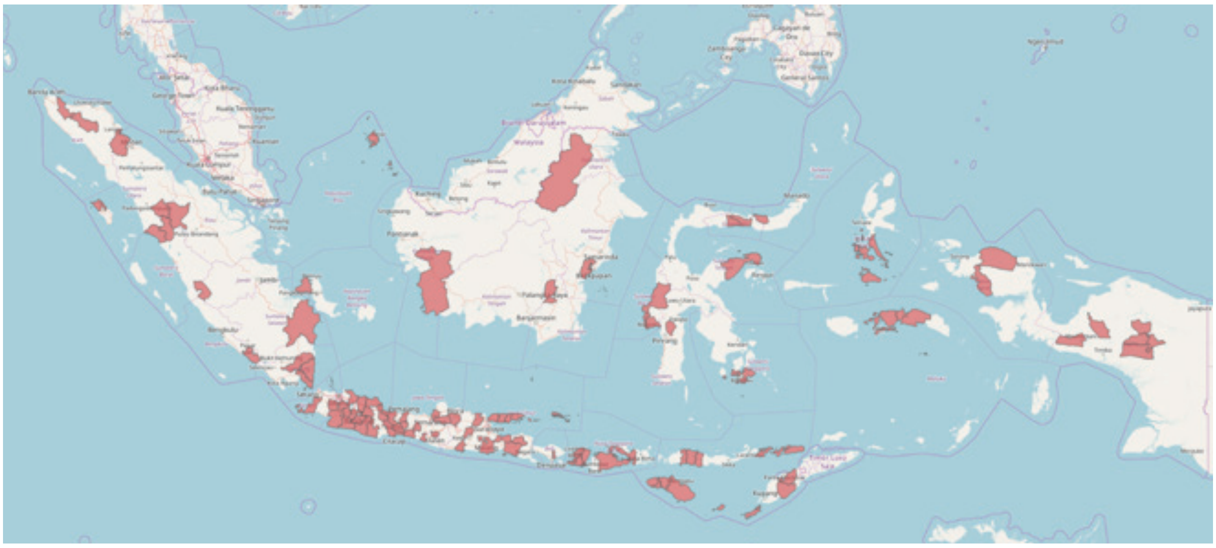
Selection of priority districts is done using three indexes (ratio): total poor population; poverty rate; and total malnutrition incidence. In determining the village composite index of stunting (7) the three indexes have the same weight, each at one-third.

Evaluation of Region Selection Results

Selected priority regions for preventing stunting are spread from west to east. The priority regions in poverty reduction have also been adopted for stunting prevention, however, most of the priority regions are in Java, due to the selection approach used, namely, the number and prevalence of children under the age of five years with stunting.

[3] Marasmus is a form of malnutrition caused by an inadequate energy intake in all forms, including protein, while kwashiorkor is a form of malnutrition caused by a protein deficiency.

Figure 6: Distribution of Priority Regions



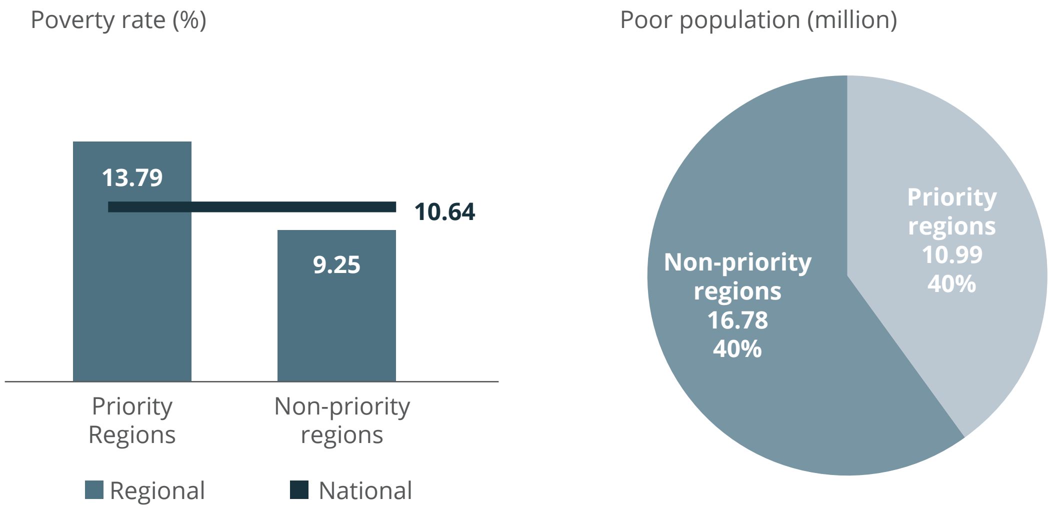
Source: Estimation Results.

In general, selected regions have relatively worse stunting indicators compared to non-priority regions. In addition to the relatively worse condition of stunting, the poverty rate is also higher in priority regions. About 40 percent of the poor population is found in priority regions, or about 10.99 million people (Table 1 and Figure 7). The priority regions also have a poverty rate of 13.79 percent, which is higher than the national rate of 10.64 percent, or to non-priority regions at 9.25 percent (Table 1).

Table 1: Comparison of Poverty Indicators and Stunting in Priority Regions

Indikator	Nasional	Daerah Prioritas	Bukan Daerah Prioritas
Jumlah Daerah	514	100	414
Kondisi Stunting			
Prevalensi Balita Stunting (%)	37,2	41.73	31,21
Jumlah Balita Stunting (ribu jiwa)	8.378	3.105	5.683
Angka Kemiskinan			
Tingkat Kemiskinan (%)	10.64	13.79	9.25
Jumlah Penduduk Miskin (Juta)	27.77	10.99	16.78

Figure 7: Comparison of Poverty Indicator in Priority Regions



Source: Analysis Results.

Recommendations

Update of District and City Index

In reference to publication of *Riskesdas* 2018 results, there is a potential for updating the stunting coefficient index at district and city levels. The update is important to provide an overview of the most current condition of nutritional status of children under the age of five years, especially stunting prevalence. This step is also important to determine priority regions after 2019, where there are still 354 districts/cities that are not yet included in the national priority.

Improving and Updating Village and Kelurahan Index Indicator

***Podes* 2018 has been completed by collecting similar information to *Podes* 2014, namely, the rate of malnourishment at village level that includes malnourished population, both marasmus and kwashiorkor for the past three years.** An update with this approach has an advantage of being consistent with previously used indicators. A disadvantage of this indicator, however, is that the collection was conducted across all age groups, whereas intervention to prevent stunting is ideally done for 0-59-month age group. The use of this indicator also received feedback from ministries/agencies regarding the accuracy of information.

To obtain a more comprehensive picture of malnourishment, there should ideally be an estimate at the village/*kelurahan* level so that the compiled composite index at the village/*kelurahan* level is the same as the index at the district/city level. To meet those needs, TNP2K and *Balitbangkes* (National Institute for Health Research and Development) should work together to provide information on the nutritional status of children under the age of five years at the village/*kelurahan* level through development of nutrition mapping. Cooperation should be encouraged to use updated data because it still uses *Riskesdas* 2013.

Updating of Priority Regions Indicators

Assuming both of the previous recommendations are adopted, priority regions after the 2019 budget year could use the most recent data but should still consider path dependence of the previous priorities. The priority regions in 2018 of 100 districts/cities and in 2019 of 60 districts/cities have, therefore, not experienced change. Specifically, for these regions, updates shall only be done on nutritional status indicators of children under the age of five years, specifically stunting and poverty rate as well as IKS without changing priority regions status. The 354 districts/cities priority regions are then determined using IKS that have been updated with new data and information.

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List of 100 Priority Districts/Cities for 2018 Budget Year

No	Province	District/City	Number of Sub-Districts ***	Number of Villages ***	2016 Population (000s of persons)**	2013 Prevalence of Stunting (%)*	2013 Number of Stunted Children Under Five (persons) **	2016 Poverty Rate (%)**	2016 Poor Population (000s of persons) **
1	ACEH	ACEH TENGAH	14	295	199.30	59.25	13,237	16.64	33.16
2		PIDIE	4	54	424.23	57.47	20,903	21.25	90.16
3	NORTH SUMATRA	LANGKAT	23	277	1,019.24	55.48	54,961	11.36	115.79
4		PADANG LAWAS	12	304	262.29	54.86	18,239	8.69	22.80
5		NIAS UTARA	11	113	134.74	54.83	9,296	30.92	41.66
6		GUNUNGSITOLI	6	101	137.28	52.32	8,618	23.43	32.17
7	WEST SUMATRA	PASAMAN	12	36	272.11	55.20	15,025	7.65	20.83
8		PASAMAN BARAT	11	19	415.62	51.54	23,435	7.40	30.76
9	RIAU	ROKAN HULU	4	54	610.38	59.01	42,142	11.05	67.42
10	JAMBI	KERINCI	16	287	235.63	55.26	9,846	7.48	17.62
11	SOUTH SUMATRA	OGANKOMERING ILIR	18	326	795.74	40.55	35,160	16.03	127.54
12	BENGKULU	K A U R	15	195	116.92	50.71	5,845	22.36	26.14
13	LAMPUNG	LAMPUNG SELATAN	17	260	979.87	43.01	42,971	16.16	158.38
14		LAMPUNG TIMUR	24	264	1,016.31	43.17	40,790	16.98	172.61
15		LAMPUNG TENGAH	28	307	1,247.10	52.68	59,838	13.28	165.67
16	BANGKA BELITUNG ISLANDS	BANGKA BARAT	6	64	199.04	39.14	8,902	2.74	5.46
17	RIAU ISLANDS	NATUNA	12	76	75.07	35.19	3,122	4.33	3.25
18	DKI JAKARTA	KEPULAUAN SERIBU	2	6	23.53	**41.29**	1.175	12.58	2.96
19	WEST JAVA	BOGOR	40	434	5,555.45	28.29	148,764	8.83	490.80
20		SUKABUMI	47	386	2,442.09	37.10	85,651	8.13	198.66
21		CIANJUR	32	360	2,249.20	41.76	95,023	11.62	261.39
22		BANDUNG	31	280	3,581.24	40.70	137,156	7.61	272.65
23		GARUT	42	442	2,564.52	37.83	100,964	11.64	298.52
24		TASIKMALAYA	39	351	1,740.74	41.73	69,401	11.24	195.61
25		KUNINGAN	32	376	1,060.29	42.00	36,672	13.59	144.07

No	Province	District/City	Number of Sub-Districts ***	Number of Villages ***	2016 Population (000s of persons)**	2013 Prevalence of Stunting (%)*	2013 Number of Stunted Children Under Five (persons) **	2016 Poverty Rate (%)**	2016 Poor Population (000s of persons) **
26	WEST JAVA	CIREBON	40	424	2,138.91	42.47	71,712	13.49	288.49
27		SUMEDANG	26	283	1,140.86	41.08	37,970	10.57	120.60
28		INDRAMAYU	31	317	1,698.50	36.12	52,636	13.95	237.00
29		SUBANG	30	253	1,541.83	40.47	55,360	11.05	170.37
30		KARAWANG	30	309	2,290.28	34.87	80,891	10.07	230.60
31		BANDUNG BARAT	16	165	1,643.66	52.55	76,148	11.71	192.48
32	CENTRAL JAVA	CILACAP	24	284	1,701.70	36.32	54,650	14.12	240.24
33		BANYUMAS	27	331	1,647.34	33.49	49,138	17.23	283.90
34		PURBALINGGA	4	54	905.23	36.75	29,880	18.98	171.78
35		KEBUMEN	26	460	1,188.03	33.82	33,611	19.86	235.90
36		WONOSOBO	15	265	779.85	41.12	29,037	20.53	160.12
37		KLATEN	26	401	1,162.10	31.29	29,708	14.46	168.01
38		GROBOGAN	19	279	1,357.18	54.97	62,847	13.57	184.14
39		BLORA	16	295	854.72	55.06	35,861	13.33	113.94
40		DEMAK	14	249	1,126.45	50.28	50,780	14.10	158.84
41		PEMALANG	14	222	1,291.98	46.28	57,370	17.58	227.08
42		BREBES	17	297	1,787.36	43.62	69,201	19.47	347.98
43	D I YOGYAKARTA	KULON PROGO	12	88	415.56	26.31	8,127	20.30	84.34
44	EAST JAVA	TRENGGALEK	14	157	690.79	38.63	19,553	13.24	91.49
45		MALANG	33	390	2,555.71	27.28	57,372	11.49	293.74
46		JEMBER	31	248	2,415.99	44.10	80,359	10.97	265.10
47		BONDOWOSO	23	219	764.15	56.38	29,159	15.00	114.63
48		PROBOLINGGO	4	54	1,146.12	49.43	46,576	20.98	240.47
49		NGANJUK	20	284	1,044.50	44.33	36,970	12.25	127.90
50		LAMONGAN	27	474	1,188.11	48.87	44,031	14.89	176.92
51		BANGKALAN	18	281	960.64	43.21	32,473	21.41	205.71
52		SAMPANG	14	186	944.92	41.46	35,371	24.11	227.80
53		PAMEKASAN	13	189	851.98	44.60	32,905	16.70	142.32

No	Province	District/City	Number of Sub-Districts ***	Number of Villages ***	2016 Population (000s of persons)**	2013 Prevalence of Stunting (%)*	2013 Number of Stunted Children Under Five (persons) **	2016 Poverty Rate (%)**	2016 Poor Population (000s of persons) **
54	EAST JAVA	SUMENEP	27	332	1,075.62	52.44	33,196	20.09	216.14
55	BANTEN	PANDEGLANG	35	339	1,199.16	38.57	46,775	9.67	115.90
56	BALI	GIANYAR	7	70	498.57	40.99	16,189	4.44	22.13
57	WEST NUSA TENGGARA	LOMBOK BARAT	10	122	662.56	46.89	28,533	16.73	110.85
58		LOMBOK TENGAH	12	139	919.81	47.79	49,092	15.80	145.37
59		LOMBOK TIMUR	20	254	1,171.04	43.77	54,051	18.46	216.18
60		SUMBAWA	24	166	444.42	50.30	22,147	16.12	71.66
61		DOMPU	8	81	241.05	47.78	10,741	14.23	34.31
62		LOMBOK UTARA	5	33	213.86	65.77	13,451	33.21	71.02
63	EAST NUSA TENGGARA	SUMBA BARAT	6	74	123.43	55.35	9,033	29.34	36.21
64		SUMBA TIMUR	22	156	248.78	51.31	15,801	31.43	78.19
65		TIMOR TENGAH SELATAN	32	278	463.20	70.43	38,773	29.89	138.43
66		TIMOR TENGAH UTARA	24	193	246.56	39.94	11,486	24.07	59.34
67		A L O R	17	175	201.11	55.66	13,058	22.35	44.95
68		LEMBATA	9	151	133.99	55.08	7,715	26.26	35.18
69		NGADA	12	151	155.75	62.14	10,648	12.69	19.76
70		MANGGARAI	11	162	322.90	58.78	22,212	22.50	72.65
71		ROTE NDAO	4	54	152.25	55.38	9,472	29.60	45.06
72		SUMBA TENGAH	5	65	69.33	63.61	5,765	36.55	25.34
73		SUMBA BARAT DAYA	11	131	324.05	61.22	26,809	30.63	99.26
74		MANGGARAI TIMUR	9	176	275.58	58.92	18,277	27.71	76.37
75		SABU RAIJUA	23	731	88.10	62.49	8,967	32.44	28.58
76	WEST KALIMANTAN	KETAPANG	20	249	483.00	34.83	15,881	10.99	53.07
77	CENTRAL KALIMANTAN	BARITO TIMUR	10	103	116.15	54.84	6,362	7.64	8.88

No	Province	District/City	Number of Sub-Districts ***	Number of Villages ***	2016 Population (000s of persons)**	2013 Prevalence of Stunting (%)*	2013 Number of Stunted Children Under Five (persons) **	2016 Poverty Rate (%)**	2016 Poor Population (000s of persons) **
78	SOUTH KALIMANTAN	HULU SUNGAI UTARA	10	219	227.35	56.03	12,176	6.76	15.38
79	EAST KALIMANTAN	PENAJAM PASER UTARA	4	54	155.71	34.63	5,965	7.49	11.66
80	NORTH KALIMANTAN	MALINAU	15	109	79.86	40.27	3,027	7.15	5.71
81	NORTH SULAWESI	BOLAANG MONGONDOW UTARA	6	107	76.95	56.66	3,212	9.38	7.22
82	CENTRAL SULAWESI	BANGGAI	23	337	358.59	35.39	11,728	9.47	33.97
83	SOUTH SULAWESI	ENREKANG	12	129	201.22	53.73	12,384	13.41	26.98
84	SOUTHEAST SULAWESI	BUTON	7	95	266.92	49.61	16,939	13.53	36.11
85	GORONTALO	BOALEMO	7	85	152.96	39.37	5,691	21.11	32.29
86		GORONTALO	19	207	372.59	42.62	14,824	21.03	78.36
87	WEST SULAWESI	MAJENE	8	82	165.83	58.62	10,885	14.89	24.69
88		POLEWALI MANDAR	4	54	428.02	48.48	21,151	17.06	73.04
89		MAMUJU	11	99	269.80	47.26	22,241	6.48	17.47
90	MALUKU	MALUKU TENGAH	18	187	370.22	42.15	16,977	21.68	80.28
91		SERAM BAGIAN BARAT	11	92	169.91	59.86	11,193	26.50	45.03
92	NORTH MALUKU	HALMAHERA SELATAN	30	256	220.57	50.60	13,083	4.11	9.06
93	WEST PAPUA	SORONG SELATAN	13	121	43.72	60.70	3,541	19.92	8.71
94		TAMBRAUW	12	83	13.69	59.29	571	36.67	5.02
95	PAPUA	JAYAWIJAYA	40	331	209.26	49.88	11,329	39.66	83.00
96		TOLIKARA	45	516	134.77	52.01	6,739	33.63	45.33
97		NDUGA	32	248	95.44	56.55	5,376	38.47	36.72
98		LANNY JAYA	37	140	173.05	60.89	6,368	41.68	72.13
99		DOGIYAI	10	79	93.40	66.12	6,143	31.21	29.15
100		INTAN JAYA	6	37	46.95	68.95	3,704	43.73	20.53

Source: *Riskesdas 2013, Kemenkes **Susenas 2013, BPS ***Podes 2014, BPS

List of 60 Priority Districts/Cities for 2019 Budget Year

No	Province	District
1	ACEH	ACEH TIMUR
2	BALI	BULELENG
3	BANTEN	LEBAK
4	BENGKULU	BENGKULU UTARA
5	DI YOGYAKARTA	BANTUL
6	GORONTALO	POHUWATO
7	JAMBI	TJG JABUNG TIMUR
8	WEST JAVA	MAJALENGKA
9	CENTRAL JAVA	Kab. PEKALONGAN
10	EAST JAVA	Kab. KEDIRI
11	WEST KALIMANTAN	SAMBAS
12		SINTANG
13	SOUTH KALIMANTAN	TANAH BUMBU
14	CENTRAL KALIMANTAN	KAPUAS
15		KOTAWARINGIN TIMUR
16	EAST KALIMANTAN	KUTAI
17	NORTH KALIMANTAN	NUNUKAN
18	ISLANDS OF BANGKA BELITUNG	BANGKA
19	ISLANDS OF RIAU	KAMPAR
20		LINGGA
21	LAMPUNG	TANGGAMUS
22	MALUKU	KEPULAUAN ARU
23	NORTH MALUKU	KEPULAUAN SULA
24	WEST NUSA TENGGARA	B I M A
25		SUMBAWA BARAT
26	EAST NUSA TENGGARA	B E L U
27		E N D E
28		FLORES TIMUR
29		KUPANG
30		MALAKA
31		MANGGARAI BARAT

No	Province	District
32	EAST NUSA TENGGARA	NAGEKEO
33		SIKKA
34	PAPUA	ASMAT
35		BIAK NUMFOR
36		BOVEN DIGOEL
37		DEIYAI
38		KEEROM
39		KEPULAUAN YAPEN
40		MAMBERAMO RAYA
41		MAMBERAMO TENGAH
42		NABIRE
43		PANIAI
44		PEGUNUNGAN BINTANG
45		PUNCAK
46		PUNCAK JAYA
47		SUPIORI
48		YAHUKIMO
49		YALIMO
50	WEST PAPUA	KOTA SORONG
51		MANOKWARI
52		PEGUNUNGAN ARFAK
53	WEST SULAWESI	MAMASA
54	SOUTH SULAWESI	Kab. B O N E
55	CENTRAL SULAWESI	PARIGI MOUTONG
56	SOUTHEAST SULAWESI	KOLAKA
57	NORTH SULAWESI	BOLAANG MONGONDOW
58	WEST SUMATRA	KAB. SOLOK
59	SOUTH SUMATRA	MUARA ENIM
60	NORTH SUMATRA	SIMALUNGUN

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WHAT HAPPENS TO POOR HOUSEHOLDS: ARE THEY LEAVING, STAYING OR FALLING? EVIDENCE FROM INDONESIA'S UNIFIED DATABASE (UDB)*

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Abstract

Understanding why some households can move out of poverty while others fail is crucial for any effort to reduce poverty. A large number of studies using survey-based data have documented and examined the possible factors that contribute to household movement in-out of poverty. To carry out this project, we constructed a household-level panel data set of approximately 20 million households in Indonesia between 2011 and 2015. We proceed using two approaches, observe the correlation using the existing welfare measure, generated by different PMT models, and observe the same correlation who use a new welfare measure resulted from the same PMT model. We found that, in general, results are lower in magnitude than the existing model, however, trends are consistent across models and groups. On the household human capital characteristic, we find that the more education that each household member earned, the more likely they help their households to move out of poverty. While we see no clear pattern on the correlation between sets of demographic variables and the household welfare change, the correlation between physical assets with changes in welfare rank seems to be consistent across different approaches.

Keywords: *UDB, PMT model, poverty reduction.*

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Abbreviations and Acronyms

BPS	*Badan Pusat Statistik* (Statistics Indonesia)
GRDP	Gross Regional Domestic Product
NTB	Nusa Tenggara Barat (West Nusa Tenggara)
NTT	Nusa Tenggara Timur (East Nusa Tenggara)
PAD	*Pendapatan Asli Daerah* (Regional [Government] Own Revenues)
TKPK	*Tim Koordinasi Penanggulangan Kemiskinan* (Coordinating Team for Poverty Reduction)
TNP2K	*Tim Nasional Percepatan Penanggulangan Kemiskinan* (National Team for the Acceleration of Poverty Reduction)
UDB	Unified Database

Section One:

Introduction

Understanding why some households can move out of poverty while others fail is crucial for any effort to reduce poverty. A large number of studies using survey-based data have documented and examined the possible factors that contribute to household movement in-out of poverty. Less is understood regarding the factors or correlates that drive household movements in or out of poverty using an actual data used to deliver social programs. This additional qualifier becomes important since any change in the factors that affect poverty movement would likely to have real-welfare implication. Household is removed from the social registry data if the change deems to have positive impact on their welfare, vice versa.

In this paper, we investigate the correlates of households ranking of Indonesia's poor in the Unified Database (UDB). UDB keeps records of social, economic and demographic indicators of the Indonesian households that lie in the bottom 40 percent of the Indonesian population and is used by various government agencies, both central and local, to target their social protection programs. We evaluate four sets of correlates that determine a household's economic performance compared to their peers: (i) human capital; (ii) demographics; (iii) owned assets; and (iv) labour market performance–by controlling whether they receive and/or participate in social protection schemes. Our main outcome variable is a household's rank in the UDB, represented by their per capita expenditure percentile.

UDB data is constructed following the PPLS (Pendataan Program Perlindungan Sosial) 2011 and its follow-up, the BDT (*Basis Data Terpadu*) 2015. We utilize all information available, both at individual and household-level, at the UDB to shed ligt the relationship between observed factors and welfare ranking. The main novelty of our study is our examination using the actual administrative data used to target the social protection program, controlling for social protection program participation and other rich characteristics. To our knowledge, our study is the first that uses the actual administrative data for examining the correlates of welfare change among the poor population. In addition, the welfare metric in our data is relatively new, since it is model-generated rather than survey-collected. We do everything within our power to consider the different methods used to derive the welfare measure.

While our investigation can proceed with other household-level surveys that collected welfare measure and the respective characteristics, both directly or indirectly, such as the National Socioeconomic Survey (Susenas) or Indonesian Family Life Surveys (IFLS), the use of the UDB has several advantages. First, UDB is a large longitudinal data collected at household, and its respective individual information, level while Susenas and IFLS are a repeated cross-section and a longitudinal data undertaken at a relatively small-scale panel household level, respectively. An analysis using UDB will, therefore, result in greater statistical power relative to these datasets. Second, administratively, households in the UDB are the candidates for receiving social programs from the central government. Any factors that could lead to a change in welfare of these households would raise the interest of policy makers. While the first argument warrants the use of UDB rather than survey-based data, the last one is the main advantage of using UDB since we can evaluate which of the socioeconomic variables/indicators correlate with household welfare. Further understanding of these two relationships will help the government in (re)shaping their poverty reduction program. If socioeconomic indicators statistically correlate with welfare improvement of the poor then government should design its social program accordingly - incentivize the poor to change their socioeconomic structures and not only giving an in-kind contribution.

A significant challenge of this project is to discern whether changes in households' welfare rank between 2011 and 2015 censuses are driven by changes in those correlates alone, and not driven by the different Proxy Means Test (PMT) methodologies used to generate the ranks or the change in a district-level poor households' quota. The PMT for the PPLS 2011 rank was estimated using the National Susenas 2010 and 2011 while the PMT for the BDT 2015 rank was estimated using the Susenas 2011, 2012, 2013, and 2014. To isolate the effect of the different PMT models and the different estimates of the poor quota, we construct our own district-level PMT models based on the same set of universe explanatory variables pooled from the Susenas data 2010, 2011, 2012, 2013 and 2014 used to generate the two PMTs and adopt the existing poor households' quota, estimated separately during the PPLS and the BDT process. Further on, we compares the empirical estimate of the correlation between household characteristics and the original rank in terms of percentiles with estimates that use the percentiles we generated. In doing so, we could reveal how much our results is due to the change in methodologies.

To carry out this project, we constructed a household-level panel data set of approximately 20 million households in Indonesia between 2011 and 2015. This data set contains information on the households' housing characteristics, asset ownership, participation in the social protection program, and the socioeconomic characteristics of household members. Importantly, the data also contains households' welfare ranking, shown by their associated per capita expenditure percentile. To our knowledge, our study has one of the largest longitudinal data sets–in terms of the number of households and individual units–ever used to document pattern of household movement in and out of poverty in a developing country, let alone the world, and their correlates.

We run a basic regression strategy that provides a benchmark estimate of the correlation between a set of household-level variables and welfare metric. In addition, we compare the correlation across poverty mobility status and districts to check whether the implied relations are sensitive to different poverty-dynamic of households. We also add time fixed effects that control for any changes over time that affect all panel households uniformly. To control for district-specific effect we include district fixed effects to capture any cross-sectional unobserved determinants of the change in household welfare mobility.

The first set of results show that, over the course of four years, we see slight mobility. About 2.2 million UDB households were classified as poor in 2011 and 2015, 2.9 million households moved out from their poor status, 3.2 million households fell into poor, while the last 12 million were never considered as poor in either period. We have a net loss of 0.3 million, more people becoming poor than those leaving poor. This finding raises an important point on whether, in the course of four years, the UDB households only experience sluggish change in their socioeconomic characteristics, which later affects their welfare mobility.

On human capital, we find that the more educated the household members, the more likely that they help their households to move out of poverty. While this finding reiterates the importance of education in helping people to move out of poverty, the exact interpretation is really hard to fathom due to the fact that education is seen to be endogenous to welfare changes. While we see no clear pattern on the correlation between other demographic variables and household welfare change, the correlation between physical assets and changes in welfare rank seems to be consistent across different specifications. Interestingly, we find that households who own a motorcycle and refrigerator are more likely to escape poverty. High-quality jobs are expected to help people move out of poverty in a more profound way. It is, therefore, not out of the realm of the two variables that we choose to include to represent labor market outcomes, that the number of adults working in the formal sector is seen to have a stronger/strong positive correlation with the households' welfare change.

This paper builds on a large volume of literature in poverty dynamics that stresses the role of household characteristics on their welfare outcomes. This includes research by Duncan & Hill (1985), Jalan and Ravallion (1998), Dercon et al. (2007), Widyanti et al. (2009), and Woolard & Klasen (2005). It also relates to poverty dynamics in the Indonesian context (Hernandez & Hadiwidjaja (2018), Sumner et al. (2014), Dartanto and Nurkholis (2013), and Miranti (2010)), as well as the determinants of relative poverty (Sumner et al. (2014) and Filmer and Pritchett (2001)). Our study also contributes to the literature in development economics on the use of national registry in evaluating poor people welfare (Bah et. al 2019).

The remainder of the paper is organized as follows: Section Two provides the literature review, Section Three describes our data and measurement, Section Four discusses results, while Section Five concludes with some policy implications.

Section Two:

Literature Review

Our study is related to a growing volume of literature in economics on the correlation between demographic variables and poverty status. Among others, Duncan & Hill (1985), Jalan and Ravallion (1998), and Woolard and Klasen (2005) provide evidence that demographic status affects poverty. These studies had the luxury of examining a relatively consistent measurement of the poverty status.

Measuring poverty may not always be straightforward–Madden (2000) emphasised that when measuring poverty, there are two issues to be addressed: identification and aggregation. Identification deals with choosing the poverty line, whether absolute, relative, or hybrid–which is the combination of both absolute and relative. Aggregation deals with the choice of aggregator–for example, the numbers of people below the poverty line–or a more complex approach that considers the distribution of income amongst the poor. In this study, the identification issue is more intriguing as there is a wide spectrum of the poor in Indonesia.

Is the absolute approach more preferable to the relative approach in identification of the poverty line? Foster (1998) states that the difference between the absolute and relative approaches is that the former is a fixed cutoff level that is applied to all potential resource distributions, while the latter uses standard of living for a certain distribution–for example, when the mean, median, or quintile income or consumption is used and the cutoff is defined as some percentage of this standard. The difference between the absolute and relative approaches is, therefore, in how the values change as the distribution changes, not the specific values obtained at a given date.

The use of different approaches yields different results, such as the case observed by Madden (2000). Using the Irish Household Budget Survey of 1987 and 1994, he found that, when the absolute approach is used, there is a significant fall in poverty, whereas it increased slightly when the relative approach was used. The use of an absolute poverty measure was further conducted by Martinez Jr (2016) to observe persistent and transient poverty dynamics in the Philippines during 2003-09. Comparing the spells and components approach, he concludes that poverty dynamics are sensitive to the poverty line or the poverty measure used. Foster (1998) notes that, for comparisons that involve long periods of time or different standards of living, the absolute line is a more important issue. The advantage of using a relative poverty measure, however, is that it is independent of income change. The proportion of the poor would be the same after there is a rise or fall of income levels, because the number of poor people would depend on the relative position of others in the society.

An example of a relative poverty measure approach was conducted by Sumner et al. (2014) using Indonesian cross-sectional data and the Demographic and Health Surveys (DHS) wealth index quintiles to measure education and health poverty. The DHS wealth index was generated by observing easy-to-collect information, for example ownership of bicycles, motorcycles, cars, sanitation facilities, and water access. They further constructed measures of education in each household by calculating the percentage of youth aged 15-24 years who have not completed primary school, and health was measured by the proportion of children who died below the age of five. They found that there was a rise in the proportion of both education and health poverty in the poorest quintile, and that the composition of education poverty remained constant during 1991-2007.

Filmer & Pritchett (2001) generated an asset index that includes 21 asset ownership indicators and 12 housing characteristics indicators. As with the DHS wealth index, their asset index is used to predict wealth, replacing average household per capita income or expenditure data. Using principal components analysis, they found that asset index is robust even when different sets of variables are used. Furthermore, it is consistent with expenditure–for example, two-thirds of those classified into the poorest 40 percent by expenditure are also classified into the poorest 40 percent by assets. Moreover, they estimated the effects of wealth–using the asset index–on children's school enrolment and found consistent results when compared to using expenditures as wealth. To further understand the difference between the absolute and relative poverty lines, Table 1 compares the two concepts.

Once the identification issue is solved, poverty can then be measured by addressing certain groups of characteristics. There is numerous literature on the correlation between demographic characteristics and poverty status. Poverty status is measured by observing whether households live below a certain income or consumption level. Observations during multiple periods will reveal how poverty dynamics take place in a region. For example, households that were poor in one period may no longer be poor in the next period. This movement in and out of poverty is driven by some characteristics related to households or its members and is valuable in assessing poverty alleviation programs. The most widely used characteristics in the literature include education attainment, asset ownership, labour market outcomes, and government assistance programs.

A household head's education attainment in much of the literature is found to be significant in lowering the probability of a household being poor. For example, Sumner et al. (2014), using six different poverty lines and panel data from the IFLS, found that the most robust determinant of the probability of being poor and remaining poor is education. Households are 20 percent less likely to be poor in the current and following period if their household heads have obtained a higher schooling.

Results are similar in other developing countries such as Bangladesh and Vietnam. Using a sample survey in Bangladesh during 2008-09, Rahman (2013) found that poverty in Bangladesh is mainly found in households with heads who are poorly educated. Illiterate household heads are 82 percent more likely to be poor than those who are literate. Moreover, the risk of being poor is 96 percent higher for households with illiterate heads, compared to heads who obtained primary schooling. Other variables used in this study are a household head's occupational status and age, household characteristics such as whether it is male or female headed, household size, and dependency ratio. Of all these variables, Rahman (2013) concludes that poverty is high in households with young household heads, low education level, female heads, large households, and with a high dependency ratio.

Whether a household head completed primary schooling or not also determines poverty status. Using a multinomial logit model observing data from the Vietnam Household Living Standards Survey, Baulch and Dat (2010) found that households whose heads have completed primary school increase the probability that the household is never poor by one-sixth. The more highly educated the household head the more likely to never be poor, respectively. As with other studies, Baulch and Dat (2010) use demographic characteristics such as household size, ethnic status, education level and age of household head, access to clean water, and dependency ratio. In addition, they also use a household's geographical location to observe different levels of poverty in each region. They found that households from an ethnic minority, with little or no education, and those living in the Northern Uplands or Central Highlands have a high probability of being chronically poor.

Although the literature finds education to be strongly significant in measuring poverty dynamics, Dercon et al. (2007) argue that it is endogenous to long-term wealth as it may not be observable whether education helps people escape poverty, or whether those who can afford education can offer other opportunities to their children. They further suggest that, instead of household panel data, one should use individual panel data to observe individual poverty dynamics and obtain a better understanding of the causality between education and poverty status. That would, however, involve higher costs in conducting surveys and may not be feasible with a large number of observations unless using methodological innovations.

Another important element in measuring poverty dynamics is asset ownership–the literature, for example, shows that endowments such as land and livestock contribute to the movement in and out of poverty. Dercon et al. (2007) used a linear regression to estimate a panel survey of Ethiopian households during 1989 and 1994 and found that households that own land and livestock can rely on them to help move out of poverty. They emphasized, however, that this may be due to economic liberalization that occurred during those periods and is likely to increase returns to these endowments. Dercon et al. (2007) use various characteristics apart from demographic, to obtain the result–such as the value of livestock and land area, export crops, amount of fertilizers used, crop prices, location, and shocks such as illness or low and high rainfall. Although they conclude that it is hard to generalize which factor is most important due to different contexts, they see a pattern that education greatly affects poverty dynamics.

In the case of Indonesia, Dartanto and Nurkholis (2013), using data from Susenas, found that physical assets such as land and house ownership play a role in determining poverty dynamics. Using a probit model, they found that a one-hectare increase in land size would increase the probability of being non-poor by 1.7 percent in Java and Bali, 1.3 percent outside Java and Bali and 1.7 percent nationally. Ownership of a larger house is also associated with a lower probability of being poor. Dartanto and Nurkholis (2013) further suggest that land and house certification may help alleviate poverty by allowing households to use them for collateral to gain credits/loans from financial institutions. Moreover, households that are able to accumulate assets are less likely to be poor in the future because they are able to deal with adverse shocks at the same consumption level (Bah 2013).

Labour outcomes, especially a household head's employment or employment sector, also play a role in household poverty dynamics. Sumner et al. (2014) found that the household head's sector of employment is not a robust determinant of staying out of poverty unless they are employed in wholesale, retail, restaurants, and hotels. Households in these sectors are seen to have higher consumption per capita and a lower probability of being poor. Meanwhile, those working in the agricultural sector have a higher likelihood of being poor due to very low productivity and low wages. Dartanto and Nurkholis (2013) confirmed that households in Java-Bali often experience crop loss, job loss, and falling prices and have a greater tendency to be poor and transient poor. Those outside Java-Bali, however, experience more negative shocks but it is insignificant to their poverty status due to their owning larger areas of land and being more able to reduce agricultural risks by diversification.

Not only does a household head's employment affect their poverty status, but their gender also plays a role because it may correlate with their expected wage. Rahman (2013) found that, in Bangladesh, households with female heads are often found to be more vulnerable to poverty than households with male heads due to their low wages in the labour market, and less years of education compared to male heads. Child to female ratio is also seen as a factor that constraints females from entering the labour force (Rahman 2013), the more children a family has, the less likely the mother would enter the labor force. Furthermore, looking closely at the case of Central Sulawesi, Indonesia using a multinomial logit model, Van Edig and Schwarze (2011) found that the probability of female-headed households to become chronically poor increases only in the case of those who were chronically poor in the US$1.00/day poverty line scenario, but not in the case of those chronically poor in the US$2.00/day scenario.

Receiving government assistance–such as health care insurance subsidies, microcredit, and in-kind transfers–may help households stay out of poverty since they act as buffers during economic shocks. Dartanto and Nurkholis (2013) confirmed that microcredit helps to alleviate poverty, particularly in Java-Bali where 5 percent of households have access to it. The probability of households being poor also decreases when cheap rice was distributed after an economic shock. Government assistance such as these, however, is most beneficial if problems relate to transient poverty instead of chronic poverty, therefore, helping them to return to their previous non-poor state. There are several studies using Indonesia's context that answer the determinant of poverty dynamics using panel data setting. Table 2 presents a summary complied from several studies that focus on Indonesia poverty dynamics.

Section Three:

Data & Measurement

3.1 Data

We use Indonesia's Unified Database (UDB) for Social Protection Programs to shed light on the relationship between household characteristics and welfare status. Established in 2011 and updated in 2015, the UDB is designed to register the poorest 40 percent of the Indonesian population and later use to deliver various social programs. The first set of data, PPLS 2011, covered around 25.2 million households across Indonesia. Using the pre-list from PPLS 2011, BDT 2015 re-interviewed approximately 80 percent of those households. Reaching 100 percent is not possible due to various factors: some households may no longer be registered due to death, emigration, the area where they live has been re-used for other purposes, or some no longer fit into the BDT criteria for a poor household–for example, by being enrolled in civil service jobs where they have a fixed income and can no longer be categorised as poor. The BDT 2015 found 5.4 million 'new households', equating to 18.1 million individuals, which were found in PPLS 2011, but were now living in different households in 2015. Despite these various types of attrition problems, the UDB includes 20.4 million households, making it the largest targeting registry with panel data households in the world (Bah et al. 2018). Furthermore, due to its innovative targeting approach, the UDB has been found to successfully reduce leakage of social assistance programs to non-poor households.

The UDB was constructed following two steps: data collection (enumeration) and PMT modeling (ranking). The data collection stage involved pre-identifying all potentially eligible households that should be surveyed. It was intended to cover a greater number of households and to avoid relying exclusively on subjective nominations from community leaders. A 'pre-list' of households to be surveyed was generated through a poverty mapping for PPLS 2011 while pre-list households for BDT 2015 were sourced from PPLS 2011 and various social protection programs.

3.2 Measurement

3.2.1 Poverty

Comprehending who are the poor very much depends on how poverty and its characteristics are measured. BPS (*Badan Pusat Statistik* - Statistics Indonesia) uses the basic needs approach, the amount of money needed to purchase the food consisting of minimum amount of calories (2,100 kcal per day) plus basic non-food necessities. This amount is then used to set the poverty line. People who spend above the poverty line are classified as not poor, while those spending below the line are classified as poor. In March 2018, BPS determined that about 9.81 percent of Indonesia's population was poor, which is approximately equivalent to the first decile or the 10^{th} percentile.

Our study observes 20 million panel households, taken from PPLS 2011 and BDT 2015 to compare how individual and household characteristics correlate with household welfare ranking**.** Embedded in the UDB data are the predicted per capita expenditures, also known as the *yhat*, and the associated household's ranking, known as the percentiles. To generate the predicted *yhat*, PMT models are employed–each with their specific estimating approach. With the percentile information, we further construct ranking information in terms of decile. If a household is always in the lowest deciles in the two years then we define it as always poor. At the other extreme, if a household was not classified in the lowest decile in either survey, we define it as never poor. In between are those households in transient poverty–that is those that were poor in 2011 but not in 2015. These are defined as moving-out households, while those households that were classified in a higher decile in 2011 but the lowest decile in 2015 are defined as falling into poverty.

3.2.2 Education

The first set of variables is human capital where we expect to see a strong correlation with a household's welfare ranking. We opt for four variables to represent human capital stock: (i) average years of education of all household members; (ii) dummy variable whether head of household has completed at least primary education; (iii) dummy variable whether head of household has completed at least a junior secondary education; and (iv) another dummy for whether the household head has completed at least a senior secondary education. One variable acts at the household level while the other three variables proxy human capital by using information on the head of household. All four variables are calculated using all educational variables that were asked in the PPLS 2011 and the BDT 2015 surveys.

3.2.3 Demographics

The second set of variables is the households' demographic structure. We calculate how many adults live in each household and whether they have an expectant mother to represent the demographics of households. With more adults, households should ideally have more resources that they can utilise to improve their welfare, assuming they are productive. If the adults in the household are not productive, then more adults translate into a drop in their welfare ranking. Unlike the number of adults, the presence of an expectant mother should correlate negatively with a household's welfare ranking. As with the set of education variables, we also calculate these two from the PPLS 2011 and the BDT 2015 data sets.

3.2.4 Assets

The next set of variables is assets which represent the ownership of capital. There are seven types of assets that were surveyed in PPLS 2011 and BDT 2015: (i) bicycle, (ii) motorcycle, (iii) fishing boat, (iv) refrigerator, (v) car, (vi) telephone, and (vii) flat-bottom wooden boat. We only consider bicycle, motorcycle, and refrigerator since economically meaningful patterns can only be found on these three while the other show no economic and statistical significance.

3.2.5 Labour Market

The most important driver of moving out of poverty is a high-quality job. While PPLS 2011 and BDT 2015 were not designed as a census for job-related information, the two have several basic questions on household members' participation in the labour market. The censuses ask whether a household member worked in the past week, in which sector each member worked, and the job status of their primary occupation. Using these three questions, we calculate how adult members in the household work and the number who work in the formal sector. The first represents how access to jobs may explain the welfare movement while the latter represents how a good-quality job, in this case participation in the formal sector, explains the welfare transition. It is expected that participation in the formal sector should drive the welfare movement better for poor households.

3.2.6 Social Protection

According to the literature, social protection has three major functions: (i) to protect those people who are near or below the poverty standard (by supporting their consumption level through the aid process); (ii) to facilitate those in persistent poor condition (by helping them to invest in the human capital development process); and (iii) to develop a systematic attempt to break the poverty cycle (Barrientos and Hulme 2005). Our model, therefore, controls for social protection participation as it may directly affect welfare ranking.

3.3 Descriptive Statistics

We perform three regression approaches; pooled OLS, panel fixed effect, and first difference. In addition to the overall regression analysis, we also try to consider the different poverty status of each household by showing how characteristics in each transition group correlate with the welfare ranking and the summary statistics when estimating the model for each district separately.

Before proceeding to regression analysis, the common approach to examining the correlates of poverty usually start with a descriptive profile of poverty mobility. Between 2011 and 2015, official poverty decreased from 12.49 percent to 11.22 percent.[4] Among the panel UDB households, we see slight mobility: 11 percent of UDB households were considered poor in both periods, 14 percent of UDB households moved out of poverty, and 16 percent of UDB households fell into poverty. Policy makers and researchers need to take these numbers with a grain of salt for they can often obscure important poverty mobility that occurred due to a significant proportion of the UDB households surveyed in 2011 that could not be identified during the 2015 census. Moreover, we only have two rounds of the poor census–with more rounds we could expect some households to be classified as 'sometime' poor (see Baulch and Hoddinott 2000).[5]

[4] The official poverty rate is calculated using the basic needs approach. In this paper we use the percentile/decile grouping to define poverty status.
[5] Of the 25.2 million households found in PPLS 2011, only 20.4 million were identified during the 2015 census. We have an approximately 19 percent attrition rate: households moved to other areas, died, cannot be identified, job status, and enumerator decision to remove them from the 2015 census. Despite 'losing' 4.8 million households, the 2015 census added roughly 5.4 million 'new' households into the database.
[6] See Dercon and Shapiro. (2007) for a survey on mobility studies.

We show four sets of household characteristics that the literature argues have some correlation with poverty mobility: (i) asset ownership; (ii) household demographics; (iii) education; and (iv) labour market outcomes.[6] We contrast three different timelines for these: start of the census, end of the census, and the average value between the two. In addition, we also compare four different groups: (i) those always poor; (ii) those who fell into poverty; (iii) those who moved out of poverty; and (iv) the never-poor households.

Household characteristic profiles of those who fell into poverty and moved out of poverty are different to those of the other two groups–the always-poor and the non-poor. Table 3 highlights the summary statistics of these selected characteristics, evaluated at the means, for all these groups. In terms of descriptive statistics, the difference between these four groups for some characteristics are statistically significant. For example, compared to those who are always poor, those who moved out of poverty had significantly more assets, more human capital (in terms of household members' years of education), and participated more in the formal labour market.

Compared to those who fell into poverty, those who moved out of poverty had a somewhat better performance in the labour market in terms of working in the formal sector. Furthermore, there is no significant difference in terms of employment. As expected, the non-poor have the 'best' characteristics–more assets, more education, and engage in the formal labour sector. In sum, this information illustrates a more general finding: those who moved out of poverty tend to be able to rely on their assets, education, and the formal labour market. One should bear in mind that this information was sourced during a period of changing social protection programs and dynamic technological advancement in Indonesia that might potentially contribute to how assets, social protection expansion coverage, education and labour market participation interact with each other.

Furthermore, both data reveals households poverty dynamics as seen in figure 1. The proportion of households living in decile 1 decreases. Out of those living in decile 1 in 2011, 43 percent of them still lives in decile 1 in 2015, while the rest moved up the ladder. In contrast, out of those living above decile 4 in 2011, just about 12 percent of them fell back into decile 1 in 2015. However, when we zoom into the bottom 10 percent as in figure 2, the proportions of households living in the first percentile are relatively stagnant throughout the years. This finding highlights that it is harder for those chronic poor people to move up the ladder.

Section Four:

Results & Discussions

4.1 General Specification

Multivariate analysis that we are presenting in the following subsections aims to improve the rigorousness by revealing the quantitative contribution of each factor to the observed changes in welfare criteria, as well as establishing the marginal contribution of each factor to potential changes in the welfare metric. In this study we are not making any causal claims about the relationship between the aforementioned characteristics on relative welfare ranking since we cannot settle all the identification issues–that is, the correlations that might result from the unobserved factors.

Our proposed general model of the correlation between four sets of household characteristics and welfare status is as follows:

$$P_{r,t}^{h} = c + f_r + f_r + \mathbf{A}^h.\gamma + \mathbf{D}^h.\beta + \mathbf{E}^h.\alpha + \mathbf{S}^h.\delta + \mathbf{L}^h.\theta + \mathbf{C}^h.\theta_1 + \varepsilon_{i.r.t} \qquad (1)$$

where $P_{r,t}^{h}$ is the *assigned-percentile* of household *h* living in district *r* in year *t*, *c* denotes a constant, f_r is district fixed effect, f_t is a time fixed effect, $\mathbf{A}^h$ is vector of household assets for household *h*, $\mathbf{D}^h$ is vector of household demographic related variables of household *h*, $\mathbf{E}^h$ is vector of educational outcomes of household *h*, $\mathbf{L}^h$ is vector of labour market outcomes of household *h*, $\mathbf{C}^h$ is a vector of household specific variables, and $\varepsilon_{i,r,t}$ denotes the error. Our parameters of interest are *γ, β, α, δ* and *θ*.

As stated earlier, these characteristics and poverty ranking are likely to be endogenous. We aim to minimize this issue in the following manner. First, we include the actual *yhat* score that was used to generate the percentile in each wave of UDB. The actual *yhat* scores are generated using a proxy means test approach that exploits rich characteristics of individual, household and even geographical conditions. In doing this, we aim to control the possible correlation between the proposed characteristics and the characteristics used to generate the *yhat.* Second, we control for the possible uniform time effects and district fixed effects. In this step we aim to control for the possible correlation our proposed characteristics with the time varying factor constant across districts and the unique characteristics in each district that is constant across time. Third, to further ameliorate the omitted variable problem, we estimate the correlation by utilising the panel setting and employ several standard methods on them such as simple pool OLS, fixed effects, and first difference models. Four, to account for possible heterogeneity at district level, we estimate the models for each district separately and then present the summary statistics of each parameter in all the districts. Lastly, we estimate all the specifications for each possible transition matrix: always poor, falling into poverty, moving out of poverty, and never poor.

4.2 Unstandardised Result

4.2.1 Results from Simple Pooled Data

We now start with the most restrictive specification of model (1) by estimating it in pooled data setting. The simple difference of the summary statistics between the two periods are shown in Table 4. Most variables show positive change, the biggest change is seen in motorcycle ownership which means that, on average, there are more households owning motorcycles but fewer are owning bicycles. Table 5 presents estimates of specification (1) for two UDBs using the simple Pooled OLS method. Column 1 presents the estimated results control for the actual *yhat* score and time fixed effects. In Column (2) we try to correct the standard error while in Column (3) we estimate the model by including district fixed effects. Table 6 puts estimates of specification (1) by poverty transition while Table 7 summarises the estimates of each coefficient of interest when we split the estimation to each district separately.

Education

Households with higher average years of education among its members display a higher welfare ranking. The coefficients for the indicator variable of years of education, as seen in table 5, are positive and statistically significant. The suggested correlation is that every extra one year of education increased a household's ranking by a 1.03 to 1.04 percentile. We also include three additional binary variables at the head of household level as a proxy for human capital: whether they completed at least a primary, junior secondary, or senior secondary school education. As expected, the correlations between human capital and percentile, as proxied by the head of household's level of education, are positive and significant for an education level greater than primary.

When we split the households' panel into their respective poverty transition, we infer the same conclusion– that more education has a positive correlation with welfare ranking. We estimate the correlation using simple pool data with correction in standard errors. The coefficient correlation of average years of education for households that are always poor is lowest compared to households that fell into poverty, let alone households that are never poor. The coefficient correlation is almost one-tenth of those ranked as never poor. From the same table, we also find that households whose head completed at least a senior secondary education have, on average, a better welfare ranking by about five percentage points, when we compare all the three categories (always poor, fell into poverty and moved out) with the never poor.

Our last attempt to picture the correlation between household's human capital and household's percentile is to estimate the specification for each district independently. This approach aims to answer heterogeneity concerns that might arise, since the percentiles from both PPLS 2011 and BDT 2015 are generated at district level. The results for this approach are summarized in Table 7. First, we estimate model (1) for each district. Second, we compare the parameters of interest in each district. Third, we calculate the summary statistics of those variables as presented in Table 7. How should we interpret the results from this exercise? The average coefficient correlations between heads who completed at least senior secondary and household percentile is around 0.2 with a standard deviation of 2.34. The findings on the positive correlation between education and moving out to a better welfare position are aligned with what is known about the effect of human capital on welfare.

Demographics

The number of adults in a household and the presence of expectant mothers are important characteristics that could determine a household's financial position. Clearly, when grouped into different poverty status, they show visible characteristics. The number of adults in a household seems to correlate negatively with household rankings. The coefficient shows that an extra adult lowers the rank down by three percentiles (Table 5). The presence of expectant mothers, on the other hand, correlates positively when district fixed effect is not controlled–when a household has a pregnant woman, the rank increases by 0.034 percentile. The negative correlation when district fixed effect is controlled shows that, at the district level, there are unobserved characteristics captured which caused the rank to be lower.

The number of adults is seen to be positively correlated amongst households that moved out of poverty–indicating that these households benefited most by having more adults compared to the other groups. The never-poor household, in contrast, would be much lower in rankings if they had more adults in their households. In other words, amongst the never-poor, an extra adult decreases their percentile by 2.3 percentage points compared to the never-poor households that do not have extra adults (Table 6). This confirms the OLS findings that the more adults, the lower the rank. Moreover, the expectant mothers' correlation seems to be less across all groups except those who fell into poverty. Amongst households who fell into poverty, therefore, expectant mothers seem to have a 0.7 points correlation to the rankings, almost oppositely mirroring those categorised as never poor.

The summary statistics from estimating the district-specific show that the number of adults in a household, on average, correlates negatively with household rankings, more than the coefficient of the presence of expectant mothers. The average coefficient correlation is −0.342 for the former and −0.058 for the latter (Table 7).

Assets

Assets are often seen to be highly correlated with welfare. Asset ownership is estimated using physical assets as a proxy. Physical assets–such as bicycle, motorcycle, and refrigerator–that can potentially help households to improve their welfare rank are included in the set of variables.

We see that bicycle ownership lowers ranking by 1.83 percentiles, however, using district fixed effect could increase the estimate, making it 0.815 (Table 5). Motorcycle and refrigerator ownership, in contrast, show a highly positive correlation across the estimation methods–11.7 higher percentiles for those owning motorcycles, and 12.08 percentiles for refrigerator ownership.

The poverty transition further shows that all asset ownership is positive across transition groups, as seen in table 6. Within the never-poor households, asset ownership helps increase rankings more than the rest. For example, bicycle ownership helps the never-poor increase in rank by 0.45, while it only helps the always-poor by 0.047. The same can be said about motorcycle and refrigerator ownership. In this case, the never-poor benefit more by having assets.

The average coefficient correlation to household ranking is only positive for motorcycle ownership–that is 1.79 with a standard deviation of around 3.37 (Table 7). The bicycle and refrigerator ownership correlation, on average, is −0.058 and −1.633 respectively.

Labour Market Outcomes

The number of working adults and the number of adults working in a formal job within a household are chosen to represent participation in the labour market. These factors correlate with household ranking because both are related to a household's income. Regression analysis shows the correlation is negative for the former, and positive for the latter.

There is a persistent pattern on the negative correlation between the number of working adults and household ranking (Table 6). Never-poor households apparently have the lowest coefficient correlation, which means that, within the never-poor, more adults working may decrease their ranking. This could be due to the type of work–this is unexplained by the data but it may relate to low-quality jobs. Formal sector employment is, therefore, relevant for measurement and is seen in the next row. The number of adults working in the formal sector is positive across transition groups and highest under the never-poor households. In other words, formal-sector jobs help the never-poor most in terms of increasing their welfare rank.

4.2.2 Results from Panel Data

Results from the above pool OLS may still suffer from the omitted variables bias problem. One way to minimise this is by estimating model (1) in utilising the panel setting of the UDB data. Table 8 summarizes our findings from panel setting. One should bear in mind that non-random attrition of households between PPLS 2011 and BDT 2015 may bias our estimates of the correlates.

Education

The average years of education in the panel result in table 8 is relatively still consistent with OLS. An extra year of education can increase a household's ranking around 0.95 to 1.04 percentile. Completing at least a junior secondary education also has a positive correlation with the ranking.

Looking closely at each transition level, there is a strong correlation between years of education and household rank amongst the never-poor. It helps increase their rank by 0.954 percentage points, while it only helps the always poor by 0.04 percentage points (Table 9) . Even compared to the transient poor, the always-poor have the lowest correlation coefficient.

Demographics

The number of adults in a household seems to correlate negatively with the ranking, by a magnitude of around 2.8 to 3 percentiles (Table 8). The presence of expectant mothers increase rankings by 2.48, higher than the OLS result, while using district fixed effect results in a statistically insignificant coefficient.

When compared between transitions, the number of adults correlates negatively with household rankings. An extra adult in a household would move their ranking down by 0.19 to 2.54 percentage points (Table 9). In contrast, the presence of expectant mothers is positively correlated by 0.09 to 2.68 across the various types of household.

Asset

Asset ownership is seen to be positively correlated across household types. Owning a motorcycle and refrigerator still seems to have a relatively high coefficient correlation, compared to bicycle ownership, however, all assets seem statistically insignificant under the district fixed effect (Table 8). In the second column, if district fixed effect is not controlled, the magnitude is around 5.379 for refrigerator. Compared to OLS, the results are more statistically significant, even if magnitudes are lower.

When split into the different types of transition groups, all assets are statistically significant. The coefficient correlation of refrigerator ownership is highest in magnitude compared to all other assets for the never-poor and those who moved out of poverty (Table 9). Compared to other groups, asset ownership seems to help the never-poor more than others in terms of welfare.

Labour Market Outcomes

The number of working adults still correlates negatively with household ranking when standard error is not clustered (Table 8). Similar to OLS results, the magnitude is up to -3.4 and is statistically significant without clustered standard error and district fixed effect. When standard error is clustered, it increases rankings up to 0.9 percentile. The number of adults working in the formal sector is positively correlated and still only statistically significant if district level fixed effect is not added.

The poverty transition table also shows a negative correlation across groups within the always-poor and those that fell into poverty and is lowest within those that fell into poverty (Table 9). The number of adults working in the formal sector is positive across groups. Within the never-poor households, an extra adult working in the formal sector could increase their ranking by up to 1.19 percentage points. The magnitude is only 0.16 for the always-poor.

4.2.3 Results from First Difference

As with the panel regression, first difference estimation aims to control for time-invariant heterogeneity amongst districts. Coefficients should be similar to fixed effect estimation in the previous section when there are only two periods. Here, column (1) in table 10 performs a first difference without district fixed effect, while column (2) uses fixed effect.

Education

The average years of education is similar in columns (1) and (2) –an extra year of education would increase household ranking by 0.953 to 0.967 percentile. Household heads who have completed junior and senior secondary school also looks important for the ranking–most importantly for heads who have completed at least senior secondary because it could increase rankings by 3.5 percentile.

The poverty transitions picture shows that education mostly helps the never-poor to increase their rankings. Within the never-poor households, average years of education correlates strongly, around 1 percentage point, to the household rankings, while, within the always-poor, the average years of education only correlates by 0.021 percentage points (Table 11). Similarly, heads that completed senior high school have a 3.4 percentage points correlation within the never-poor. It means that completing senior secondary school helps the never-poor to move up the rank compared to the never-poor that did not complete senior secondary school.

Demographics

Within the scope of demographics, the number of adults in a household correlates negatively towards rankings**.** An extra adult in a household could decrease their ranking by 2.9 percentile (Table 10). In contrast, the presence of expectant mothers correlate positively by 2.36 to 2.48 and is statistically significant in both estimations.

Diving into poverty transitions, the number of adults correlates more positively to households that fell into poverty. Within households that fell into poverty, the coefficient correlation is 0.428, strongest compared to the rest of the groups (Table 11). The coefficient is lowest within the never-poor households which means that, within this group, those with more adults are 2.887 percentile lower than those never-poor households without extra adults.

The presence of expectant mothers seems to be correlated positively across all groups except the ones that fell into poverty. The never-poor households, however, have the highest coefficient correlation of around 2.6, much higher than the panel regression outcome. Expectant mothers, therefore, better correlates with rankings within this transition group. This may capture the possibility that having a pregnant woman in a household is an indication that the never-poor household is more financially sound, compared to their counterpart.

Asset

Asset ownership is positively correlated across all asset types. The coefficient for bicycle ownership is again lowest compared to the other two assets. It increases rankings by only about 0.5 percentile, while motorcycle and refrigerator ownership could increase ranking by 12.26 and 6.59 percentile, respectively (Table 10).

Spread into different transition groups, within the always-poor households owning a motorcycle seems to have the highest coefficient correlation towards rankings, that is 0.387, almost similar to the coefficient of owning a refrigerator **(**Table 11**).** Amongst the transient poor, owning a motorcycle again positively correlates with rankings, more so for the ones who moved out of poverty.

Labour Market Outcomes

Both variables in this category are positively correlated with rankings, and also statistically significant. An extra working adult could increase rankings by 0.93 percentile. Meanwhile, an extra adult working in a formal sector job increases rankings by 1.5 percentile (Table 10).

Within the group that is always poor, the number of working adults in a household correlates negatively with rankings. The coefficient correlations are positive in other groups and strongest amongst the never-poor, which means that more adults working contributes to better welfare for the household except for the never-poor. Amongst the transient poor, the coefficient is higher within the households who moved out of poverty. The number of adults working in formal sector jobs has the highest correlation amongst the never-poor, and lowest amongst those who fell into poverty.

4.3 Standardised Result

In this section, we want to determine whether the correlation between observed characteristics and their welfare rank is sensitive to the PMT specifications used to generate the predicted per capita expenditure**.** We use two different scenarios for this purpose. The first scenario (Scenario A) uses the existing *yhat* obtained from PPLS 2011 and BDT 2015 (the actual *yhat*). As noted in the appendix, both have different variable sets to estimate PMT. Because we try to find out what would happen if we standardise the variables, we create the second scenario (Scenario B) that unifies the characteristics used in both data sets and generate our own *yhat* using the same specification as equation (1). We then rank them using the existing quota. To do this, we do the following steps:

1. We synchronize the Susenas data set between 2010-2014. PPLS 2011 relies on Susenas 2010
2. and 2011 to estimate their PMT model, while BDT 2015 uses Susenas 2011 to 2014.
3. Both PPLS 2011 and BDT 2015, estimate their PMT models at the district level. We design our PMT model for 50 selected districts (list of districts are available upon request). Further, we perform a similar, as carried out by the PPLS and the BDT, stepwise approach to find the optimal PMT model
4. We use the coefficients obtained from step (2) to estimate households' *yhat* for both panel households of PPLS 2011 and BDT 2015.

5. We then combine this *yhat* with the existing 40 percent household quota for the 50 districts directly adopted from PPLS 2011 and BDT 2015 quota.
6. Lastly, the outcome is associated with the percentile ranks.

Out of the 10 percentiles used in the regression, we grouped them into four categories: the always-poor; transient poor; and the never-poor. The first category consists of the lowest decile, that is the group that is always poor (poor in both periods), while the second and third categories are the transient poor, those who move out and fall back into poverty. They live close to the poverty line, therefore, easily entering and exiting poverty, depending on the circumstances. The fourth decile and above are grouped into the never-poor, they were neither poor in 2011 nor in 2015. Table 12 highlights the summary statistics of these selected characteristics, evaluated at the means, for all these groups. Similarly, we further perform ordinary least square, panel, and first difference regression. In each regression table we try to compare the magnitude between the two different scenarios. This may be due to the different PMT models used to generate the *yhat* or driven by the correlates. The difference in correlates between 2011 and 2015 (Table 13) confirms that, regardless of the model, changes are apparent. By isolating the effect of the models, Scenario B provides evidence of the correlates between each variable and household rank, controlling for the same methods to generate *yhat.*

Similar to the previous section, we first observe the poverty dynamics of our data set. This time, we present two scenarios. Figure 3 and 4 represent scenario A, while figure 5 and 6 represent scenario B. In scenario A the proportion of households living in decile 1 decreases. Out of those living in decile 1 in 2011, almost 50 percent of them still lives in decile 1 in 2015, while the rest moved up the ladder. In contrast, out of those living above decile 4 in 2011, just about 10 percent of them fell back into decile 1 in 2015. Similarly, when divided into percentiles, the proportions of households living in the first percentile are relatively stagnant throughout the years.

4.3.1 Results from Simple Pool Data

We first run a simple pooled OLS regression model, with and without district cluster, controlling for *yhat* score and year dummy (Table 14). We then provide a detailed poverty transition using both percentiles as dependent variables. Table 15 shows household characteristics by poverty transitions using Scenario A, and Table 16 uses Scenario B. Table 17 shows summary statistics between districts.

Education

Table 14 shows that there is a relatively wide difference between both scenarios for education. A one year increase in education attainment increased household rankings by 1.17 percentiles in Scenario A, whereas only 0.108 in Scenario B. Household heads who completed at least senior secondary schooling are also seen to be able to move up the rank. Although the magnitude differs, it displays a positive sign.

Breaking down the poverty transition clustered by district using Scenario A, those who moved out of poverty and the never-poor have higher average years of education correlation compared to the always-poor or those who fell into poverty (Table 15). Moreover, completing at least senior secondary school is also seen to be highly correlated with better status within these groups. Scenario B (Table 16) shows that the most statistically significant correlate is household head's senior secondary school completion. It correlates positively within households that fell into poverty and the never-poor.

The average coefficients of correlation differs slightly between districts for the two scenarios (Table 17). Furthermore, the correlation between primary and junior secondary completion is negative on the household percentile level. In other words, on average, those households with heads who have completed schooling up to junior secondary level are associated with lower ranks. When they complete senior secondary school, however, the average coefficient correlation to the rank becomes positive, and are both more than 1. Completing senior high school, therefore, correlates highly with household percentile rank.

Demographics

Under the OLS result, there appears to be a negative correlation between the number of adults and household rank. All other things being constant, comparing the two households with the same characteristics, an extra adult in a household would decrease rankings up to 6 percentiles in Scenario B (Table 14). In other words, the more adults, the less likely they escape poverty because there is a higher burden compared to households with fewer adults. The coefficient of the presence of expectant mothers is positive in Scenario B, but negative in Scenario A. Isolating the effect of PMT models might, therefore, contribute to this difference.

The correlation between the number of adults to household ranking is positive within the always-poor and households that moved out of poverty (Table 15). In contrast, the presence of expectant mothers are not seen to have a statistically significant correlation, at least in Scenario A. In Scenario B, however, the correlates are positive and statistically significant within several groups (Table 16). Furthermore, the number of adults in a household is negative across all transition groups and lowest within the never-poor.

The summary statistics table shows that, between districts, the average coefficient correlation between the number of adults and household rank differs in magnitude between the two scenarios, but both correlate negatively (Table 17). Thus, in poor households, the more adults, the less they are able to help themselves. This might be counter-intuitive and can only be explained by examining their employment status, quality of work or the level of wage they receive. The average coefficient of the presence of expectant mothers differs quite a lot between the two scenarios.

Asset

Bicycle ownership negatively correlates with household rank in both scenarios (Table 14). When a household owns a bicycle, they could be 1.39 to 2.3 percentiles lower than households that do not own a bicycle. On the other hand, the coefficients are highly positive for motorcycle and refrigerator ownership.

Looking at the poverty transitions, motorcycle ownership seems to correlate highly positively amongst those who moved out of poverty and the never-poor, while refrigerator ownership only correlates positively within the never-poor (Table 15). Under Scenario B (Table 16), motorcycle and refrigerator ownership is better correlated across groups. Refrigerator ownership, in particular, greatly affects ranking within the never-poor, by up to 7 percentage points, but only around 3 percentage points for the transient poor. Summary statistics (Table 17) between districts makes clear that the average coefficient correlation between having assets and household rankings are positive, particularly under Scenario B.

Labour Market Outcomes

Employment and working status may correlate with household ranks–as previously stated, the quality of work and wage contributes to whether or not a household can escape poverty. The number of working adults correlates negatively to their household percentile ranks (Table 14). For example, under Scenario A, an extra working adult is associated with a 5.7 lower percentile, and even lower under Scenario B. This is in line with the previous result on demographics that the more adults in a household, the less likely they are able to escape poverty. The type of job may contribute to the reasons why this is the case. Looking at the next row, the number of adults working in the formal sector may still correlate negatively to the ranks, but it contributes more towards moving up the ranks than the number of working adults.

When broken down into transition groups, the number of working adults amongst households that are never poor correlates negatively by about 3.7 percentage points (Table 15). Formal job sector also do not appear to have positive correlation. Scenario B shows consistent trend for both variables (Table 16). On average, working in the formal sector positively correlates with household rankings between districts in both scenarios (Table 17), however, the number of working adults still appears to be correlated negatively–more so under Scenario B. Therefore, the number of working adults may not be as important in moving them up the ranks as working in the formal sector.

4.3.2 Results from Panel Data

As with results in the previous section, here we perform a panel regression analysis to take attrition into account. Furthermore, we also complement the estimation using fixed effect to control for time-invariant unobserved heterogeneity. The same set of characteristics are estimated following the same households in the second survey period. We discuss how each set of categories differs between the two percentile scenarios. Table 18 shows the general panel regression result, indicating the two scenarios and whether or not fixed effect is used. Tables 19 and 20 show the breakdown of transition levels using Scenarios A and B while controlling for fixed effect.

Education

The results for the trend in education coefficients are similar to the OLS result. In Scenario A, more years of schooling increase the household percentile level to about 1.16 when panel fixed effect is controlled. In line with previous findings, heads who completed lower than senior secondary schooling do not correlate much with moving up the household welfare ranks. A smaller magnitude is seen when PMT effect is controlled. Nevertheless, both scenarios are persistent in showing positive and statistically significant findings for these two particular characteristics under the education category. Poor households have the least correlates towards education endowment, both in terms of years of education, and the level of schooling, even when PMT effect is controlled, because the same pattern can be seen in Tables 19 and 20.

Demographics

There is an interesting change in demographics under Scenario A where the sign and magnitude differs significantly with OLS for the presence of an expectant mother (Table 18). Furthermore, Scenario B displays a higher magnitude. When a pregnant woman lives in a certain household, that household is likely to be 4.2 percentile higher in ranking than those without pregnant women.

The number of adults living in a household has a persistently negative correlation to the rankings–this finding is also consistent with the OLS result. Splitting into poverty transitions, we see that in both scenarios, the richer a household is, the more negative they correlate with the number of adults. On the other hand, the richer a household is, the more positive they correlate with the presence of an expectant mother.

Asset

Asset characteristics are also somewhat consistent with OLS findings–bicycle ownership is associated with lower household rankings, while motorcycle and refrigerator ownership are associated with higher rankings. Magnitudes, in general, are biggest compared to other categories, showing how much their ability to buy or afford certain things links to their poverty status. Clearer evidence is shown under different poverty transition groups. Motorcycles, and refrigerator ownership especially, correlates highly positively with those who moved out of poverty and the never-poor but not so much for the poor.

Labour Market Outcomes

Several modest differences are seen when comparing with the previous OLS result (Table 18). The number of working adults still displays a negative correlation, except under Scenario A with fixed effect, although this is quite small. Interestingly, the number of adults working in the formal sector becomes positive in both scenarios when fixed effect is controlled, which means that the type of job may actually matter to raising the welfare rank, not just whether or not they work.

The number of working adults is only negative within the always-poor (Table 19), however, in Scenario B it becomes negative across all groups (Table 20) so the effect of PMT modelling might be strong here. Moreover, working in a formal job is seen to be correlated negatively under Scenario A but positively under Scenario B, except for those who fell into poverty. Only those who fell into poverty seem to not be having strong correlates with labour market outcomes.

4.3.3 Results from First Difference

First difference estimation is used to control characteristics that do not change over time, similar to fixed effect. When there are two periods, as in our case, fixed effect and first difference estimation would yield the same results, however, it is more efficient than fixed effect when the change in the error term is uncorrelated (Wooldridge, 2010). Table 21 displays the general first difference result for both scenarios. Table 22 shows the poverty transitions using Scenario A, and lastly Table 23 uses Scenario B.

Education

When compared between OLS, panel regression, and first difference, we see consistent results. There is a positive correlation between average years of schooling and household head completing at least senior secondary and household ranking. Scenario B in table 21 have smaller magnitude than Scenario A, although signs are both positive. Furthermore, the never-poor are seen to benefit more than the rest on these two characteristics in Scenario A, but not as much under Scenario B (Tables 22 and 23).

Demographics

Demographics also show a consistent trend between the three estimations. The number of adults persistently correlates negatively with household rank. The magnitude does not differ much across estimations. The coefficient of the presence of expectant mother is higher in first difference and fixed effect model than OLS which may imply that there is unobserved heterogeneity captured in this case. Splitting into poverty transitions, it also appears that both scenarios have similar trends.

Asset

All three types of asset ownership show a positive correlation towards household ranking, with motorcycle ownership having the highest coefficient correlates (Table 21). When split into different transition groups, motorcycle ownership very much favours the never-poor. Their ranking could be about 10 percentage points higher than their counterparts who do not own motorcycles under Scenario B. The magnitude is only about 1 percentage point within the always-poor.

Labour Market Outcomes

Both coefficients show a consistent result with the fixed effect model. The number of working adults is only negative under Scenario B, and positive under Scenario A, while the formal sector coefficient is positive in both. Looking at the poverty transition tables, the number of working adults is mostly positive under Scenario A, but negative under Scenario B, while the number of adults working in the formal sector has a mostly positive correlation under Scenario B.

Section Five:

Conclusion

Using Indonesia's UDB, this paper analyses longitudinal patterns of relative poverty among the bottom 40 percent group of the Indonesian population. In doing so, this study aims to better understand why households move into and out of poverty.

The results from simple transition matrix show that, over the course of four years, we see slight mobility: 11 percent of UDB households were considered poor in both periods, 14 percent moved out of poverty, and 16 percent fell into poverty. There is a difference of 2 percent. Policy makers and researchers need to take these numbers with a grain of salt for they can often obscure the important poverty mobility due to attrition.

To observe how household characteristics correlate with welfare ranking, we proceed using two approaches, observe the correlation using the existing welfare measure, generated using two PMT models, and generating our own PMT model to create our own welfare measure which latter used to identify the correlation between the examined characteristics and the new welfare metric. We found that, in general, results are lower in magnitude than the existing model, however, trends are consistent across models and groups.

On the household human capital characteristic, we find that the more education that each household member earned, the more likely they help their households to move out of poverty. While this finding reiterates the importance of education in helping people to move out of poverty, the exact interpretation is hard to determine due to the fact that education is seen to be endogenous to long-term poverty changes.

While we see no clear pattern on the correlation between sets of demographic variables and the household welfare change, the correlation between physical assets with changes in welfare rank seems to be consistent across different specifications. Interestingly, we find that households who own a motorcycle and refrigerator are more likely to escape the poor condition. High-quality jobs are expected to help people move from poverty in a more profound way. It is, therefore, not out of the realm of the two variables that we choose to represent the labour market outcomes. Moreover, the number of adults working in the formal sector is seen to have a stronger positive correlation with the households' welfare chang

Appendix: PMT in the UDBs

One crucial issue when using welfare status in the UDBs is the different model that is being used to estimate it. The two UDBs, PPLS 2011 and BDT 2015, use the same PMT approach but the exact model to produce the welfare is different. Suppose the following general model is used to estimate real per capita expenditure in PMT 2011:

$$\boldsymbol{W}_{i,r,p,2011} = a_{2011} + \boldsymbol{X}'_{i,r,p,2011/2015} \cdot b_{2011} + \boldsymbol{S}'_{i,r,p,2011} \cdot c_{2011} + e_{i,r,p,2011} \quad \textbf{(2)}$$

where $\boldsymbol{X}'_{i,r,p,2011/2015}$ denotes vector of variables used in PMT 2011 and available in PMT 2015 and $\boldsymbol{S}'_{i,r,p,2011}$ represents vector of variables specific in PMT 2011.

Following the estimate of real per capita expenditure for the households in the UDB, the next step is constructing the *relative* ranking of households. In general household *i* relative ranking can be expressed as follows.

$$\boldsymbol{P}_{i,r,p,2011} = \boldsymbol{G}(\boldsymbol{w}_{Wi,r,p,2011,}\ \mathbf{W}_{-\ i,r,p,2011,}\ \mathbf{C}_{\mathbf{r},p,2011}) \quad \textbf{(3)}$$

where $\mathbf{P}_{i,r,p,2011}$ denotes percentile of household i live in region r province p at year 2011. Thus household *i* percentile ranking is a function of its estimated real per capita expenditure, other households in the same region estimated real per capita expenditure, and vector of regional characteristics.

While to estimate the real per capita expenditure in PMT 2015, the following model is used:

$$\boldsymbol{W}_{i,r,p,2015} = a_{2015} + \boldsymbol{X}'_{,r,p,2015} \cdot b_{2015} + \boldsymbol{Z}'_{i,r,p,2015} \cdot c_{2015} + e_{i,r,p,2015} \quad \textbf{(4)}$$

where $\boldsymbol{X}'_{i,r,p,2011/2015}$ denotes vector of variables used in PMT 2011 and available in PMT 2015 and $\boldsymbol{S}'_{i,r,p,2015}$ represents vector of variables specific in PMT 2015.

Subtracting (4) from (2) we get:

$$\begin{aligned}\boldsymbol{W}_{i,r,p,2015} - \boldsymbol{W}_{i,r,p,2011} = {} & a_{2015} - a_{2011} + \boldsymbol{X}'_{i,r,p,2015} \cdot b_{2015} - \boldsymbol{X}'_{i,r,p,2011} \cdot b_{2011} \\ & + \boldsymbol{Z}'_{,r,p,2015} \cdot c_{2015} - \boldsymbol{S}_{ti,r,p,2011} \cdot c_{2011} + e_{i,r,p,2015} - e_{i,r,p,2011}\end{aligned} \quad \textbf{(5)}$$

The change in welfare status is, therefore, induced by change in the intercept, change in vector of variables used both in PMT 2011 and PMT 2015, change in the slopes of $\boldsymbol{X}'_{2011/2015}$, change in the specific variables, $\boldsymbol{Z}'$ and $\boldsymbol{S}'$, and change in the slopes of those specific variables.

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Table 1. Absolute and Relative Poverty Line

Absolute Poverty Line	Relative Poverty Line
Aims to have the same purchasing power, irrespective of the country and time.	Set at a constant proportion of the current mean or median income.
When incomes grow at the same proportionate rate, the absolute poverty line fails because measures should be homogenous of degree 0 between the mean and the poverty line.	People may attach value to their income relative to the mean in their country of residence, thus relative income is a source of utility.
Aggregate poverty increases when poverty increases in any subgroup and does not change for any other group.	Social inclusion should be considered and that the cost of social inclusion is proportional to the mean income.
Moving a person between groups with no absolute loss to own consumption, cannot increase aggregate poverty.	

Ravallion and Chen (2011)

Table 2. Literature Review

Author	Sample	Method	Findings
Sumner et al. (2014)	IFLS 2000 & 2007 and Susenas 2000 - 2013	IFLS 2000 & 2007 and Susenas 2000 - 2013	Their findings show that: 1. Determinants of the probability of a household staying poor are education and asset ownership. 2. In the case of transient poverty, when one defines security from poverty as a 10 percent chance of being poor in the future, at poverty lines of US$2.00, US$4.00 and US$5.00 PPP/day, one has to double the poverty line to get to a security line of US$4.00, US$8.00 or US$13.00 respectively. 3. When the 'national poverty line' is used, large numbers of people have a low probability of remaining poor.
Dartanto & Nurkholis (2013)	Susenas 2005 & 2007	'Spell' approach to identify poverty and ordered probit model to examine the determinants of poverty dynamics.	Their findings show that: 1. The determinants of poverty dynamics in Indonesia are educational attainment, the number of household members, physical assets, employment status, health shocks, the microcredit program, access to electricity, and changes in employment sector, employment status, and the number of household members. 2. 28 percent of poor households are classified as chronically poor (remaining poor in two periods), and 7 percent of non-poor households are vulnerable to being transient poor. 3. Households in Java–Bali are more vulnerable to negative shocks than those outside Java–Bali.

Author	Sample	Method	Findings
Sumner (2012)	Demographic and Health Surveys 1991, 1994, 1997, 2002/3 & 2007	Correlations between education/ health poverty and residence, wealth quintile, and education of household head.	Findings show that: 1. Education poverty has a positive correlation with place of residence and a negative correlation with wealth quintile and education of household head. 2. Health poverty has weaker correlations to place of residence, wealth quintile and household head.
Van Edig & Schwarze (2011)	Randomly selected households in 2005 & 2007 at Lore Lindu National Park.	Multinomial Logit Model	They found that: 1. Higher education increases transitory poverty; non-agricultural employment increases the probability of staying out of poverty, household size is another determinant of poverty. 2. Using two different poverty lines (namely, the US$1.00/day and US$2.00/day) yields the same result, that poverty increased.
Miranti (2010)	Panel Susenas 1984-2002	Fixed Effects	Findings show that: 1. A 10 percent increase in consumption per capita reduces poverty by 24.3 percent. 2. Growth Elasticity of Poverty (GEP) was stable during the three episodes (policy liberalisation, slower liberalisation, and recovery period of the Asian financial crisis) at around -2.37 to -2.49. 3. Inequality elasticity of poverty ranged between 0.78 to 1.30 across the three episodes.

Author	Sample	Method	Findings
Kim et al. (2009)	IFLS 1993 & 1997	Propensity Score Matching	They found that: 1. Equivalence scale greatly affects how having a new-born child highly affects household's welfare. 2. When the equivalence scale used is that food share indicates the inverse of the level of household welfare, then households experience 20-65 percent reduction in consumption of that obtained when per-capita consumption is used as a measure of household consumption. 3. Households with a new-born child between 1993 & 1997 experience about a 20 percent reduction in consumption when per-capita consumption is used as a measure of household consumption.
Widyanti et al. (2009)	IFLS 1993, 1997 & 2000	Foster-Greer-Thorbecke (FGT) to calculate poverty indicators, ordered probit to examine the relationship between household composition and poverty status.	Results show that: 1. The larger the household size, the higher the probability of a household being chronically poor. 2. There is no evidence that households change their compositions (such as sending their children to live with relatives) to cope with poverty and unemployment.

Table 3. Household Correlates by Poverty Transition

Category	**Correlates**	**Always poor**	**Fell into Poverty (nonpoor in 2011, poor in 2015)**	**Moved out of poverty (Poor in 2011, nonpoor in 2015)**	**Always nonpoor**	**Overall mean**
Asset	HH has bicycle	0.233	0.235	0.264	0.432	0.241
	HH has motorcycle	0.215	0.288	0.340	0.293	0.352
	HH has refrigerator	0.036	0.060	0.092	0.070	0.109
Demographics	# Adults in household	3.140	2.888	3.041	2.669	2.778
	Presence of expectant mother	0.030	0.032	0.026	0.024	0.026
Education	Years of education of all members	4.388	4.488	5.122	5.289	5.080
	Mean years of education of adults	4.809	4.867	5.661	5.717	5.521
	Mean years of education of male adults	4.783	5.087	5.711	6.259	5.827
	Head completed primary education	0.731	0.766	0.754	0.784	0.772
	Head completed junior secondary education	0.252	0.288	0.344	0.380	0.355
	Head completed senior secondary education	0.175	0.200	0.215	0.257	0.236
Labour market outcome	# Adults working	0.860	0.830	0.819	0.792	0.780
	# Adults work in formal sector	0.148	0.159	0.152	0.168	0.161

Table 4. Summary Statistics: Difference Between 2011 and 2015

Correlates	Difference	Std. Deviation	Min	Max
HH has bicycle	-0.019	0.432	-1	1
HH has motorcycle	0.214	0.536	-1	1
HH has refrigerator	0.115	0.371	-1	1
# Adults in household	-0.0458	1.198	-19	18
Presence of expectant mother	-0.001	0.225	-5	6
Average years of education	0.139	3.667	-23	23
Head completed at least primary education	0.014	0.518	-1	1
Head completed at least junior secondary education	0.024	0.507	-1	1
Head completed at least senior secondary education	0.010	0.454	-1	1
# Adults working	-0.027	0.468	-1	1
# Adult working in formal sector	-0.004	0.454	-1	1

Table 5. Correlates of Households Ranking: Pooled OLS

Correlates	Dependent Variable: Percentile in UDB		
	(1)	(2)	(3)
Education			
Average years of education	1.042 (0.001)	1.042 (0.047)	1.035 (0.001)
HH head completed at least primary education	-5.972 (0.012)	-5.972 (0.276)	-5.536 (0.011)
HH head completed at least junior secondary education	1.185 (0.012)	1.185 (0.250)	1.237 (0.012)
HH head completed at least senior secondary education	5.673 (0.014)	5.673 (0.279)	5.805 (0.014)
Demographics			
# Adults in household	-2.759 (0.002)	-2.759 (0.172)	-3.022 (0.002)
Presence of expectant mother	0.034 (0.022)	0.034 (0.194)	-0.967 (0.021)
Assets			
Household owns bicycle	-1.838 (0.009)	-1.838 (0.404)	0.815 (0.009)
Household owns motorcycle	10.541 (0.008)	10.54 (0.331)	11.679 (0.008)
Household owns refrigerator	11.213 (0.012)	11.213 (0.450)	12.085 (0.012)
Labour Market Outcome			
# Adults working	-3.892 (0.009)	-3.892 (0.344)	-4.588 (0.009)
# Adults working in formal sector	0.111 (0.010)	0.111 (0.338)	1.091 (0.010)
Other Controls			
Social protection coverage	Yes	Yes	Yes
Actual yhat score	Yes	Yes	Yes
District fixed effect	No	No	Yes
Time fixed effect	Yes	Yes	Yes
Clustered Standard Error	No	Yes	No
Number of observations	40,529,166	40,529,166	40,529,166

Table 6. Correlates of Household Welfare Ranking by Poverty Transition

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.022 (45.95)**	0.079 (32.76)**	0.348 (274.97)**	0.959 (571.27)**
HH head completed at least primary education	-0.205 (59.84)**	-0.290 (14.97)**	-2.197 (202.84)**	-5.141 (320.51)**
HH head completed at least junior secondary education	0.117 (32.86)**	0.089 (4.37)**	1.042 (96.86)**	0.641 (40.19)**
HH head completed at least senior secondary education	0.050 (10.13)**	0.278 (10.82)**	1.623 (127.07)**	4.804 (279.93)**
# Adults in household	-0.085 (120.38)**	-0.160 (34.20)**	0.008 (3.23)**	-2.335 (546.14)**
Presence of expectant mother	-0.047 (9.55)**	0.700 (23.74)**	-0.363 (18.42)**	-0.717 (23.19)**
Household owns bicycle	0.047 (20.39)**	0.062 (4.42)**	0.321 (37.96)**	0.450 (34.51)**
Household owns motorcycle	0.500 (219.15)**	2.209 (174.54)	2.218 (271.57)**	9.984 (865.86)**
Household owns refrigerator	0.630 (130.62)**	1.453 (60.35)**	5.461 (451.37)**	10.459 (672.93)**
# Adults working	-0.159 (61.61)**	-0.359 (24.15)**	-1.089 (123.04)**	-3.623 (288.18)**
# Adults working in formal sector	0.086 (34.18)**	0.270 (17.72)**	0.275 (29.56)**	1.070 (77.88)**
Number of observations	4,421,400	6,400,208	5,766,064	23,941,494
R^2	0.50	0.66	0.60	0.19

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 7. Summary Statistics of Estimated Parameters

Correlates	Mean	Standard Deviation	Minimum	Maximum
Education				
Average years of education	0.016	0.365	-1.261	2.198
HH head completed at least primary education	0.085	2.017	-12.589	6.662
HH head completed at least junior secondary education	-0.002	1.739	-5.826	12.514
HH head completed at least senior secondary education	0.213	2.342	-14.234	11.404
Demographics				
# Adults in household	-0.342	1.105	-7.118	2.096
Presence of expectant mother	-0.058	1.227	-11.645	4.168
Asset				
Household owns bicycle	-0.058	2.013	-13.735	10.378
Household owns motorcycle	1.790	3.371	-11.371	22.887
Household owns refrigerator	-1.633	5.967	-21.050	22.377
Labour Market Outcome				
# Adults working	-0.376	2.289	-12.237	12.348
# Adults working in formal sector	0.444	2.414	-18.978	18.268

Table 8. Correlates of Households Ranking: Panel Results

Correlates	Dependent Variable: Percentile in UDB		
	(1)	(2)	(3)
Education			
Average years of education	1.040 (780.85)**	0.953 (382.00)**	1.035 (0.001)
HH head completed at least primary education	-5.764 (478.95)**	-3.487 (186.47)**	-5.536 (0.011)
HH head completed at least junior secondary education	1.215 (96.87)**	1.314 (68.20)**	1.237 (0.012)
HH head completed at least senior secondary education	5.589 (393.32)**	3.417 (148.89)**	5.805 (0.014)
Demographics			
# Adults in household	-2.816 (927.98)**	-2.938 (538.57)**	-3.022 (0.002)
Presence of expectant mother	0.386 (17.55)**	2.486 (87.54)**	-0.967 (0.021)
Assets			
Household owns bicycle	-1.734 (198.42)**	0.549 (37.04)**	0.815 (0.009)
Household owns motorcycle	10.791 (1,290.65)**	11.901 (975.74)**	11.679 (0.008)
Household owns refrigerator	10.690 (868.42)**	5.379 (307.71)	12.085 (0.012)
Labour Market Outcome			
# Adults working	-3.415 (357.40)**	0.934 (66.09)**	-4.588 (0.009)
# Adults working in formal job	0.278 (27.46)**	1.132 (79.31)**	1.09 (0.010)
Other Controls			
Social protection coverage	Yes	Yes	Yes
Actual yhat score	Yes	Yes	Yes
District fixed effect	No	No	Yes
Time fixed effect	Yes	Yes	Yes
Clustered Standard Error	No	Yes	No
Number of observations	40,529,166	40,529,166	40,529,166
R^2	0.13	0.18	

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 9. Correlates of Household Welfare Ranking by Poverty Transition

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.040 (40.94)**	0.223 (44.61)**	0.463(181.09)**	0.954 (281.92)**
HH head completed at least primary education	-0.228 (35.16)**	-0.941 (26.37)**	-2.525 (134.79)**	-3.706 (141.39)**
HH head completed at least junior secondary education	0.102 (15.17)**	0.167 (4.51)**	0.824 (43.03)**	1.218 (45.86)**
HH head completed at least senior secondary education	0.011 (1.19)	0.997 (20.64)**	2.098 (89.39)**	3.171 (104.54)**
# Adults in household	-0.199 (128.73)**	-0.788 (77.22)**	-0.649 (133.85)**	-2.544 (309.21)**
Presence of expectant mother	0.097 (12.66)**	1.162(25.46)**	0.407 (13.96)**	2.681 (63.58)**
Household owns bicycle	-0.017 (3.95)**	0.109 (4.14)**	0.318 (21.47)**	0.578 (27.43)**
Household owns motorcycle	0.702 (183.49)**	3.782 (171.77)**	2.408 (191.64)**	11.580 (661.45)**
Household owns refrigerator	0.879 (113.62)**	2.437 (60.36)**	5.526 (306.63)**	5.115 (224.97)**
# Adults working	-0.02 4(5.49)**	-0.057 (2.22)*	0.162 (11.05)**	0.723 (36.91)**
# Adults working in formal sector job	0.164 (39.04)**	0.430 (17.15)**	0.308 (20.87)**	1.196 (59.15)**
R^2	0.39	0.69	0.72	0.21
Number of observations	4,421,400	6,400,208	5,766,064	23,941,494

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 10. Correlates of Households Ranking: First Difference Result

Correlates	Dependent Variable: Percentile in UDB	
	(1)	(2)
Education		
Average years of education	0.953 (382.00)**	0.967 (408.62)**
HH head completed at least primary education	-3.487 (186.47)**	-3.707 (208.74)**
HH head completed at least junior secondary education	1.314 (68.20)**	1.227 (67.19)**
HH head completed at least senior secondary education	3.417 (148.89)	3.506 (161.22)**
Demographics		
# Adults in household	-2.938 (538.57)**	-2.975 (574.30)**
Presence of expectant mother	2.486 (87.54)**	2.361 (87.69)
Asset		
Household owns bicycle	0.549 (37.04)**	0.565 (40.06)**
Household owns motorcycle	11.901 (975.74)**	12.262 (1,053.78)**
Household owns refrigerator	5.379 (307.71)**	6.595 (391.73)
Labour Market Outcome		
# Adults working	0.934 (66.09)**	0.755 (56.25)**
# Adults working in formal job	1.132 (79.31)**	1.519 (111.82)**
Other controls		
Social protection coverage	Yes	Yes
Actual yhat score	Yes	Yes
District fixed effect	No	Yes
R2	0.11	0.20
Number of observations	20,178,760	20,178,760

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 11. Correlates of Household Welfare Ranking by Poverty Transition

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.021 (27.18)**	-0.006 (1.48)	0.493 (209.39)**	1.004 (314.89)**
HH head completed at least primary education	-0.181 (35.91)**	0.115(4.20)**	-2.604 (150.85)**	-4.130 (167.22)**
HH head completed at least junior secondary education	0.060 (11.66)**	-0.057 (2.02)*	0.984 (56.02)**	1.225 (49.02)**
HH head completed at least senior secondary education	0.103 (14.03)**	-0.059 (1.59)	2.121 (98.50)**	3.397 (119.02)**
# Adults in household	-0.123 (100.65)**	0.428 (53.62)**	-0.932 (204.42)**	-2.887 (371.48)**
Presence of expectant mother	0.116 (19.72)**	-0.074 (2.13)*	0.541 (20.24)**	2.675(67.40)**
Household owns bicycle	-0.010 (2.84)**	-0.027 (1.33)	0.333 (24.42)**	0.579 (29.10)**
Household owns motorcycle	0.387 (127.39)**	0.446 (25.87)**	3.131 (264.38)**	12.443 (749.53)**
Household owns refrigerator	0.375 (60.26)**	-1.760 (56.24)**	6.170 (359.23)**	6.780 (311.92)**
# Adults working	-0.019 (5.44)**	0.067 (3.40)**	0.115 (8.47)**	0.561 (30.36)**
# Adults working in formal sector job	0.05 1(15.79)**	-0.041 (2.15)*	0.490(36.00)**	1.617 (84.65)**
R^2	0.58	0.66	0.22	0.20
Number of observations	2,191,511	3,185,494	2,862,612	11,939,143

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 12. Household Correlates by Poverty Transition

Category	Correlates	Always Poor	Fell into Poverty (non-poor in 2011, poor in 2015)	Moved out of Poverty (poor in 2011, nonpoor in 2015)	Always Nonpoor	Overall Mean
Asset	Household has bicycle	0.219	0.205	0.239	0.201	0.209
	Household has motorcycle	0.262	0.317	0.358	0.389	0.359
	Household has refrigerator	0.070	0.099	0.143	0.184	0.153
Demographics	# Adults in household	3.458	2.961	3.372	2.605	2.861
	Presence of expectant mother	0.030	0.037	0.025	0.024	0.027
Education	Average years of education	4.580	4.999	4.790	5.237	5.064
	Head completed at least primary education	0.726	0.760	0.746	0.779	0.75
	Head completed at least junior secondary education	0.308	0.350	0.344	0.399	0.374
	Head completed at least senior secondary education	0.183	0.210	0.218	0.262	0.239
Labour Market Outcomes	# Adults working	0.879	0.847	0.810	0.748	0.786
	# Adults working in formal sector	0.196	0.197	0.196	0.198	0.197

Table 13. Summary Statistics: Difference Between 2011 and 2015

Correlates	Difference	Standard Deviation	Minimum	Maximum
Household owns bicycle	-0.014	0.431	-1	1
Household owns motorcycle	0.229	0.545	-1	1
Household owns refrigerator	0.147	0.421	-1	1
# Adults in household	-0.043	1.243	-15	18
Presence of expectant mother	-0.002	0.230	-4	4
Average years of education	0.156	3.741	-23	18
HH head completed at least primary education	0.013	0.517	-1	1
HH head completed at least junior secondary education	0.02	0.499	-1	1
HH head completed at least senior secondary education	0.008	0.448	-1	1
# Adults working	-0.032	0.475	-1	1
# Adults working in formal sector	0.004	0.490	-1	1
Household owns refrigerator	-1.633	5.967	-21.050	22.377
Labour Market Outcome				
# Adults working	-0.376	2.289	-12.237	12.348
# Adults working in formal sector	0.444	2.414	-18.978	18.268

Table 14. Comparison of Correlates on 50 Districts for Two Sets of Percentiles: Pooled Least Square

Correlates	Scenario A		Scenario B	
	(1)	**(2)**	**(3)**	**(4)**
Education				
Average years of education	1.176 (0.003)***	1.176 (0.125)***	0.108 (0.004)***	0.108 (0.124)
HH head completed at least primary education	-5.805 (0.034)***	-5.805 (0.719)***	0.0328 (0.0366)	0.0328 (0.661)
HH head completed at least junior secondary education	0.648 (0.034)***	0.648 (0.613)	-1.68 (0.037) ***	-1.685 (0.766)**
HH head completed at least senior secondary education	7.101 (0.036)***	7.101 (0.915)***	2.673 (0.039)***	2.673 (0.651)***
Demographics				
# Adults in household	-2.199 (0.008)***	-2.199 (0.616)***	-6.275 (0.008)***	-6.275 (0.361)***
Presence of expectant mother	-0.228 (0.0633)***	-0.228 (0.752)	2.215 (0.068)***	2.215 (0.849)
Assets				
Household owns bicycle	-1.391 (0.026)***	-1.391 (1.157)	-2.314 (0.027)***	-2.314 (1.182)*
Household owns motorcycle	10.27 (0.024)***	10.27 (1.201)***	5.668 (0.025)***	5.668 (0.780)***
Household owns refrigerator	10.79 (0.031)***	10.79 (0.943)***	7.219 (0.034)***	7.219 (1.357)***
Labour Market Outcomes				
# Adults working	-5.723 (0.027)***	-5.723 (1.141)***	-6.398 (0.029)***	-6.398 (1.761)**
# Adults working in formal sector	-0.847 (0.027)***	-0.847 (0.927)	-1.054 (0.029)***	-1.054 (1.181)
Other controls				
Social protection coverage	Yes	Yes	Yes	Yes
Yhat score	Yes	Yes	Yes	Yes
District cluster	No	Yes	No	Yes
R^2	0.178	0.178	0.295	0.295
Number of observations	5,485,773	5,485,773	5,485,773	5,485,773

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 15. Correlates of Household Welfare Ranking by Poverty Transition (Scenario A with District Cluster)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.056 (0.98)	-0.164 (2.07)*	0.491 (3.26)**	1.184 (10.03)**
HH head completed at least primary education	-0.695 (1.82	0.941 (1.64)	-3.015 (4.12)**	-6.326 (9.27)**
HH head completed at least junior secondary education	-0.557 (2.01)*	-1.115 (2.75)**	0.473 (1.00)	0.943 (1.23)
HH head completed at least senior secondary education	1.196 (2.36)*	1.220 (1.91)	3.225 (3.59)**	7.094 (7.58)**
# Adults in household	0.423 (3.59)**	-0.448 (1.03)	0.512 (1.59)	-1.410 (2.01)*
Presence of expectant mother	0.154 (1.67)	0.93 (1.66)	0.174(0.54)	-0.046 (0.06)
Household owns bicycle	-0.538 (1.23)	-0.687 (0.46)	-0.749 (1.66)	-1.552 (1.16)
Household owns motorcycle	0.173 (0.49)	1.848 (2.00)	2.737 (4.06)**	9.212 (7.49)**
Household owns refrigerator	-1.134 (2.18)*	-2.394(1.91)	1.94 2(1.86)	9.526 (9.46)**
# Adults working	-0.738 (3.00)**	0.126 (0.22)	-1.333 (1.79)	-3.778 (3.08)**
# Adults working in formal sector job	-0.844 (2.72)**	-2.620 (2.33)*	-0.859 (2.40)*	-1.297 (1.30)
R^2	0.62	0.63	0.34	0.17
Number of observations	687,446	768,126	707,903	3,322,298

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 16. Correlates of Household Welfare Ranking by Poverty Transition (Scenario B with District Cluster)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	-0.026 (1.95)	0.011(0.15)	0.025(0.40)	0.181 (1.31)
HH head completed at least primary education	0.151 (1.78)	0.594(1.43)	-0.299(0.96)	-0.294 (0.39)
HH head completed at least junior secondary education	-0.149 (2.67)*	-0.246(0.39	-0.649(2.02)*	-1.866 (2.52)*
HH head completed at least senior secondary education	0.001 (0.04)	1.256(2.76)**	0.615(1.78)	2.636 (3.79)**
# Adults in household	-0.165 (5.27)**	-2.467(8.05)**	-1.430(10.82)**	-6.958 (14.74)**
Presence of expectant mother	0.106 (2.69)**	1.823(2.23)*	0.185(0.67)	2.689 (3.05)**
Household owns bicycle	0.021 (0.15)	-0.955(1.30)	-0.611(1.13)	-2.956 (2.40)*
Household owns motorcycle	0.509 (5.32)**	2.524(4.45)**	0.277(0.64)	4.898 (5.36)**
Household owns refrigerator	0.156 (1.19)	3.844(5.73)**	3.143(3.11)**	7.151 (4.94)**
# Adults working	-0.203 (1.96)	-4.564(4.10)**	-2.278(3.59)**	-5.143 (3.10)**
# Adults working in formal sector job	-0.216 (1.54)	-0.856(1.37)	-1.075(2.22)*	-1.358 (1.07)
R^2	0.27	0.32	0.36	0.23
Number of observations	687,446	768,126	707,903	3,322,298

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 17. Summary Statistics of Estimated Parameters: OLS Between Districts

Correlates	Scenario A	Scenario B
Education		
Average years of education	0.098	0.141
HH head completed at least primary education	-0.302	-0.232
HH head completed at least junior secondary education	-0.181	-0.75
HH head completed at least senior secondary education	1.037	1.777
Demographics		
# Adults in household	-0.386	-5.425
Presence of expectant mother	-0.074	1.167
Asset		
Household owns bicycle	0.396	1.353
Household owns motorcycle	2.337	4.933
Household owns refrigerator	-0.178	6.863
Labour Market Outcome		
# Adults working	-1.119	-6.748
# Adults working in formal sector	1.027	1.277

Table 18. Correlates of Households Ranking: Panel Results

Correlates	Scenario A		Scenario B	
	(1)	**(2)**	**(3)**	**(4)**
Education				
Average years of education	1.182 (0.003)***	1.159 (0.007)***	0.126 (0.004)***	0.682 (0.007)***
HH head completed at least primary education	-5.709 (0.034)***	-4.253 (0.053)***	0.130 (0.037)***	-0.394 (0.058)***
HH head completed at least junior secondary education	0.692*** (0.035)	1.010*** (0.054)	-1.669 (0.037)***	-0.722 (0.059)***
HH head completed at least senior secondary education	7.022 (0.037)***	4.509 (0.062)***	2.565 (0.040)***	0.908 (0.067)***
Demographics				
# Adults in household	-2.249 (0.008)***	-2.419 (0.015)***	-6.437 (0.009)***	-8.372 (0.0168)***
Presence of expectant mother	0.0407 (0.063)	2.353 (0.082)***	2.388 (0.067)***	4.243 (0.089)***
Assets				
Household owns bicycle	-1.345 (0.026)***	0.667 (0.043)***	-2.144 (0.028)***	0.857 (0.047)***
Household owns motorcycle	10.45 (0.024)***	11.26 (0.035)***	6.020 (0.026)***	9.409 (0.038)***
Household owns refrigerator	10.37 (0.031)***	4.891 (0.045)***	7.348 (0.034)***	8.007 (0.049)***
Labour Market Outcomes				
# Adults working	-5.215 (0.027)***	0.826 (0.041)***	-6.167 (0.03)***	-3.027 (0.045)***
# Adults working in formal sector job	-0.705 (0.027)***	0.145 (0.039)***	-0.817 (0.029)***	1.424 (0.043)***
Other controls				
Social protection coverage	Yes	Yes	Yes	Yes
Yhat score	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effect	No	Yes	No	Yes
R^2		0.216		0.144
Number of observations	5,485,773	5,485,773	5,485,773	5,485,773
Number of panels	2,752,154	2,752,154	2,752,154	2,752,154

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 19. Correlates of Household Welfare Ranking by Poverty Transition (Scenario A with Panel Fixed Effect

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.162 (20.48)**	0.095 (7.23)**	0.595 (47.61)**	1.211 (126.18)**
HH head completed at least primary education	-1.123 (20.04)**	-0.442 (4.44)**	-2.976 (32.32)**	-4.505 (60.73)**
HH head completed at least junior secondary education	-0.334 (5.95)**	-0.385 (3.92)**	0.830 (8.78)**	1.251 (16.56)**
HH head completed at least senior secondary education	1.162 (16.76)**	0.587 (5.10)**	2.848 (25.84)**	4.564 (54.28)**
# Adults in household	0.505 (34.13)**	-0.438 (14.12)**	-0.109 (5.12)**	-2.192 (90.62)**
Presence of expectant mother	0.086 (1.14)	0.479 (3.70)**	0.589 (4.11)**	2.675 (22.10)**
Household owns bicycle	-0.127 (2.92)**	0.291 (3.55)**	-0.057 (0.81)	0.536 (8.71)**
Household owns motorcycle	0.312 (8.51)**	2.979 (44.88)**	3.580 (59.39)**	11.564 (230.05)**
Household owns refrigerator	-0.238 (4.08)**	0.271 (2.70)**	1.514 (20.10)**	4.804 (79.99)**
# Adults working	-0.210 (2.56)*	1.651 (20.93)**	0.824 (11.74)**	1.191 (21.48)**
# Adults working in formal sector job	-0.169 (4.43)**	-0.577 (8.17)**	-0.206 (3.14)**	-0.075(1.35)
R^2	0.61	0.68	0.32	0.24
Number of observations	687,446	768,126	707,903	3,322,298

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 20. Correlates of Household Welfare Ranking by Poverty Transition (Scenario B with Panel Fixed Effect)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.044 (20.44)**	0.147 (8.95)**	0.327 (26.10)**	0.835 (76.15)**
HH head completed at least primary education	-0.096 (6.27)**	0.626 (5.02)**	-1.243 (13.43)**	-0.415 (4.90)**
HH head completed at least junior secondary education	-0.044 (2.85)**	0.026 (0.21)	0.001 (0.01)	-0.939 (10.88)**
HH head completed at least senior secondary education	0.055 (2.92)**	0.179 (1.24)	0.966 (8.71)**	0.837 (8.71)**
# Adults in household	-0.368 (91.09)**	-4.665 (120.30)**	-3.750 (174.95)**	-10.124 (366.20)**
Presence of expectant mother	0.320 (15.55)**	2.991 (18.43)**	0.788 (5.46)**	4.981 (36.01)**
Household owns bicycle	0.249 (21.02)**	-0.435 (4.24)**	0.160 (2.25)*	0.776 (11.04)**
Household owns motorcycle	1.055 (106.86)**	4.322 (52.69)**	1.626 (26.94)**	10.173 (177.06)**
Household owns refrigerator	1.028 (64.63)**	2.982 (23.79)**	4.544 (60.09)**	8.736 (127.26)**
# Adults working	-0.126 (9.82)**	-2.107 (21.30)**	-0.760 (10.77)**	-3.237 (51.09)**
# Adults working in formal sector job	0.276 (26.54)**	-0.966 (10.90)**	0.361 (5.47)**	1.435 (22.68)**
R^2	0.18	0.48	0.51	0.14
Number of observations	687,446	768,126	707,903	3,322,298
Number of observations	687,446	768,126	707,903	3,322,298

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 21. Correlates of Households Ranking: First Difference Result

Correlates	Scenario A (1)	Scenario B (2)
Education		
Average years of education	1.159 (0.007)***	0.682 (0.007)***
HH head completed at least primary education	-4.253 (0.053)***	-0.394 (0.058)***
HH head completed at least junior secondary education	1.010 (0.054)***	-0.722 (0.059)***
HH head completed at least senior secondary education	4.509 (0.062)***	0.908 (0.067)***
Demographics		
# Adults in household	-2.419 (0.015)***	-8.372 (0.0168)***
Presence of expectant mother	2.353 (0.081)***	4.243 (0.089)***
Asset		
Household owns bicycle	0.667 (0.043)***	0.857 (0.047)***
Household owns motorcycle	11.26 (0.035)***	9.409 (0.038)***
Household owns refrigerator	4.891 (0.045)***	8.007 (0.049)***
Labour Market Outcome		
# Adults working	0.826 (0.041)***	-3.027 (0.0448)***
# Adults working in formal sector job	0.145 (0.039)***	1.424 (0.043)***
Other controls		
Social protection coverage	Yes	Yes
Yhat score	Yes	Yes
Year Dummy	Yes	Yes
Number of observations	2,733,619	2,733,619
R^2	0.111	0.115

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 22. Correlates of Household Welfare Ranking by Poverty Transition (Scenario A using First Difference)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.162 (20.48)**	0.095 (7.23)**	0.595 (47.61)**	1.211 (126.18)**
HH head completed at least primary education	-1.123 (20.04)**	-0.442 (4.44)**	-2.976 (32.32)**	-4.505 (60.73)**
HH head completed at least junior secondary education	-0.334 (5.95)**	-0.385 (3.92)**	0.830 (8.78)**	1.251 (16.56)**
HH head completed at least senior secondary education	1.162 (16.76)**	0.587 (5.10)**	2.848 (25.84)**	4.564 (54.28)**
# Adults in household	0.505 (34.13)**	-0.438 (14.12)**	-0.109 (5.12)**	-2.192 (90.62)**
Presence of expectant mother	0.086 (1.14)	0.479 (3.70)**	0.589 (4.11)**	2.675 (22.10)**
Household owns bicycle	-0.127 (2.92)**	0.291 (3.55)**	-0.057 (0.81)	0.536 (8.71)**
Household owns motorcycle	0.312 (8.51)**	2.979 (44.88)**	3.580 (59.39)**	11.564 (230.05)**
Household owns refrigerator	-0.238 (4.08)**	0.271 (2.70)**	1.514 (20.10)**	4.804 (79.99)**
# Adults working	-0.120 (2.56)*	1.651 (20.93)**	0.824 (11.74)**	1.191 (21.48)**
# Adults working in formal sector job	-0.169 (4.43)**	-0.577 (8.17)**	-0.206 (3.14)**	-0.075 (1.35)
R^2	0.58	0.54	0.28	0.11
Number of observations	343,497	383,795	350,426	1,655,901

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 23. Correlates of Household Welfare Ranking by Poverty Transition (Scenario B using First Difference)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.044 (20.44)**	0.147 (8.95)**	0.327 (26.10)**	0.835 (76.15)**
HH head completed at least primary education	-0.096 (6.27)**	0.626 (5.02)**	-1.243 (13.43)**	-0.415 (4.90)**
HH head completed at least junior secondary education	-0.044 (2.85)**	0.026 (0.21)	0.001 (0.01)	-0.939 (10.88)**
HH head completed at least senior secondary education	0.055 (2.92)**	0.179 (1.24)	0.966 (8.71)**	0.837 (8.71)**
# Adults in household	-0.368 (91.09)**	-4.665 (120.30)**	-3.750 (174.95)**	-10.124 (366.20)**
Presence of expectant mother	0.320 (15.55)**	2.991 (18.43)**	0.788 (5.46)**	4.981 (36.01)**
Household owns bicycle	0.249 (21.02)**	-0.435 (4.24)**	0.160 (2.25)*	0.776 (11.04)**
Household owns motorcycle	1.055 (106.86)**	4.322 (52.69)**	1.626 (26.94)**	10.173 (177.06)**
Household owns refrigerator	1.028 (64.63)**	2.982 (23.79)**	4.544 (60.09)**	8.736 (127.26)**
# Adults working	-0.126 (9.82)**	-2.107 (21.30)**	-0.760 (10.77)**	-3.237 (51.09)**
# Adults working in formal sector job	0.276 (26.54)**	-0.966 (10.90)**	0.361 (5.47)**	1.435 (22.68)**
R^2	0.07	0.06	0.09	0.10
Number of observations	343,497	383,795	350,426	1,655,901

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Figure 1. Welfare Dynamics of Indonesia's Bottom 40 Percent (2011 & 2015)

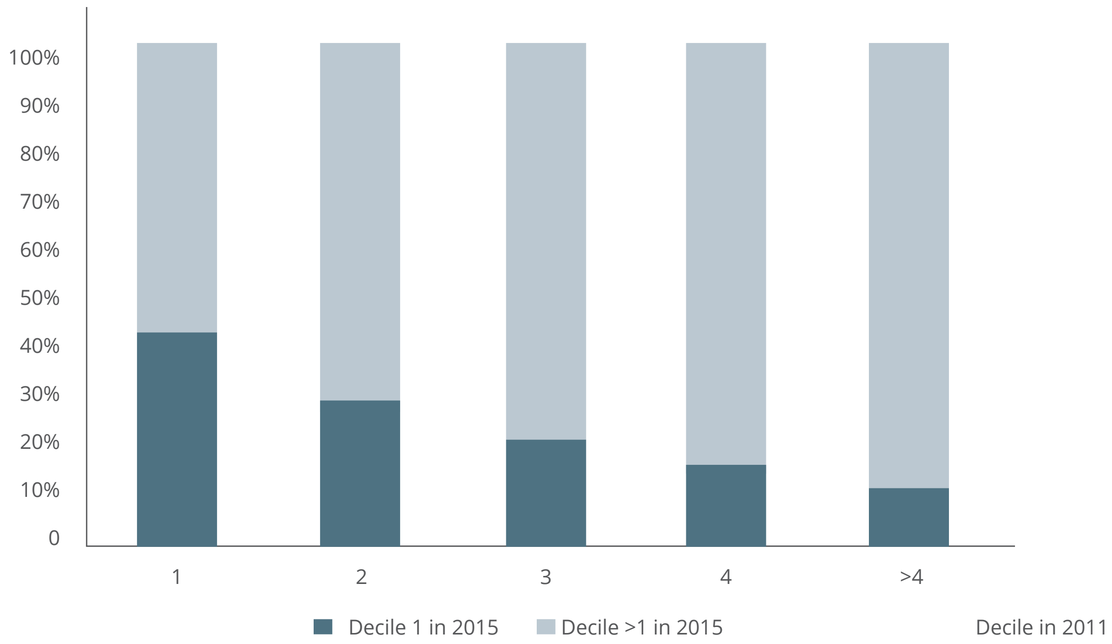


Figure 2. Welfare Dynamics of Indonesia's Bottom 10 Percent (2011 & 2015)

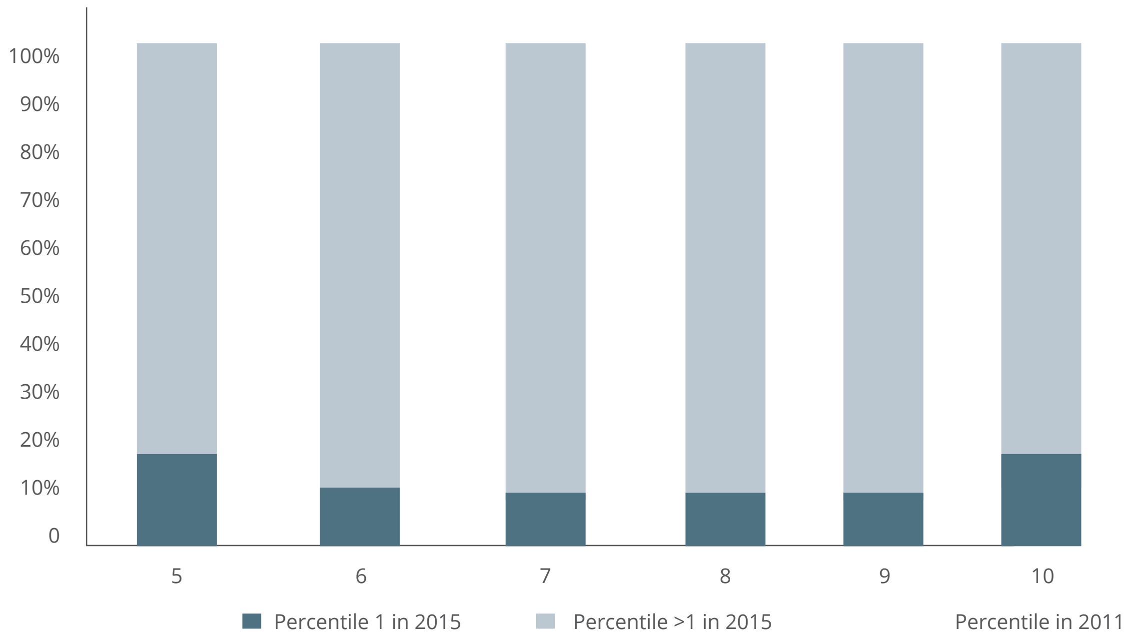


Figure 3. Scenario A: Welfare Dynamics of Indonesia's Bottom 40 Percent- 50 Districts (2011 & 2015)

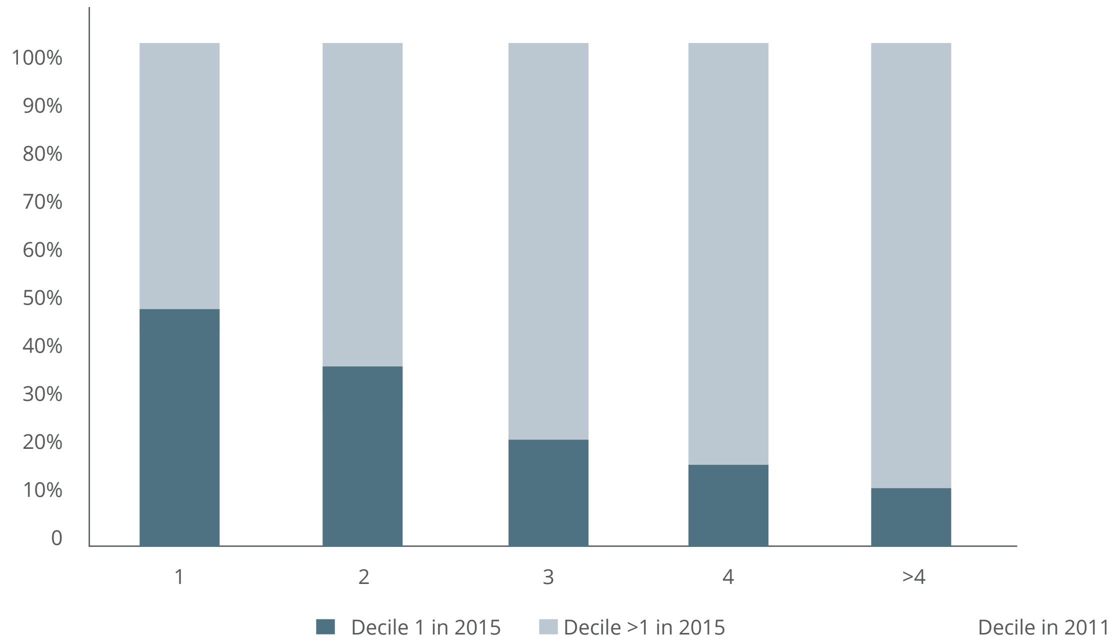


Figure 4. Scenario A: Welfare Dynamics of Indonesia's Bottom 10 Percent- 50 Districts (2011 & 2015)

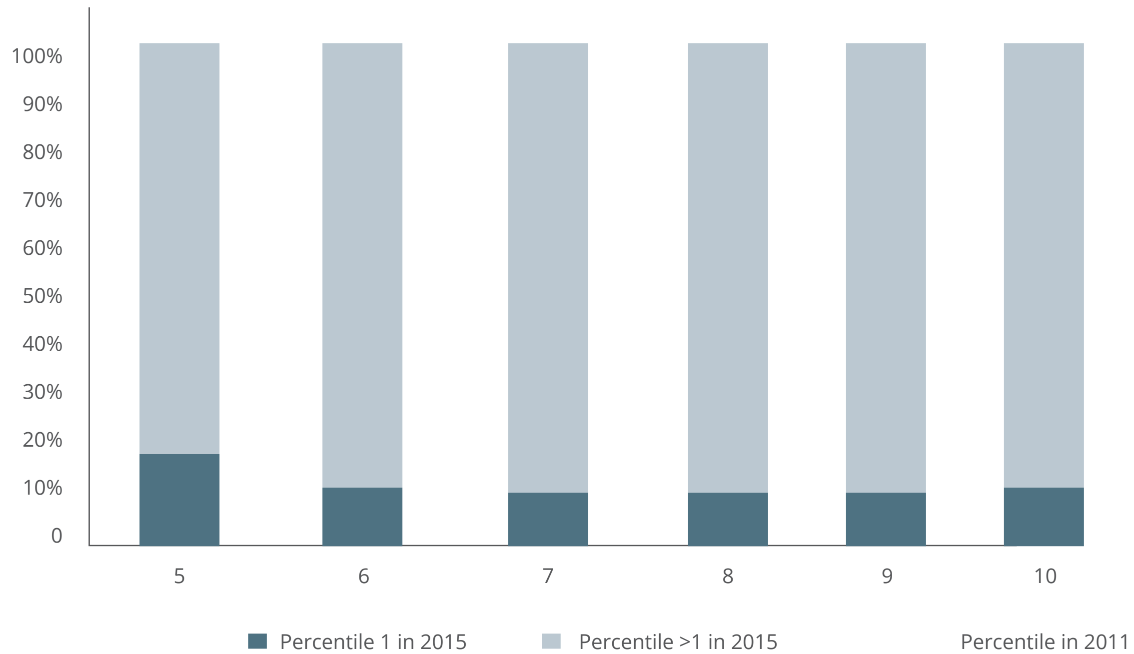


Figure 5. Scenario B: Welfare Dynamics of Indonesia's Bottom 40 Percent- 50 Districts (2011 & 2015)

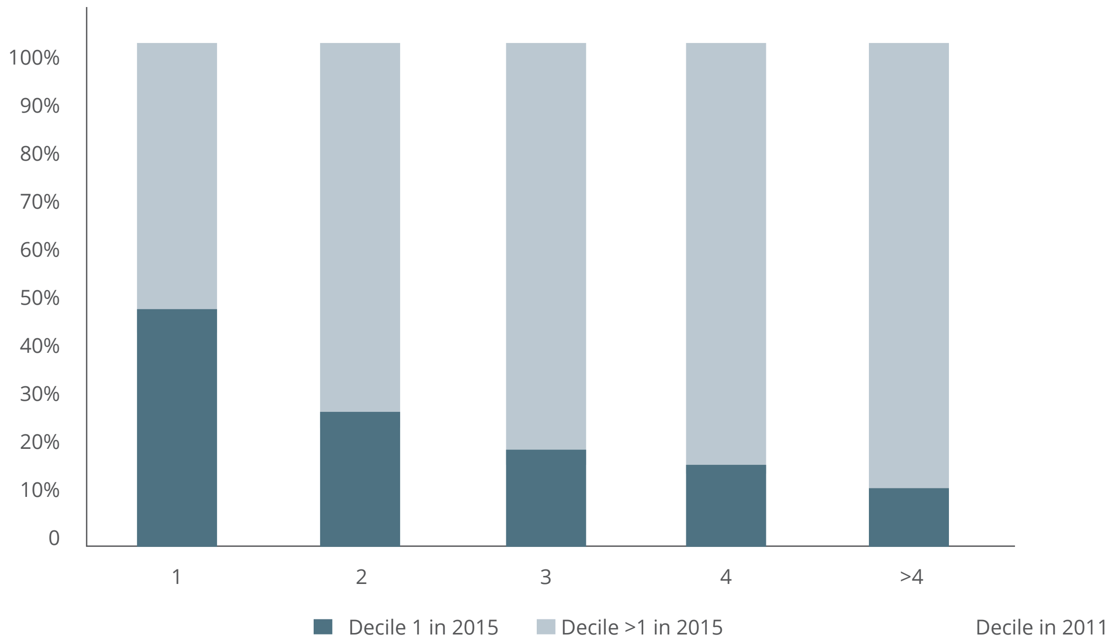
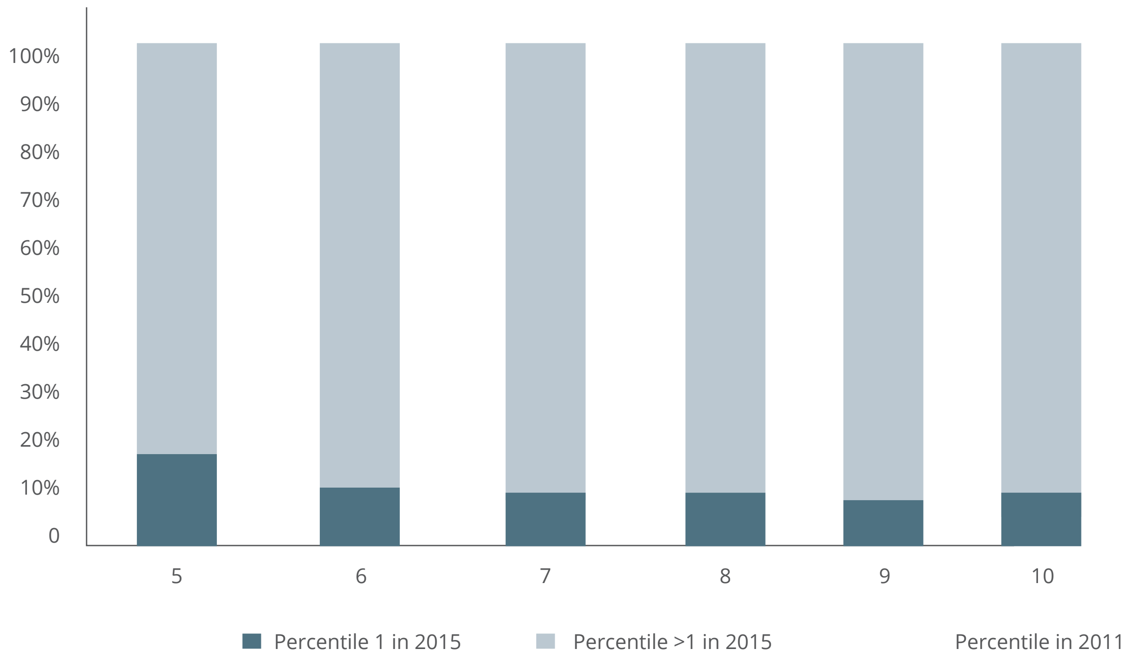


Figure 6. Scenario B: Welfare Dynamics of Indonesia's Bottom 10 Percent- 50 Districts (2011 & 2015)



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DECENTRALISATION AND POVERTY REDUCTION: THE ROLE OF LOCAL ECONOMIES AND INSTITUTIONAL CAPACITY IN INDONESIA

Esha Chaudhuri, Sandra Kurniawati, Sudarno Sumarto

Abstract

Over the two decades to 2019, a decentralised Indonesia has made significant progress in reducing the poverty rate by more than 50 percent. Despite a significant decline at the national level, progress in poverty reduction has been uneven across districts. This study aims to investigate those factors that may explain these regional variations using panel regressions. Using district panel data set with annual observations from 2010 to 2016, we find that poverty reduction and regional economic output are strongly interrelated. We find that poverty tends to decrease more in districts with: (a) higher district economic output per capita; (b) higher outputs of manufacturing and service sectors; and (c) an active local office for the coordination of poverty reduction initiatives (*Tim Koordinasi Penanggulangan Kemiskina*n: TKPK). Poverty is also more likely to decrease in districts with: (a) a higher share of villages led by local leaders with a secondary education or higher; (b) higher educational attainment among the rural population; and (c) a higher share of villages with good road conditions. We find no correlation, however, between progress in poverty reduction and local government spending on education, health, and social protection. This suggests that simply increasing the amount of local government spending on social programs may not be effective in reducing poverty. Our findings also indicate that sufficient institutional capacity appears to be one of the critical preconditions for the delivery of more effective public services for poverty alleviation.

Abbreviations and Acronyms

BPS	*Badan Pusat Statistik* (Statistics Indonesia)
GRDP	Gross Regional Domestic Product
NTB	Nusa Tenggara Barat (West Nusa Tenggara)
NTT	Nusa Tenggara Timur (East Nusa Tenggara)
PAD	*Pendapatan Asli Daerah* (Regional [Government] Own Revenues)
TKPK	*Tim Koordinasi Penanggulangan Kemiskinan* (Coordinating Team for Poverty Reduction)
TNP2K	*Tim Nasional Percepatan Penanggulangan Kemiskinan* (National Team for the Acceleration of Poverty Reduction)
UDB	Unified Database

Introduction

Indonesia has made tremendous progress in maintaining economic growth and reducing poverty since decentralisation[1]. Over the two decades to 2019, Indonesia has reduced the poverty rate by more than 50 percent–with the poverty headcount declining from 19.14 percent of the population in 2000 to 9.41 percent in 2019. This progress coincided with two major events: substantial poverty reduction occurred alongside a period of rapid economic growth, and in this year marks twenty years since Indonesia's decentralisation. There are also two caveats to this success: poverty reduction at the local level has varied widely across provinces and districts, and progress appears to be slowing.

Political and economic theory describe multiple mechanisms linking decentralization to poverty reduction. Three important advantages decentralization could offer are, briefly: better bureaucratic knowledge of local contexts, increased government accessibility and accountability, and greater local budgeting and revenue collection autonomy (Steiner, 2005). A combination of these supposedly has the potential to provide the information, incentives, and funding to implement more efficient, better-targeted public services, accelerate economic growth, and, through these channels, reduce poverty.

While there are many factors that have contributed to reducing poverty during the decentralisation era, economic growth is found to be one of the main drivers of poverty alleviation in Indonesia (Miranti et al. 2014; Sumarto et al. 2014; Ilmma and Wai-Poi 2014; Suryahadi et al. 2012; Suryahadi et al. 2009; Balisacan et al. 2002). Using provincial panel data from 1984 to 2010, Miranti et al. (2014) found that the growth elasticity of poverty during decentralisation–from 2002 to 2010–was greater than any period since 1984. Using the basic model formulated by Ravallion and Datt (1996) in estimating the impact of economic growth on poverty, Suryahadi et al. (2012) found no evidence that growth elasticity of poverty in Indonesia declined after the Asian Financial Crisis.

While previous studies find that overall economic growth is negatively associated with poverty reduction in Indonesia, specific sector growth helps determine the magnitude of the impact. Suryahadi et al. (2009) find that urban services growth in Indonesia has the highest impact on the poverty rate for both rural and urban areas. They also find that agriculture growth remains crucial for poverty reduction in rural areas. Their findings suggest, however, that there is no correlation between industrial growth and poverty reduction. Using more recent data, Edwards (2015) finds that plantation-based agricultural growth–focusing on palm oil–is strongly associated with a reduction in the poverty rate. He estimated that a ten percentage points increase in palm oil's share of land led to a ten percent reduction in the poverty rate and a narrowing of the poverty gap. These findings suggest that, in addition to overall economic growth, sectoral economic growth may also explain variations in the rate of poverty reduction across regions.

In addition to growth that varies by regions, another critical factor that may accelerate progress in reducing poverty is the government's commitment that has been translated into various poverty alleviation programs and policies. Over the two decades to 2019, the Indonesian Government has made efforts to make growth

1 Indonesia adopted a "Big Bang" decentralization approach in 1999 which implemented fiscal, administrative, and political decentralization simultaneously according to 1999 and 2000 laws on regional autonomy (Hoffman and Kaiser 2003).

more inclusive by ensuring social protection programs work more effectively. Through Presidential Regulation No. 15/2010, the Government of Indonesia established the National Team for the Acceleration of Poverty Reduction (TNP2K)[2] to promote coordination across ministries and agencies to improve the implementation of poverty alleviation programs. These programs include subsidised rice (Rastra), conditional cash transfer (*Program Keluarga Harapan*), scholarships for the poor (*Bantuan Siswa Miskin*), and other social programs. One of TNP2K's main mandates is to develop a national targeting system–namely the Unified Database (UDB)–to ensure that these programs reach beneficiaries (TNP2K 2014). The UDB captures data on poor and vulnerable members of households in the bottom 40 percent of the consumption distribution. Previous research found that the UDB effectively improves targeting performance of social protection programs compared to previous targeting approaches (Tohari et al. 2017; Bah et al. 2014).

In a decentralized country, local governments have an important role in delivering public services including the implementation of social protection programs. However, institutional capacity is variable, and was quite low initially following decentralization. To support local government institutions, the national government established poverty coordination teams at the province and district levels, *Tim Koordinasi Penanggulangan Kemiskinan (TKPK*), which are chaired by the deputy head of each district (*Wakil Bupati* or *Wakil Walikota*). In 2011, around a third-quarter districts (373 out of 497) had established TKPKs. Sumarto et al. (2014) found that TKPK's years of establishment were associated with poverty reduction over the five-year period from 2006 to 2010. We therefore include measures of TKPK and local government capacity in our analysis.

This paper proceeds as follows. The second part of this paper presents existing evidence on decentralization, poverty reduction, and the determinants of regional poverty rates in Indonesia. The third part provides an overview of regional heterogeneity of poverty reduction and shows the variation in economic output and institutional capacity across districts. The fourth section explains the methodology. The fifth presents and discusses the results, while the sixth section presents our conclusions.

Theory and Evidence on Decentralization and Poverty Reduction

Public Services and Decentralization

Evidence on decentralization's impact on public services in Indonesia is limited, and mixed. The existing literature primarily covers local government spending and public service provision, intergovernmental transfers, and the effects of direct elections at the district level. Hodge et al. (2015) assess public health service quality before and after 1999, proxied by access to neonatal care and mortality, and find no significant overall trend following decentralization. However, they do find that geographical disparities in health services (across regions) have increased post-decentralization.

2 *Tim Nasional Percepatan Penanggulangan Kemiskinan.*

Other research addresses the impact of local governments' fiscal capacity. Controlling for poverty rate and prior level of economic and infrastructure development, Lewis (2017) finds a U-shaped relationship between per capita local government expenditure and public service access from 2006-2010. At approximately the 75th percentile, the relationship between expenditure and access becomes negative. However, this effect disappears when controlling for financial audit results: districts with better fiscal oversight records exhibit a positive relationship between investment and key outcomes across the entire range of spending.[3]

Decentralization also has some drawbacks. Services may not improve, for example, if incentives for public officials are not aligned with public needs. Direct elections are one mechanism that can help increase local accountability in decentralized systems, but may also lead to vote buying and corruption, especially in poorer districts (Steiner, 2005). In Indonesia, district-level direct elections were not an initial condition of decentralization, but were mandated by law several years later. Skoufias et al. (2014) find no statistically significant difference in the quality of public service provision across four years following their implementation. They do find increases in certain budgets in pre-election years, however, and a significant increase in health expenditure only in years immediately following elections. Budget increases in pre-election years suggest vote buying by incumbents. Increases in health budgets *following* elections, however, may be a sign of real, positive accountability.

Overall, more evidence is needed to determine decentralization's impact on public service provision. If public services do improve as a result of decentralization, they have the potential to be instruments for poverty reduction. However, they may also increase inequality: in a review of literature on the impacts of decentralization across developing countries, Smoke et al. (2013) discover that "most studies find that better-off segments of the population benefit disproportionately from service improvements" after decentralization, "while access and/or usage for the poor often deteriorates."[4] Similarly, although the papers reviewed find average improvements or mixed results in living conditions and livelihoods, those address distributional effects most often find *increases* in inequality following decentralization.

Indonesia's national poverty rate has decreased significantly since 2000, but the impact of decentralization specifically is still unclear. One study, using panel data from 1993-2005, did conclude that the decentralization "shock" had a statistically significant, negative impact on provincial poverty rates (Aritenang, 2010). Regarding district financial capacity, however, the same paper finds no evidence that increases in shared revenue affected poverty rates.[5] Dyah (2012) discovers a similar relationship at the district level, where DBH per capita (*Dana Bagi Hasil* or revenue-sharing funds) is *positively* correlated with income inequality. These findings could simply indicate that financial capacity is not a limiting factor for local government action on poverty reduction. Neither paper addresses accountability (as studies of direct elections do) or institutional capacity.

3 Echoing this result, Lewis and Smoke (2017) find that increased general-purpose grants are associated with greater local spending on personnel, a pattern which is sometimes considered a warning sign of corruption.

4 The authors also note that this conclusion was drawn from the few papers they found that did address the distributional and poverty-related effects of decentralization.

5 Shared revenue consists of natural resource rents and local taxes, which are split between the federal and district governments. District governments have complete jurisdiction over how their portion of shared revenue is spent.

Economic Growth and Poverty Reduction

Apart from public services, local economic growth contributes to district-level poverty reduction. Some research has focused on growth trends and regional heterogeneity in both the pre- and post-decentralization eras: Vidyattama (2010) finds that transportation access, infrastructure development, and trade openness were the most significant determinants of provincial economic growth from 1985-2005. Human capital, proxied by average years of education, was weakly significant, and surprisingly, local government investment was negatively correlated with per capita GRDP. Aritenang (2010), studying a similar period (1993-2005), finds a convergence effect on economic growth: controlling for human capital, oil and gas sector dominance, and other variables, poor provinces grew faster than rich ones.

The goal of this paper is not to discuss the impact of decentralization directly, but rather poverty reduction trends in its aftermath. Several papers have addressed this question. Suryahadi et al. (2009) examine the impact of sectoral components of economic growth on provincial poverty rates from 1986-2002. Accounting for migration across regions, they find that urban and rural service-sector and rural agriculture-sector growth all decrease poverty rates. Urban service-sector growth has the largest negative impact on urban and rural poverty rates, across all sectors. Aritenang (2010) finds a statistically significant, negative impact of human capital growth on poverty rates, but even controlling for numerous other economic characteristics, his analysis explained little of the variation in regional poverty rates (18%).

Local Institutional Capacity and Poverty Reduction

Sumarto et al. (2014), the motivation for this paper, discuss the determinants of poverty rates at the district level. The authors are therefore able to control for variation in unobserved provincial characteristics. They find that poverty rates are slightly lower in districts with higher budgets (as a share of local GRDP), more educated local leaders, and higher GRDP per capita (although this last effect is not statistically significant). More educated and urban districts have significantly lower poverty levels, as do districts with local offices for coordinating poverty reduction (TKPKs). Furthermore, districts with older TKPKs reduced poverty more over the years studied. Offices that were at least three years old were significantly associated with greater poverty reduction over the five-year period.

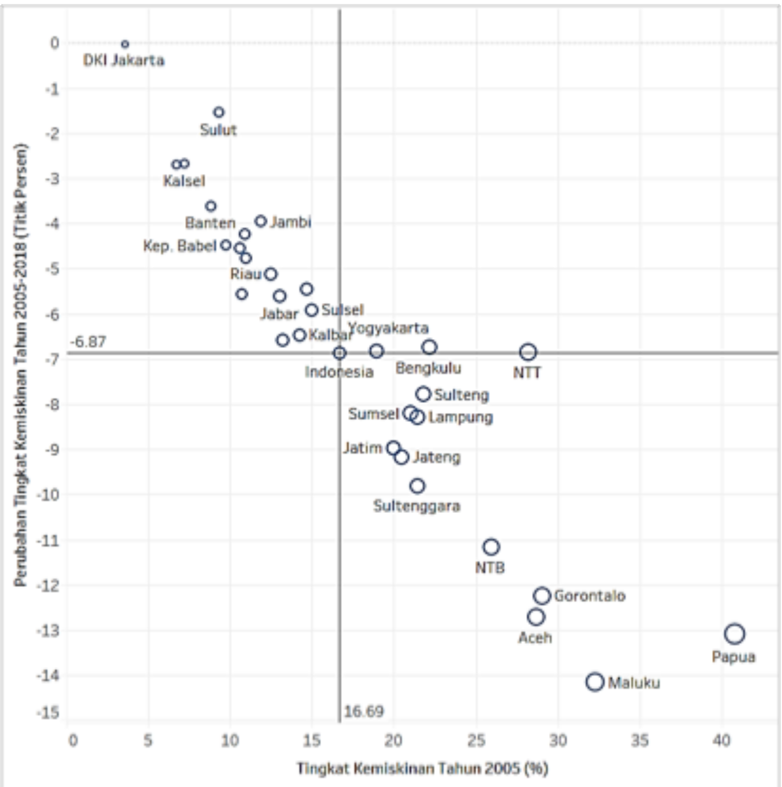
This last result is especially notable because the authors also observed a nation-wide convergence effect: districts with lower initial poverty rates reduced poverty less overall. Although the paper makes no causal claims, the relationship of TKPKs with lower poverty incidence *and* greater reduction suggests a potential causal relationship. Since the success of TKPKs can be assessed as one measure of institutional strength at the local level, it is one of the relationships we investigate further in this paper.

Regional Variation in Poverty Reduction, Economic Growth, and Institutional Capacity in Indonesia

Poverty Reduction at the Local Level

Since 2000 the national poverty rate in Indonesia has been reduced substantially–from 19.14 percent to 9.41 percent in 2019–however, despite significant progress at the national level, the reduction at the local level varied across provinces and districts. We find that regions with a high initial poverty rate experienced a larger reduction in their poverty rate between 2005 and 2018 compared to those that had a relatively lower poverty rate in 2005. Figures 1 and 2 show the convergence in poverty rate at the provincial and district levels respectively. Provinces with a high poverty rate in 2005–such as Papua and Maluku–managed to reduce poverty by around 13–14 percentage points between 2005 and 2018. On the other hand, provinces with a lower poverty rate in 2005 such as South Kalimantan and Banten reduced poverty by less than five percentage points over this period.

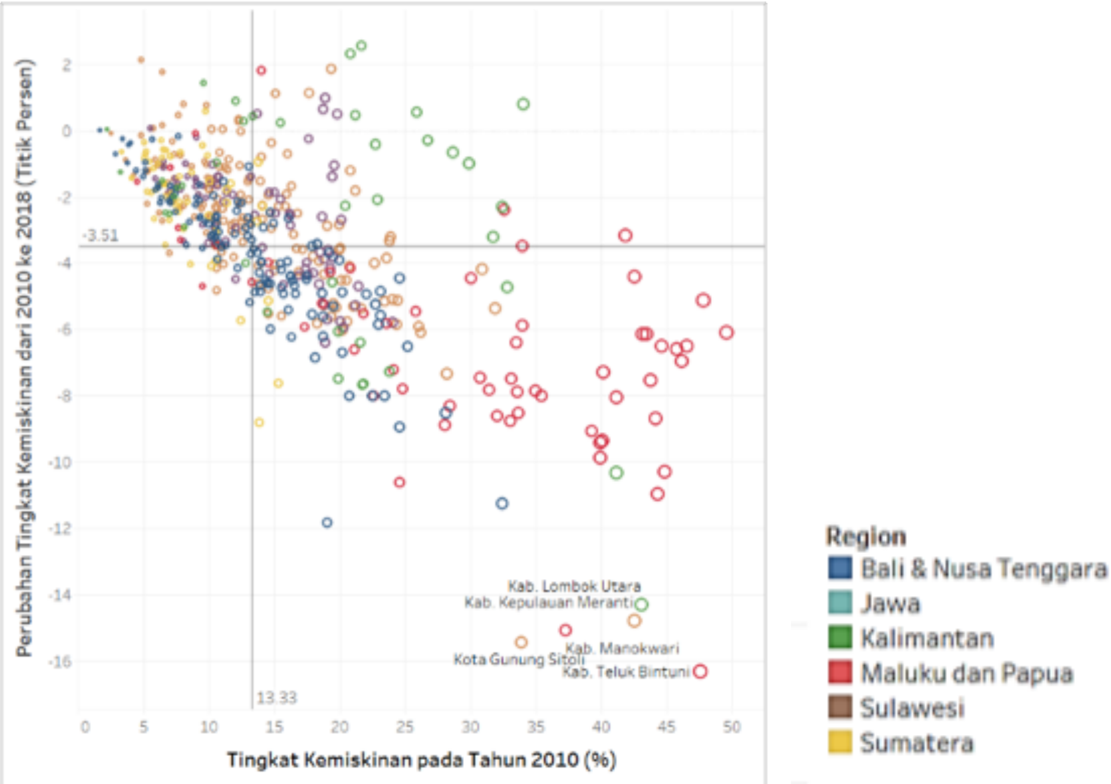
Figure 1: Convergence in Poverty Rates at the Province Level (2005–2018)



Note: x-axis shows the poverty rate in 2005, while y-axis shows the changes in poverty rate between 2005 and 2018. Source: Authors' analysis based on Susenas 2005–2018.

Figure 1 also shows that regions with similar initial poverty rates have made different progress in reducing poverty. For example, NTB, NTT, Aceh, and Gorontalo had poverty headcount ratios from 25 to 30 percent in 2005. In terms of their progress, however, NTT had the smallest reduction–around seven percentage points–in its poverty rate compared to the other three provinces. The variation is also evident in the regions that had an initial poverty rate lower than the national one in 2005. North Sulawesi (Sulut) has made slower progress in reducing poverty compared to Kepulauan Bangka Belitung (Kep. Babel).

Figure 2: Convergence in Poverty Rate at the District Level (2010–2018)



Note: x-axis shows the poverty rate in 2010, while y-axis shows the changes in poverty rate between 2010 and 2018.
Source: Susenas 2010-2018 (Authors' analysis).

We also find that the poverty rate at the district level tends to converge (Figure 2). Districts with a poverty rate higher than the national average in 2010 which are mostly located in the Papua and Maluku regions (Figure 3) tend to have larger reductions in their poverty rate compared to regions with poverty rates lower than the national one. Teluk Bintuni, Manokwari, Kota Gunung Sitoli, Kepulauan Meranti, and Lombok Utara are districts with the greatest reduction of around 14 to 16 percentage points in the period of 2010–2018. The figure also shows that the variation in the rate of poverty reduction is quite large among districts with similar initial poverty rates. There are some districts with an initial poverty rate higher than 25 percent that experienced relatively slower progress in reducing poverty.

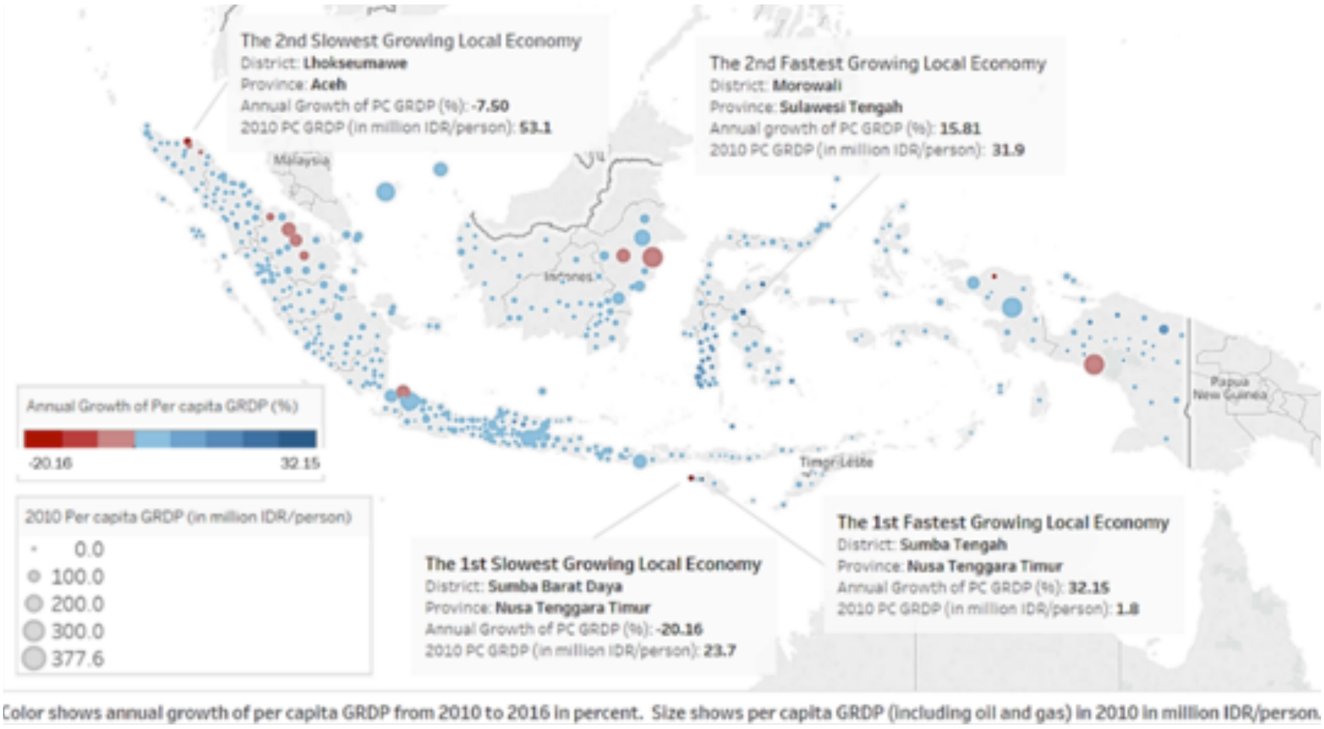
Figure 3: Regional Variation in Changes in Poverty Rate (2010-2016)

Source: Susenas 2010–2016 (Authors' analysis).

Local Economic Outputs

Economic growth was found to be one of the factors that strongly correlate with decreasing rates of poverty. Using the district panel data set, we are able to map the growth of per capita output of 511 districts, proxied by Gross Regional Domestic Product (GRDP) per capita from 2010 to 2016 (Figure 4). Most districts experienced a positive growth of GRDP per capita. Local economic growth in this period varied from -20.16 to 32.15 percent–with the fastest and slowest growing local economies located in the same province (NTT).

Figure 4: Regional Variation in Changes in Economic Output (2010-2016)



Source: BPS 2010-2016 (Authors' analysis).

Local Institutional Capacity for Poverty Reduction

Since 2010, TNP2K through its Advocacy Unit has implemented various activities to build the technical capacity of regional TKPKs and strengthen their ability to plan and execute regional poverty alleviation programs. Based on *Permendagri* No. 42/2010, TKPKs are mandated to develop poverty reduction strategies through coordination meetings and submit annual reports on the implementation of poverty reduction programs. TKPKs are also encouraged to participate in various capacity-building activities such as technical consultations, internships, and training organised by TNP2K or the TKPK at the provincial level. In this study, we extend the analysis of Sumarto et al. (2014) by exploiting variations in TKPK's ability to perform their functions from 2011 to 2016.

TNP2K's Advocacy Unit has mapped TKPKs based on the administrative data that recorded each TKPK's activities each year between 2011 and 2016. In this paper, a TKPK at the district level is considered active if the district conducted regular coordination meetings at least once per year, always submitted annual reports, and participated in technical consultations and training at least once in two years. Most districts in the western region have an active TKPK while, in the eastern region, an institution's capacity to perform the required mandate is more varied across districts (Figure 5).

Figure 5: Mapping TKPK Based on Their Activities and Engagement (2011-2016)

Source: TNP2K's Advocacy Unit, 2018 (Authors' analysis).

Methodology

Data

We constructed the district panel data set with annual observations from 2010 to 2016. In this period there are some formations of new districts *(pemekaran)* which led to an increase from 497 districts in 2010 to 511 districts in 2016. We adjust the annual data to match the borders of the 497 districts as they were in 2010.

We used poverty figures published by Statistics Indonesia (*Badan Pusat Statistik:* BPS) and merged the poverty data with the other four data sets. First, we use GRDP published by BPS as a measure of regional economic output. We use both the total and sectoral GRDP data in real terms–with the prices fixed at 2010 rupiah. Second, we merged the main data set with district government spending data published by Directorate General Fiscal Balance, Ministry of Finance. We only use district government spending on social programs such as education, health, and social protection. Third, we use administrative data from the local TKPK office between 2011 to 2016 collected by TNP2K's Advocacy Unit. Lastly, we merged the main data set with other socioeconomic indicators such as local leaders' education attainment, average education attainment by region (urban/rural), and basic infrastructure such as roads. We collected these indicators using *Susenas* and *Podes* data sets. Table 1 shows the descriptive statistics.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Poverty rate (%)	3,478	13.85	8.58	1.33	49.58
Number of poor people (person)	3,478	58,245	66,416	1,300	499,100
Poverty Gap	3,478	2.35	2.16	0.09	19.16
Population (person)	3,479	499,606	598,249	6,144	5,555,259
GRDP per capita (real):					
Total (IDR/person)	3,476	31,900,000	40,700,000	1,756,528	381,000,000
Primary sector (IDR/person)	3,476	11,800,000	26,100,000	13,818	319,000,000
Secondary sector (IDR/person)	3,476	8,837,373	20,000,000	64,443	348,000,000
Tertiary/service sector (IDR/person)	3,476	11,300,000	15,600,000	758,090	325,000,000
Agriculture (IDR/person)	3,476	5,838,537	4,769,094	13,818	55,700,000
Mining (IDR/person)	3,307	6,214,680	24,900,000	107	314,000,000
Manufacturing (IDR/person)	3,474	5,841,494	18,800,000	1,282	335,000,000

Variable	Obs	Mean	Std. Dev.	Min	Max
District government spending per capita:					
Total (IDR/person)	3,233	4,146,625	5,726,817	594	93,700,000
Health (IDR/person)	3,227	400,184	413,619	195	6,464,360
Education (IDR/person)	3,230	1,031,851	778,486	11,546	14,900,000
Social protection (IDR/person)	3,220	76,827	141,339	16	2,500,885
Active TKPK (==1, if active)	3,479	0.79	0.41	0	1
Average years of schooling:					
Total (years)	3,432	7.82	1.62	0.54	12.36
Rural (years)	3,142	7.00	1.36	0.54	11.16
Urban (years)	3,162	9.18	1.28	2.84	12.36
Proportion of village led by leaders who completed at least junior secondary school	3,447	0.95	0.14	0.04	1.00
Proportion of village with concrete/ asphalt road	3,447	0.67	0.29	0.00	1.00

Methods

In estimating the determinants of poverty reduction, we use the district panel data set to exploit the variation in the poverty rate and our variable of interests across regions and years. The regional fixed effects allow us to control for regional/local characteristics that are constant over time (such as cultural attitudes, geographic and climatic conditions). Given the complex interrelationship between poverty and other socioeconomic conditions, no causality is claimed in this study.

The first variable of interest in this study is local economic output. To examine the relationship between economic output and poverty rate, we construct the following model:

$$POV_{d,t} = \beta 0 + \beta 1 \ ln \ Y_{d,}t + \Phi \ X_{d,t} + \eta d + \delta t + u_{\ d,t} \qquad (1)$$

where $POV_{d,t}$ is the poverty rate (P0) and poverty gap (P1) of district d in year t; Y_{dt} is GRDP per capita of district *d* in year *t*; $X_{d,t}$ is a set of time-varying factors that may correlate with district poverty rate; *d* is a set of dummy regional variables which consists of five major islands in Indonesia; *t* is a set of dummy year variables; and $u_{g,t}$ is the idiosyncratic error.

Secondly, we disaggregate the economic output by sectors. Equation (1) is modified to construct the following model:

$$POV_{d,t} = \beta_0 + \beta_1 \ ln\ AG_{d,t} + \beta_2 \ ln\ MI_{d,t} + \beta_3 ln\ MN_{d,t} + \beta_4 \ ln\ SR_{d,t} + \Phi\ X_{d,t} + \eta d + \delta t + u_{d,t}$$

where $AG_{d,t}$ is the agricultural output per capita; $MIN_{d,t}$ is the mining per capita output; $MNF_{d,t}$ is the manufacturing output per capita; and $SRV_{d,t}$ is the service output per capita. The regional outputs used in this study are all in real terms.

Lastly, in addition to economic output, we aim to examine the correlation between local institutional capacity using local government spending and TKPK engagement as proxies.

$$POV_{\ d,t} = \beta_0 + \beta_1 \ ln\ Y_{d,t} + \beta 2\ lnG_{d,t} + \gamma TKPK_d + \Phi\ X_{d,t} + \eta d + \delta t + u_{d,t} \text{ (3)}$$

where $G_{d,t}$ is the local government spending per capita and $TKPK_d$ is the dummy variable for a district with an active TKPK. The local government spending data that we use in this study only consists of spending on health, education, and social protection because spending on social programs is expected to be more related to progress in reducing poverty. In our models, control variables include average years of schooling, local leaders' education attainment, and road condition as a proxy for basic infrastructure.

Results

Table 2 provides the main estimation results using both random and fixed effects–with Column (1) showing that a higher level of local economic output is associated with a lower poverty rate. A one percent increase in GRDP per capita is correlated with a 0.94 percentage point decrease in the poverty rate. Looking at the sectoral analysis, we find that the manufacturing and service sectors have the strongest correlation with a reduction in the poverty rate and poverty gap, while districts with higher output in mining tend to have a higher poverty rate. We find no correlation between the agriculture sector's output and poverty rate, but it correlates with a lower poverty gap. The tables in the Appendix provide more detailed regression results.

We find no association between government spending per capita on education, health, and social protection and poverty rate. As a robustness check, we also use share of spending on these sectors instead of the per capita spending. The results remain consistent–with no correlation between district government spending on social programs and the poverty rate. In terms of fiscal capacity, we also find no evidence of a correlation between progress in reducing poverty and fiscal autonomy of districts which is proxied by local government own revenues (*Pendapatan Asli Daerah: PAD*).

With regards to local institution (TKPK) engagement, our main estimation results indicate that districts with an active TKPK tend to reduce poverty at around 1.7–2.1 percentage points larger than those with an inactive TKPK. Active engagement of the TKPK also correlates with a reduction in the poverty gap of around 0.4 points.

Poverty is also more likely to decrease in districts with a population who attained a higher level of education, especially in rural areas. A one-year increase in average years of schooling of the rural population is associated with around a 0.3 percentage points reduction in the district's poverty rate. The main results also indicate that districts with a larger proportion of village leaders who attained at least a junior high school education tend to experience larger reductions in the poverty rate, although the effects seem to disappear when applying fixed effect method. Lastly, districts with better access to transportation also tend to produce a larger reduction in the poverty rate by around 1.3–1.8 percentage points.

Table 2: Main Estimation Results

VARIABLES	Dependent variables:							
	Poverty Rate (Column 1–4)				Poverty Gap (Column 5–8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Random Effects		Fixed Effects		Random Effects		Fixed Effects	
Total GRDP per capita	-0.944*		0.501		-0.134		0.223	
	(0.499)		(0.621)		(0.150)		(0.330)	
Agriculture GRDP per capita		0.550		-0.848		-0.030		-0.760**
		(0.385)		(0.984)		(0.098)		(0.373)
Mining GRDP per capita		0.152**		-0.848		-0.030		-0.760**
		(0.076)		(0.088)		(0.030)		(0.036)
Manufacturing GRDP per capita		-0.713***		-0.848		-0.030		-0.760**
		(0.212)		(0.293)		(0.073)		(0.150)
Service GRDP per capita		-0.964*		-0.848		-0.030		-0.760**
		(0.574)		(1.119)		(0.197)		(0.451)
Local government revenue: local own revenue, per capita	0.074	0.075	0.110	0.095	-0.037	-0.034	-0.014	-0.014
	(0.115)	(0.121)	(0.117)	(0.118)	(0.055)	(0.064)	(0.064)	(0.064)
Health spending, per capita	0.032	0.011	0.009	0.013	0.091**	0.080*	0.060	0.059
	(0.086)	(0.087)	(0.088)	(0.087)	(0.046)	(0.047)	(0.045)	(0.045)
Education spending, per capita	-0.018	-0.004	-0.003	0.000	-0.041	-0.026	-0.007	-0.001
	(0.088)	(0.088)	(0.088)	(0.086)	(0.045)	(0.045)	(0.046)	(0.046)
Social protection spending, per capita	-0.040	-0.053	-0.039	-0.048	-0.031	-0.034	-0.040	-0.045
	(0.077)	(0.076)	(0.075)	(0.075)	(0.034)	(0.034)	(0.036)	(0.036)
Years of schooling (urban)	-0.025	-0.029	-0.025	-0.028	-0.043	-0.044	-0.057*	-0.063**
	(0.044)	(0.044)	(0.044)	(0.044)	(0.027)	(0.027)	(0.030)	(0.029)

VARIABLES	Dependent variables:							
	Poverty Rate (Column 1–4)				Poverty Gap (Column 5–8)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Random Effects		Fixed Effects		Random Effects		Fixed Effects	
Years of schooling (rural)	-0.335***	-0.293***	-0.286***	-0.242***	-0.085***	-0.067**	-0.040	-0.023
	(0.085)	(0.068)	(0.088)	(0.069)	(0.029)	(0.026)	(0.033)	(0.030)
Village head education: at least completed junior secondary school	-1.900*	-1.668*	-0.581	-0.476	-1.229*	-1.170*	0.570	0.620
	(1.055)	(1.014)	(0.995)	(0.977)	(0.682)	(0.689)	(0.590)	(0.592)
Road (asphalt or concrete)	-1.872***	-1.710***	-1.210*	-1.323**	-0.695***	-0.642**	-0.338	-0.382
	(0.610)	(0.621)	(0.655)	(0.648)	(0.228)	(0.258)	(0.336)	(0.339)
Active TKPK (==1, if active)	-2.065**	-1.704**			-0.471**	-0.426**		
	(0.851)	(0.805)			(0.207)	(0.188)		
Constant	35.786***	33.930***	8.260	5.778	7.524***	8.878***	-1.023	3.304
	(9.169)	(10.986)	(10.886)	(15.167)	(2.774)	(3.283)	(5.658)	(6.448)
Observations	2,633	2,606	2,633	2,606	2,633	2,606	2,633	2,606
R-squared	0.492	0.492	0.497	0.501	0.117	0.119	0.128	0.131
Number of Districts	433	427	433	427	433	427	433	427
Random Effects	Yes	Yes	No	No	Yes	Yes	No	No
Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies	Yes	Yes	No	No	Yes	Yes	No	No
Region*Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

In addition to the main findings using a complete data set, we also conducted an analysis using subset of our data by disaggregating into western and eastern regions (Table 3). We run regressions using the same models to examine whether there is heterogeneity in the effects of our variable interests by regions. In our analysis, the western region covers districts in Sumatra, Java, Kalimantan, and Bali, while the eastern region covers the rest.

Table 3: Regression Results (by Regions)

VARIABLES	Western Region		Eastern Region	
	Dependent variable: Poverty Rate			
	(1)	(2)	(3)	(4)
Total GRDP per capita	-1.416***		-0.508	
	(0.465)		(0.852)	
Agriculture GRDP per capita		0.611		0.387
		(0.438)		(0.739)
Mining GRDP per capita		0.067		0.561*
		(0.077)		(0.287)
Manufacturing GRDP per capita		-0.868***		-0.608
		(0.247)		(0.409)
Service GRDP per capita		-0.106		-2.351**
		(0.755)		(0.918)
Local government revenue: local own revenue, per capita	-0.048	-0.068	0.137	0.160
	(0.145)	(0.149)	(0.177)	(0.185)
Health spending, per capita	-0.108	-0.117	0.029	0.001
	(0.103)	(0.106)	(0.209)	(0.206)
Education spending, per capita	0.165	0.175	-0.249	-0.259
	(0.103)	(0.107)	(0.194)	(0.200)
Social protection spending, per capita	0.008	-0.004	-0.109	-0.108
	(0.082)	(0.082)	(0.154)	(0.157)
Years of schooling (urban)	0.029	0.021	-0.021	-0.029
	(0.052)	(0.051)	(0.078)	(0.078)
Years of schooling (rural)	-0.253**	-0.181**	-0.508***	-0.509***

VARIABLES	Western Region		Eastern Region	
	Dependent variable: Poverty Rate			
	(1)	(2)	(3)	(4)
	(0.111)	(0.073)	(0.118)	(0.119)
Village head education: at least completed junior secondary school	-2.838*	-2.169	-1.162	-1.149
	(1.456)	(1.511)	(1.473)	(1.416)
Road (asphalt or concrete)	-1.579**	-1.525**	-2.397*	-1.984
	(0.676)	(0.711)	(1.262)	(1.212)
Active TKPK (==1, if active)	-1.376	-1.104	-2.733**	-2.000
	(1.039)	(0.960)	(1.332)	(1.328)
Constant	43.140***	21.907	38.455**	60.395***
	(7.715)	(14.320)	(15.259)	(16.080)
Observations	1,843	1,816	790	790
R-squared	0.481	0.484	0.540	0.548
Number of Districts	295	289	138	138
Random Effects	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	No
Year Dummies	Yes	Yes	Yes	Yes
Region Dummies	Yes	Yes	Yes	Yes
Region X Trend	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

As we can see from both tables, overall economic output appears to correlate with poverty reduction only in the western region. The magnitude is even higher than the average using a complete data set. A one percent increase in per capita GRDP is associated with around 1.4 percentage points decrease in the poverty rate. On the other hand, we find no correlation between the overall economic output and reduction in poverty in the eastern region.

If we conduct an analysis using sectoral economic outputs, we find that manufacturing and service output sectors are associated with reduction in poverty rate. Manufacturing sector output appears to correlate with a reduction in poverty only in the western region, while service sector outputs only appear to be associated with progress in the eastern region. Output of the agriculture sector seems to have no correlation with poverty rate in both regions. Our findings also indicate that higher level of mining output may correlate with higher poverty rate in the eastern region.

Regarding the local institution, the results indicate that TKPK engagement appears to correlate with progress in poverty reduction, particularly in the eastern region. The magnitude is even larger than the one using a complete data set. On average, districts with an active TKPK in the eastern region tend to reduce the poverty rate 2.7 percentage points larger than those with an inactive TKPK. This significance sign disappears, however, once we use sectoral GRDP rather than the overall economic output.

With regard to government spending, the results remain consistent in both regions–that there is no association between district spending on social programs and progress in poverty reduction. The results suggest that improving the amount of spending may not be effective in reducing poverty. A further analysis on district government spending may be needed to examine whether the money was spent on capital, staff or other things.

We also find that improvement in average years of schooling–particularly in rural regions–is associated with poverty reduction. The magnitude of the effects in the eastern region is more than double that in the western region. A one-year increase in average years of schooling in rural areas is correlated with around a 0.2 and 0.5 percentage points fall in the poverty rate in the western and eastern regions, respectively. The education attainment level of local leaders is, however, only correlated with progress in poverty reduction in the western region. Lastly, improvement in road conditions at the village level appears to be associated with better progress in reducing poverty.

Conclusions

Our findings suggest that rapid and sustainable regional economic growth is essential for poverty reduction. Poverty reduction and regional economic output are found to be strongly interrelated. Looking at the economic sectoral contribution, poverty tends to decrease more in districts with higher output from the manufacturing and service sectors, while output growth in the mining sector tends to worsen both the poverty rate and poverty gap.

Institutional capacity appears to correlate with progress in reducing poverty at the district level. The poverty rate also tends to fall in districts with an active TKPK that conducted regular coordination meetings, submitted annual reports, and participated in technical consultations and training from 2011 to 2016. Significant correlation is found particularly in districts in the Eastern region.

Overall, our findings are consistent with previous studies that indicate that a successful development strategy requires effective, region-specific combinations of growth and sound social policies. Simply increasing the share of government spending on health, education, and social programs may not, however, be effective in reducing poverty. Sufficient institutional capacity seems to be a critical precondition for the delivery of efficient public services aimed at poverty reduction.

To follow up our research, further investigating the role of TKPKs may be needed to examine the underlying mechanisms leading to a positive correlation between regional TKPKs and progress in poverty reduction. Most importantly, it is necessary to improve the measurement of TKPK institutionalisation and effectiveness as well as to address issues of endogeneity.

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Appendix One

Table 1A.1: Changes in Poverty Rate and Gap (2010-2016)

Province	Poverty Rate in 2010	Poverty Rate in 2016	Changes in Poverty Rate	Poverty Gap in 2010	Poverty Gap in 2016	Changes in Poverty Gap
Aceh	20.30	17.06	-3.24	3.51	3.11	-0.40
North Sumatra	14.19	12.61	-1.59	2.43	1.95	-0.47
West Sumatra	9.48	7.06	-2.42	1.51	0.98	-0.53
Riau	12.18	9.54	-2.64	2.31	1.59	-0.71
Jambi	8.20	8.30	0.10	1.14	1.20	0.06
South Sumatra	14.45	13.37	-1.08	2.32	1.83	-0.49
Bengkulu	16.06	16.86	0.81	2.70	2.76	0.07
Lampung	16.38	13.52	-2.86	2.77	2.34	-0.43
Kep. Bangka Belitung	7.69	5.34	-2.35	1.10	0.66	-0.44
Kep. Riau	8.56	7.52	-1.04	1.50	0.91	-0.59
DKI Jakarta	5.61	5.32	-0.30	0.74	0.44	-0.30
West Java	11.37	9.42	-1.95	1.80	1.43	-0.37
Central Java	15.46	12.73	-2.74	2.48	2.12	-0.36
Di Yogyakarta	16.35	14.02	-2.33	2.48	2.43	-0.05
East Java	14.84	11.88	-2.97	2.35	1.79	-0.57
Banten	6.89	5.50	-1.38	0.99	0.68	-0.31
Bali	6.28	4.77	-1.50	0.89	0.52	-0.37
West Nusa Tenggara	21.86	16.57	-5.29	4.06	3.15	-0.91
East Nusa Tenggara	23.19	23.17	-0.02	4.34	4.36	0.02
West Kalimantan	9.31	8.17	-1.14	1.36	1.23	-0.12

Province	Poverty Rate in 2010	Poverty Rate in 2016	Changes in Poverty Rate	Poverty Gap in 2010	Poverty Gap in 2016	Changes in Poverty Gap
Central Kalimantan	7.53	5.56	-1.97	1.06	0.79	-0.27
South Kalimantan	6.06	5.12	-0.93	0.82	0.67	-0.15
East Kalimantan	9.93	6.62	-3.31	1.72	1.01	-0.71
North Sulawesi	10.65	9.18	-1.47	1.73	1.60	-0.13
Central Sulawesi	17.89	14.91	-2.98	3.27	2.48	-0.79
South Sulawesi	12.24	10.25	-2.00	1.96	1.86	-0.11
Southeast Sulawesi	16.01	13.20	-2.81	2.53	2.51	-0.02
Gorontalo	16.70	17.64	0.94	2.87	3.93	1.06
West Sulawesi	14.06	11.45	-2.60	2.17	1.65	-0.53
Maluku	28.66	22.71	-5.95	6.31	3.86	-2.45
North Maluku	11.75	7.73	-4.01	2.13	0.82	-1.31
West Papua	33.31	27.81	-5.50	8.34	6.77	-1.57
Papua	36.15	30.06	-6.09	8.64	7.66	-0.98
Indonesia	15.51	13.07	-2.44	2.82	2.35	-0.47

Source: BPS (Authors' analysis).

Table 1A.2: Regression results of random effect estimation with poverty rate as the dependent variable

VARIABLES	Dependent variable: Poverty Rate (P0)									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Total GRDP per capita	-0.596	-0.765*	-0.697	-0.925*	-0.944*					
	(0.390)	(0.403)	(0.495)	(0.490)	(0.499)					
Agriculture GRDP per capita						1.180***	0.999***	0.804**	0.617	0.550
						(0.317)	(0.297)	(0.381)	(0.383)	(0.385)
Mining GRDP per capita						0.091	0.115	0.172**	0.151**	0.152**
						(0.087)	(0.081)	(0.077)	(0.075)	(0.076)
Manufacturing GRDP per capita						-1.191***	-1.203***	-0.705***	-0.734***	-0.713***
						(0.232)	(0.225)	(0.215)	(0.215)	(0.212)
Service GRDP per capita						-0.135	-0.223	-0.997*	-0.949*	-0.964*
						(0.466)	(0.462)	(0.587)	(0.574)	(0.574)
Local government revenue: local own revenue, per capita		0.026	0.070	0.068	0.074		0.018	0.076	0.071	0.075
		(0.125)	(0.114)	(0.116)	(0.115)		(0.130)	(0.120)	(0.121)	(0.121)
Health spending, per capita		0.063	0.021	0.032	0.032		0.066	-0.000	0.011	0.011
		(0.092)	(0.086)	(0.086)	(0.086)		(0.099)	(0.087)	(0.087)	(0.087)
Education spending, per capita		-0.075	-0.002	-0.023	-0.018		-0.087	0.012	-0.008	-0.004
		(0.106)	(0.087)	(0.088)	(0.088)		(0.116)	(0.087)	(0.088)	(0.088)
Social protection spending, per capita		-0.065	-0.046	-0.036	-0.040		-0.072	-0.058	-0.050	-0.053
		(0.088)	(0.077)	(0.077)	(0.077)		(0.090)	(0.077)	(0.076)	(0.076)
Years of schooling (urban)			-0.033	-0.026	-0.025			-0.034	-0.029	-0.029
			(0.044)	(0.044)	(0.044)			(0.044)	(0.044)	(0.044)

VARIABLES	Dependent variable: Poverty Rate (P0)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Years of schooling (rural)			-0.328***	-0.338***	-0.335***			-0.288***	-0.295***	-0.293***
			(0.085)	(0.085)	(0.085)			(0.068)	(0.068)	(0.068)
Village head education: at least completed junior secondary school				-2.001*	-1.900*				-1.749*	-1.668*
				(1.077)	(1.055)				(1.033)	(1.014)
Road (asphalt or concrete)				-1.929***	-1.872***				-1.747***	-1.710***
				(0.614)	(0.610)				(0.624)	(0.621)
Active TKPK (==1, if active)					-2.065**					-1.704**
					(0.851)					(0.805)
Constant	23.929***	27.034***	26.986***	33.993***	35.786***	13.647*	18.194**	26.089**	31.737***	33.930***
	(6.623)	(7.147)	(8.646)	(8.885)	(9.169)	(7.282)	(7.456)	(11.097)	(10.922)	(10.986)
Observations	3,475	3,153	2,633	2,633	2,633	3,304	3,029	2,606	2,606	2,606
R-squared	0.503	0.521	0.491	0.492	0.492	0.513	0.526	0.490	0.492	0.492
Number of Districts	497	482	433	433	433	473	464	427	427	427
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1A.3: Regression results of fixed effect estimation with poverty rate as the dependent variable

VARIABLES	Dependent variable: Poverty Rate (P0)									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Total GRDP per capita	0.633	0.423	0.636	0.501	0.501					
	(0.464)	(0.454)	(0.616)	(0.621)	(0.621)					
Agriculture GRDP per capita						-0.769	-1.266	-0.814	-0.848	-0.848
						(0.923)	(0.902)	(0.985)	(0.984)	(0.984)
Mining GRDP per capita						-0.020	-0.003	0.109	0.096	0.096
						(0.129)	(0.123)	(0.086)	(0.088)	(0.088)
Manufacturing GRDP per capita						-0.284	-0.175	0.102	0.092	0.092
						(0.290)	(0.304)	(0.291)	(0.293)	(0.293)
Service GRDP per capita						2.003**	2.090**	1.394	1.352	1.352
						(1.001)	(1.005)	(1.133)	(1.119)	(1.119)
Local government revenue: local own revenue, per capita		0.075	0.112	0.110	0.110		0.040	0.097	0.095	0.095
		(0.126)	(0.116)	(0.117)	(0.117)		(0.128)	(0.117)	(0.118)	(0.118)
Health spending, per capita		0.053	0.006	0.009	0.009		0.074	0.010	0.013	0.013
		(0.092)	(0.088)	(0.088)	(0.088)		(0.099)	(0.087)	(0.087)	(0.087)
Education spending, per capita		-0.045	0.007	-0.003	-0.003		-0.058	0.011	0.000	0.000
		(0.104)	(0.087)	(0.088)	(0.088)		(0.113)	(0.085)	(0.086)	(0.086)
Social protection spending, per capita		-0.087	-0.045	-0.039	-0.039		-0.089	-0.054	-0.048	-0.048
		(0.086)	(0.075)	(0.075)	(0.075)		(0.087)	(0.075)	(0.075)	(0.075)
Years of schooling (urban)			-0.028	-0.025	-0.025			-0.031	-0.028	-0.028
			(0.044)	(0.044)	(0.044)			(0.044)	(0.044)	(0.044)

VARIABLES	Dependent variable: Poverty Rate (P0)									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Years of schooling (rural)			-0.279***	-0.286***	-0.286***			-0.237***	-0.242***	-0.242***
			(0.088)	(0.088)	(0.088)			(0.069)	(0.069)	(0.069)
Village head education: at least completed junior secondary school				-0.581	-0.581				-0.476	-0.476
				(0.995)	(0.995)				(0.977)	(0.977)
Road (asphalt or concrete)				-1.210*	-1.210*				-1.323**	-1.323**
				(0.655)	(0.655)				(0.648)	(0.648)
Constant	4.954	8.287	4.634	8.260	8.260	0.449	4.886	2.946	5.778	5.778
	(7.809)	(7.936)	(10.489)	(10.886)	(10.886)	(8.650)	(8.042)	(14.969)	(15.167)	(15.167)
Observations	3,475	3,153	2,633	2,633	2,633	3,304	3,029	2,606	2,606	2,606
R-squared	0.506	0.525	0.494	0.497	0.497	0.521	0.535	0.498	0.501	0.501
Number of Districts	497	482	433	433	433	473	464	427	427	427
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1A.4: Regression results of random effect estimation with poverty gap (P1) as the dependent variable

VARIABLES	Dependent variable: Poverty Rate (P0)									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Total GRDP per capita	-0.235*	-0.197	-0.079	-0.123	-0.134					
	(0.137)	(0.146)	(0.160)	(0.144)	(0.150)					
Agriculture GRDP per capita						0.182*	0.151	0.078	-0.006	-0.030
						(0.099)	(0.096)	(0.100)	(0.100)	(0.098)
Mining GRDP per capita						0.067**	0.073**	0.078**	0.072**	0.073**
						(0.034)	(0.034)	(0.031)	(0.030)	(0.030)
Manufacturing GRDP per capita						-0.304***	-0.292***	-0.230***	-0.230***	-0.221***
						(0.079)	(0.078)	(0.077)	(0.074)	(0.073)
Service GRDP per capita						-0.084	-0.068	-0.117	-0.053	-0.081
						(0.186)	(0.202)	(0.202)	(0.200)	(0.197)
Local government revenue: local own revenue, per capita		-0.051	-0.053	-0.045	-0.037		-0.009	-0.036	-0.040	-0.034
		(0.092)	(0.057)	(0.056)	(0.055)		(0.101)	(0.065)	(0.065)	(0.064)
Health spending, per capita		0.061	0.085*	0.089*	0.091**		0.054	0.073	0.080*	0.080*
		(0.062)	(0.046)	(0.046)	(0.046)		(0.066)	(0.046)	(0.047)	(0.047)
Education spending, per capita		-0.103*	-0.040	-0.046	-0.041		-0.085	-0.025	-0.031	-0.026
		(0.054)	(0.044)	(0.045)	(0.045)		(0.058)	(0.044)	(0.045)	(0.045)
Social protection spending, per capita		0.014	-0.027	-0.027	-0.031		0.005	-0.029	-0.030	-0.034
		(0.048)	(0.034)	(0.034)	(0.034)		(0.048)	(0.034)	(0.034)	(0.034)
Years of schooling (urban)			-0.050*	-0.044	-0.043			-0.048*	-0.044	-0.044
			(0.028)	(0.027)	(0.027)			(0.028)	(0.027)	(0.027)

VARIABLES	Dependent variable: Poverty Rate (P0)									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Years of schooling (rural)			-0.094***	-0.087***	-0.085***			-0.073***	-0.069***	-0.067**
			(0.028)	(0.029)	(0.029)			(0.025)	(0.026)	(0.026)
Village head education: at least completed junior secondary school				-1.340*	-1.229*				-1.270*	-1.170*
				(0.688)	(0.682)				(0.692)	(0.689)
Road (asphalt or concrete)				-0.741***	-0.695***				-0.679***	-0.642**
				(0.228)	(0.228)				(0.259)	(0.258)
Active TKPK (==1, if active)					-0.471**					-0.426**
					(0.207)					(0.188)
Constant	6.359***	6.703***	4.923*	7.218***	7.524***	4.377	4.806	6.092*	8.090**	8.878***
	(2.330)	(2.559)	(2.901)	(2.685)	(2.774)	(3.577)	(3.436)	(3.646)	(3.352)	(3.283)
Observations	3,475	3,153	2,633	2,633	2,633	3,304	3,029	2,606	2,606	2,606
R-squared	0.114	0.117	0.123	0.116	0.117	0.115	0.117	0.124	0.117	0.119
Number of Districts	497	482	433	433	433	473	464	427	427	427
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1A.5: Regression results of fixed effect estimation with poverty gap (P1) as the dependent variable

VARIABLES	Dependent variable: Poverty Rate (P0)									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Total GRDP per capita	0.639**	0.577*	0.204	0.223	0.223					
	(0.324)	(0.316)	(0.337)	(0.330)	(0.330)					
Agriculture GRDP per capita						0.007	-0.281	-0.747**	-0.760**	-0.760**
						(0.597)	(0.615)	(0.372)	(0.373)	(0.373)
Mining GRDP per capita						0.045	0.031	0.038	0.041	0.041
						(0.045)	(0.049)	(0.035)	(0.036)	(0.036)
Manufacturing GRDP per capita						-0.334*	-0.265	-0.235	-0.242	-0.242
						(0.198)	(0.216)	(0.150)	(0.150)	(0.150)
Service GRDP per capita						1.037	1.245	0.829*	0.883*	0.883*
						(0.909)	(0.925)	(0.458)	(0.451)	(0.451)
Local government revenue: local own revenue, per capita		0.036	-0.016	-0.014	-0.014		0.032	-0.016	-0.014	-0.014
		(0.108)	(0.064)	(0.064)	(0.064)		(0.108)	(0.064)	(0.064)	(0.064)
Health spending, per capita		0.029	0.062	0.060	0.060		0.021	0.061	0.059	0.059
		(0.061)	(0.045)	(0.045)	(0.045)		(0.065)	(0.045)	(0.045)	(0.045)
Education spending, per capita		-0.034	-0.008	-0.007	-0.007		-0.024	-0.002	-0.001	-0.001
		(0.051)	(0.045)	(0.046)	(0.046)		(0.057)	(0.046)	(0.046)	(0.046)
Social protection spending, per capita		-0.034	-0.041	-0.040	-0.040		-0.041	-0.046	-0.045	-0.045
		(0.046)	(0.036)	(0.036)	(0.036)		(0.047)	(0.036)	(0.036)	(0.036)
Years of schooling (urban)			-0.057*	-0.057*	-0.057*			-0.062**	-0.063**	-0.063**
			(0.030)	(0.030)	(0.030)			(0.030)	(0.029)	(0.029)

VARIABLES	Dependent variable: Poverty Rate (P0)									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Years of schooling (rural)			-0.041	-0.040	-0.040			-0.024	-0.023	-0.023
			(0.034)	(0.033)	(0.033)			(0.032)	(0.030)	(0.030)
Village head education: at least completed junior secondary school				0.570	0.570				0.620	0.620
				(0.590)	(0.590)				(0.592)	(0.592)
Road (asphalt or concrete)				-0.338	-0.338				-0.382	-0.382
				(0.336)	(0.336)				(0.339)	(0.339)
Constant	-7.923	-6.906	-0.369	-1.023	-1.023	-9.425	-9.099	4.253	3.304	3.304
	(5.451)	(5.424)	(5.723)	(5.658)	(5.658)	(6.970)	(6.819)	(6.749)	(6.448)	(6.448)
Observations	3,475	3,153	2,633	2,633	2,633	3,304	3,029	2,606	2,606	2,606
R-squared	0.119	0.123	0.126	0.128	0.128	0.120	0.123	0.129	0.131	0.131
Number of Districts	497	482	433	433	433	473	464	427	427	427
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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HARMONISATION OF SUSENAS AND RISKESDAS

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Abstract

To succeed in implementing programs to reduce the number of stunted children, accurate and timely data and information are required to serve as the basis for target and goal setting. The use of Riskesdas (Riset Kesehatan Dasar: Basic Health Research) is highly important to generate indicators on the Indonesian people's health status and monitor the success of various government programs in the health sector. Susenas (*Survei Sosial Ekonomi Nasional*: National Socioeconomic Survey) is used to generate indicators associated with household and individual welfare status.

Since 2018, there have been measures to harmonise Riskesdas, which is produced by Balitbangkes (*Badan Penelitian dan Pengembangan Kesehatan*: National Centre for Health Research and Development), Ministry of Health (MoH), with Susenas, which is produced by Statistics Indonesia (*Badan Pusat Statistik*: BPS). The MoH and BPS have been collaborating for quality assurance in the Riskesdas data collection. Quality assurance aims to ensure that the implementation of Riskesdas data collection is in accordance with the Standard Operating Procedures (SOP). Quality assurance also aims to identify any signs of content error and provide early warnings throughout the enumeration. The outcome of this activity is expected to serve as a reference tool for the MoH to follow up the findings of the Riskesdas enumeration to reduce content error that might have a broader impact.

Background

Stunting–often referred to as runt or short stature–is a failure of growth amongst children under the age of five (toddler). It is due to chronic malnutrition and repetitive infection–particularly within the child's first 1,000 days of life (Hari Pertama Kehidupan: HPK). A child is considered to be experiencing stunting if his/her body's length and height are more than two standard deviations below the World Health Organization Child Growth Standards median.

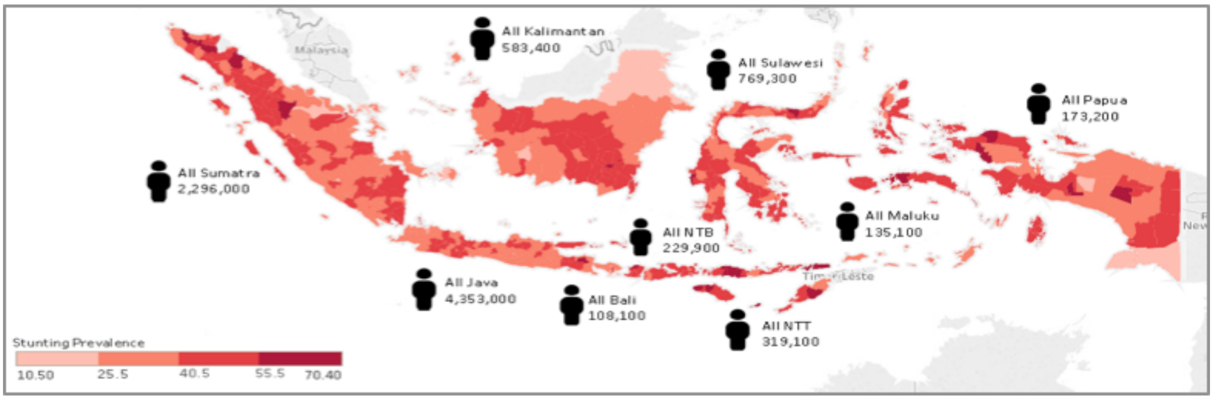
Indonesia is one of 47 countries with the worst rate of toddler stunting and anemia amongst women of reproductive age in the world. Since 2017, the Government of Indonesia through TNP2K has, therefore, been raising stunting as a national priority issue. The Global Nutrition Report 2016 (IFPRI 2016) noted that the stunting prevalence in Indonesia ranked 108th of 132 countries, while the 2014 report (IFPRI 2014) noted that Indonesia was one of 17 countries undergoing a double nutritional burden of overnutrition and undernutrition. In Southeast Asia, the stunting prevalence in Indonesia is the second highest after Cambodia (IFPRI 2016). Riskesdas 2018 results show there was an increase from 48.6 percent (2013) to 57.8 percent (2018) in the proportion of children with a normal development status at the national level and a fall of 6.4 percent in stunting prevalence over the same period–namely, from 37.2 percent (2013) to 30.8 percent (2018). The remaining 11.4 percent suffered from other nutritional conditions.

The main government source of stunting data is Riskesdas, a household survey that is conducted by the MoH every 3-5 years and collects information on individual health, including measurements of stunted children. The Riskesdas conducted in April 2018 and its data collection was coordinated with the implementation of Susenas that had been carried out in March 2018. Through this coordination, household and individual samples from Susenas of March 2018 also became samples in Riskesdas of April 2018.

Riskesdas data has been utilised several times to measure stunting with the following results: 35.6 percent (2010), 37.2 percent (2013), and 36.8 percent (2017). Errors in the accuracy and timeliness of data and information used as inputs results in plans that are not useful or even detrimental if they are implemented. The use of Riskesdas is highly important to produce indicators to observe Indonesian people's health status and monitor the success of various government programs in the health sector. Since 2018, Riskesdas has been routinely conducted by Balitbangkes in the expectation that, in 2018, there would be an integration between Riskesdas data and socioeconomic data issued by BPS through Susenas.

The incidence of stunting is widely spread across different regencies/cities in Indonesia (Figure 1). The highest prevalence of toddler stunting occurred in 2013 in the regency of South Timor Tengah (TTS) at 70.43 percent (38,772 people), while the highest absolute number of toddlers suffering from stunting occurred in the regency of Bogor which composed of 148,764 children and a stunting prevalence of 28.29 percent.

Figure 1: Stunting Incidence by Region 2013



Source: Data on Prevalence of Stunting, Basic Health Research (Riskesdas) 2013, Ministry of Health

Goals

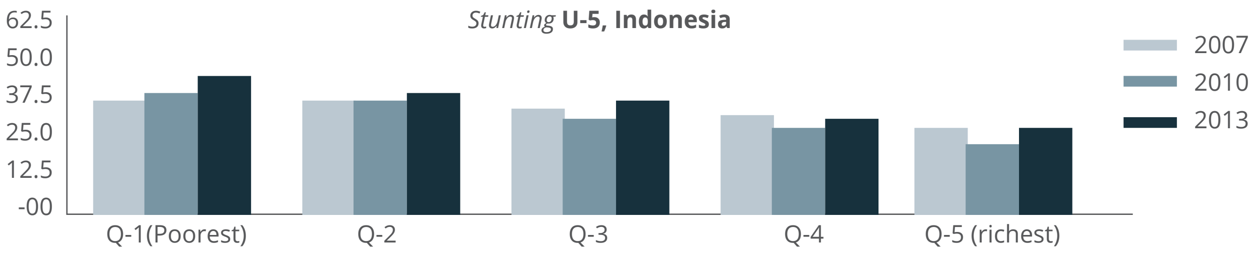
The harmonisation of Susenas with Riskesdas is very important–especially to enable the mapping of a toddler's nutritional and welfare status, particularly those associated with stunting–and has two goals: (i) data integration; and (ii) improving data quality. Firstly, integrating the data from Riskesdas 2018 with those from Susenas 2018 is expected to enable the mapping of the health status condition of households and individuals and their welfare level which is based on the level of household expenditure. The second objective is to increase the quality of Riskesdas data through quality assurance of Riskesdas data collection (integration between BPS and the MoH). This is crucial to maintaining consistency between surveys conducted by the respective agencies.

Consideration for Harmonisation

Stunting Prevalence Happened in All Income Groups

When viewed from the distribution of income of those households with a stunted toddler, the prevalence of stunted children amongst the poorest population is significantly higher than that of other groups (Figure 2). The incidence of stunting in the middle income group and up to the richest one is also fairly high at above 25 percent. This indicates that the high number of stunted toddlers is not only related to poverty, which is measured by household income and expenditure, but is also highly related to other factors, such as nutritional consumption of the toddler and mother, parenting, access to and quality of health services, and environmental health. To find out more details about factors associated with stunting prevalence, the integration of Susenas and Riskesdas aims to ensure that the information on household socioeconomic characteristics that is often found in Susenas can be connected to the basic health data that are often found in Riskesdas.

Figure 2: Stunting Prevalence (%) by Distribution of Income Group (2007-13)



Source: Estimate from Riskesdas (stunting rate) and population projection by BPS.

Stunting Rate Is A National Development Target

Data on stunting can also be obtained from the Nutritional Status Monitoring (*Pemantauan Status Gizi*: PSG) which is a monitoring activity of toddler nutritional status development that is carried out annually to provide a description of a toddler's nutritional status. The 2017 PSG was conducted in 34 provinces and 514 regencies/cities. PSG implementation aims to safeguard and hence make community nutrition improvement effort more effective and efficient, by monitoring the change of nutritional status and program performance from time to time, so as to accurately determine the appropriate measures, change of policy formulation, and relevant program planning needed. In PSG 2017, a Nutritional Consumption Monitoring (Pemantauan Konsumsi Gizi: PKG) on toddlers was also conducted.

Another source of data on stunting is the National Health Indicator Survey (Surkesnas) of 2016, which is one of the inter-Riskesdas national health research activities conducted by Balitbangkes. The survey was conducted since there was no assessment system to comprehensively measure the achievements of indicators in the Renstra (Rencana Strategis: Strategic Plan) and RPJMN (Rencana Pembangunan Jangka Menengah Nasional: National Medium-term Development Plan) 2015-19 in the health sector. The routine recording and reporting system has not fulfilled all the health indicators and there is a need to strengthen and support the survey. Surkesnas 2016 measured and observed primary data and explored secondary data in health facilities and the community to determine the most updated situation of the community health status. This was obtained from the regency/city Health Office, community health centre (Pusat Kesehatan Masyarakat: puskesmas), and household/individual. Data on coverage in regency/city and puskesmas refers to the record of 2015.

Since the commencement of his term of office, President Jokowi's administration has prioritised the growth disturbance that is caused by a lack of nutrition in toddlers. All determinant data and indicators on stunting, wasting, and overweight were obtained from anthropometric measurement in Riskesdas. The Riskesdas has been conducted since 2007 by Balitbangkes and the data are sectoral data that are under the responsibility of the MoH.

Riskesdas Sampling Method

Riskesdas is a survey with a cross-sectional design. The Riskesdas of 2007, 2013 and 2018 aimed to describe population health problems in all parts of Indonesia with population sampling at the national, provincial, and regency/city level, while Riskesdas 2010 conducted a representative sample only at the national and provincial level (Table 1).

Table 1: Riskesdas Sample (Various Years)

Unit	RKD 2007	RKD 2010	RKD 2013	RKD 2018
Household Sample	280,000	70,000	300,000	300,000
Representation	District	Province	District	District
Sample Unit	Census Block	Census Block	Census Block	Census Block
Number of Census Blocks	18,000	2,800	12,000	30,000
Choice of Census Block Sample	Same as Susenas	Independent	Independent	Same as Susenas
Number of Households per Census Block	16	25	25	10

Note: RKD: *Riset Kesehatan Dasar* (Basic Health Research).

The number of Riskesdas and Susenas samples was relatively the same but varied across the individuals and households that were surveyed. Riskesdas samples of 2007 and 2018 were the same as the Susenas samples of 2007 and 2018, however, there was no data integration process and weighting in the analysis of Riskesdas and Susenas for 2007. The Riskesdas Sample Framework of 2007 and 2013 were also similar to what was done in Susenas.

S**ampling was undertaken in two phases:**

The first phase was the selection of the primary sampling unit (PSU) list in the main sample. The number of PSUs in the main sample was 30,000, which was selected using the probability-proportional-to-size method with the number of households from the population survey of 2010. The PSU is a merger of several census blocks which is the work area of the enumeration team for the 2010 population census. The PSU was also equipped with information on numbers and names of household heads, their address, and educational background–classified by urban/rural area.

The second phase selection sample was the entire census building which included normal households but did not include institutional households (orphanage, police/military barrack, prison) of the full enumeration result of the 2010 population census (SP2010-C1). Data on census building were selected, and the selected households within the census were updated first. Data updating was conducted by the Riskesdas 2013 enumerator prior to conducting an interview.

Harmonisation Phase

The fact that Riskesdas data collection was conducted partially by the MoH resulted in the data rarely being used by stakeholders from outside the health sector. It is referred to as a partial data collection due to the fact that there is a difference between the sample framework and sample selected in the socioeconomic survey conducted by BPS, while the sample framework aimed for by Susenas and Riskesdas was actually the same as the representative target at the regency/city level.

The unit of analysis that became the target of interviews and its implementation period were relatively similar. The integration of Riskesdas and Susenas means both surveys use the same sample framework. This will enable an analysis of households or individuals with much richer information due to the integration of variables existing in both surveys.

It is hoped that integrating Riskesdas with Susenas data can provide for the wider use of Riskesdas data for policies to accelerate the reduction of prevalence and stunting numbers in Indonesia. As already known, the cause of stunting is multidimensional. The framework for handling stunting is by: (i) Specific Nutritional Intervention (contributes 30 percent) that is an intervention aimed at children in their first 1,000 HPK. The activity is generally conducted by health sector, is short-term, and its results can be recorded in a relatively short time; and (ii) Sensitive Nutritional Intervention (contributes 70 percent) that is an intervention conducted through various development activities outside the health sector. The targets are the general public, and not specifically for the first 1,000 HPK. Most data and information needed to handle the Sensitive Nutritional Intervention are unavailable in Riskesdas data and, therefore, with the integration of Riskesdas and Susenas data of 2018, information needed to support sensitive nutrition intervention can be obtained.

The plenary session of ministers that was chaired by the Vice President of Indonesia on 12 July 2017 on an Action Plan to Address Stunting (Chronic Malnutrition) came up with five pillars of stunting mitigation, one of which–where TNP2K plays an important role–is Monitoring and Evaluation, which comprises:

1. **Monitoring exposure to national campaign, understanding and behavioural change as the result of a national campaign on stunting;**
2. **Conducting monitoring and evaluation routinely to ensure the delivery and quality of stunting program services;**
3. **Routinely measuring and publishing the results of stunting handling and childhood development on an annual basis for accountability;**
4. **Results-based planning and budgeting program at national and sub-national level; and**
5. **Controlling stunting handling programs.**

Routine monitoring and evaluation is needed–supported by data that are accurate and integrated with data on socioeconomic conditions–so that all programs can be simultaneously implemented to accelerate a reduction in the incidence of stunting.

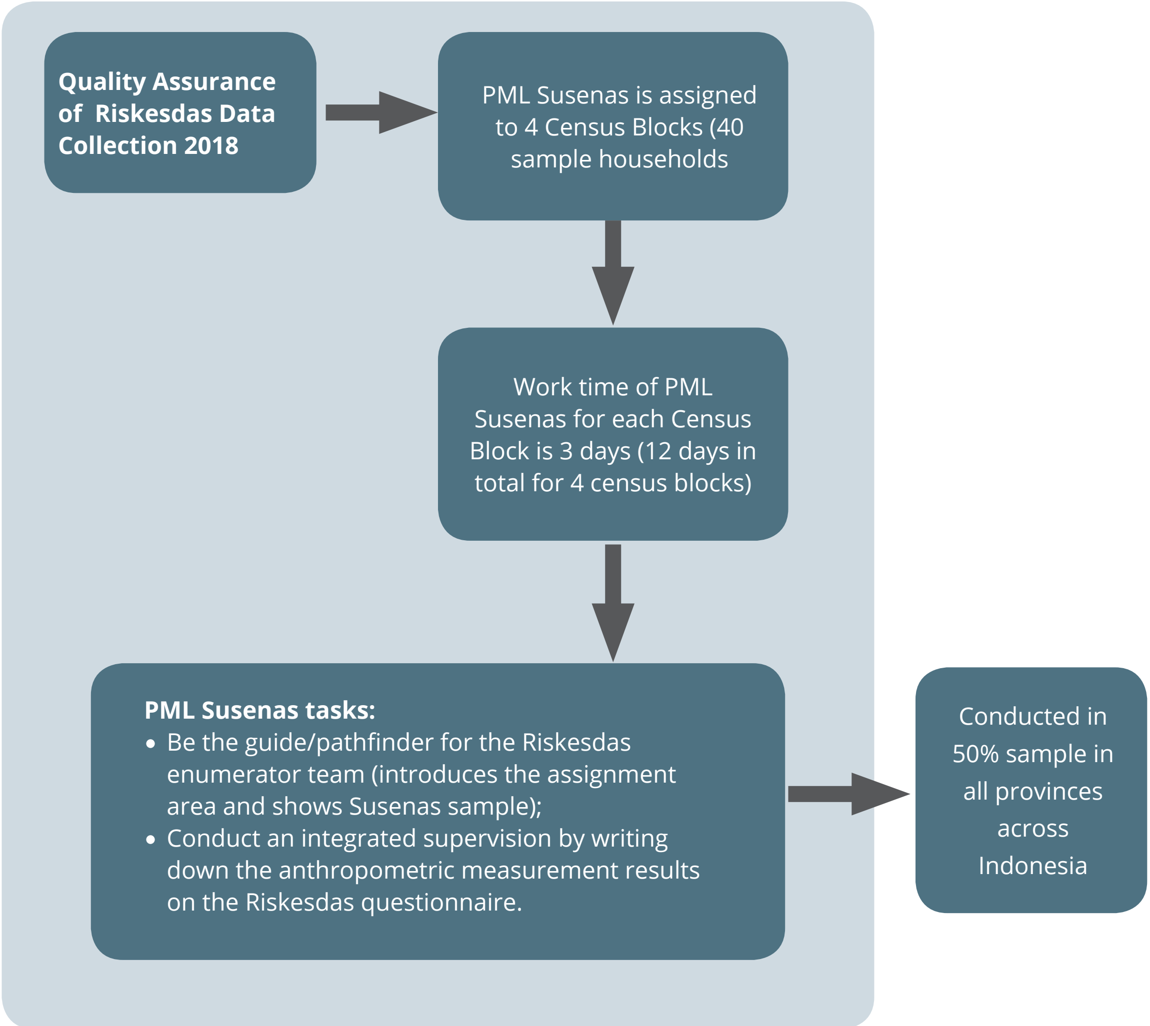
Quality Control

The quality of evidence-based data obtained from Riskesdas 2013 must be maintained through various measures including instrument testing and validation. The test was carried out by researchers from Balitbangkes, academics, and professional organisations, with validation by a university team (University of Indonesia, Airlangga University, and Hasanuddin University). In general, the quality control steps have met the standards required in a survey, but due to the strategic value of the data to be measured, quality control of data collection of Riskesdas is needed. This is done by collaborating with BPS and the MoH in the effort to control data collection quality in the field.

The MoH has vast experience in sectoral data collection down to the regency/city level, especially for the Basic Health Research data that was collected in 2007, 2010, and 2013. Unlike that commonly used by BPS, the data for this particular Riskesdas were collected by data collectors who have strong knowledge of the health sector. Data collectors who have the necessary knowledge and skill in the health sector can understand specific information on health, and yet BPS is the most experienced institution with regard to field mastery and management in survey process, hence it needs integrated supervision to assure the quality of Riskesdas 2018 data.

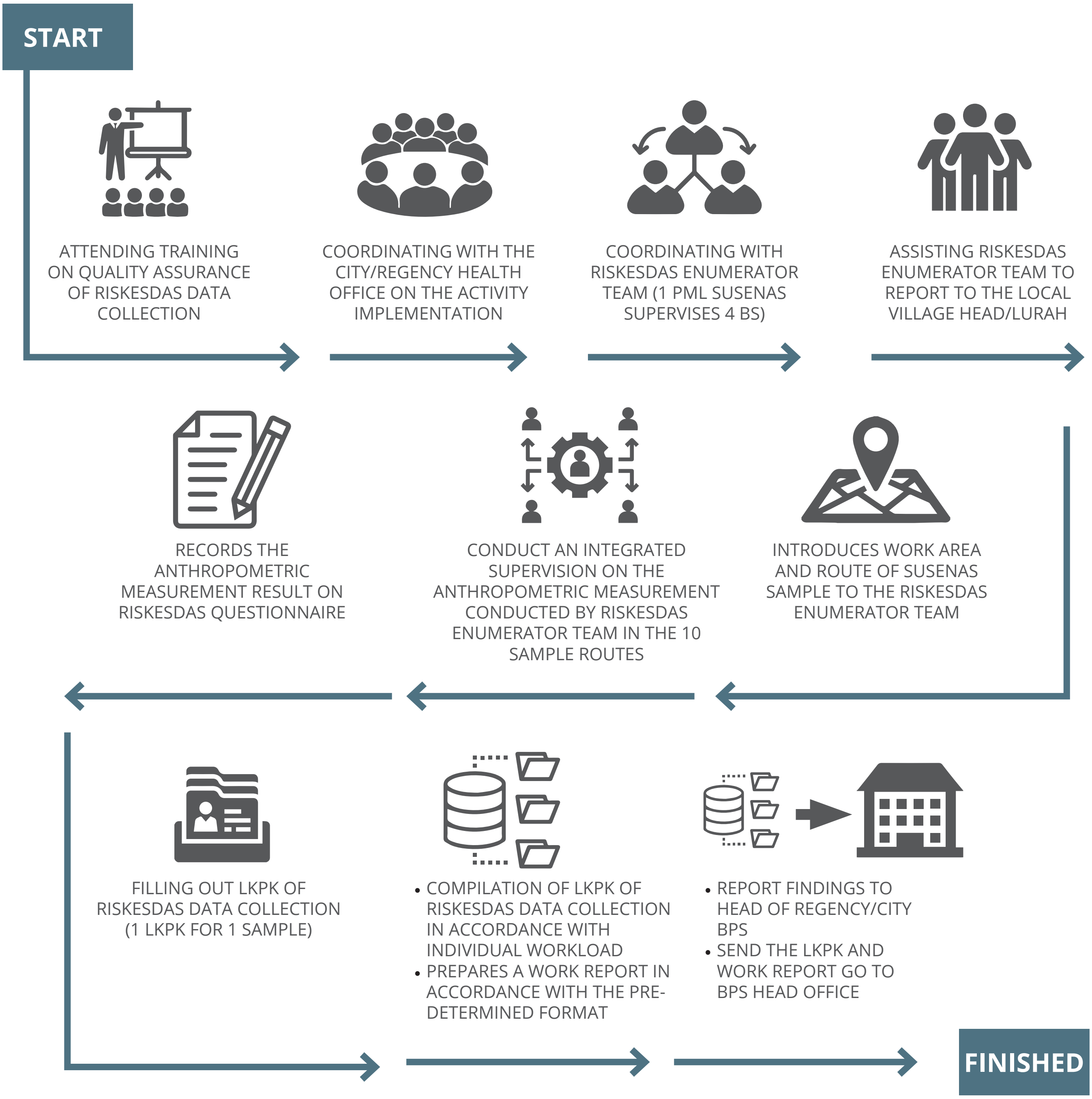
The MoH and BPS coordinate to ensure the quality of the Riskesdas data collection. Quality assurance aims to ensure that the implementation of Riskesdas data collection is in accordance with the SOP. In addition, quality assurance also aims to identify indications of content error and provide early warning throughout the enumeration. The outcome of this activity is expected to serve as a reference for the MoH regarding the findings in Riskesdas enumeration to reduce content error that might cause broader impact. It can also be used to deploy a supervision team or taskforce when necessary.

Figure 3: Mechanism of Quality Assurance of Riskesdas Data Collection



Quality assurance for the Riskesdas data collection is conducted by PML (Field Supervisor) of Susenas (Figure 4). The PML must have had previous experience before he/she can supervise the Susenas in March 2018. It is expected that the PMLs can show the location of households whose data was collected in Susenas March 2018 for the Riskesdas data collection which was about to start in May 2018. In addition, PMLs will also conduct an integrated supervision by ensuring that the anthropometric measurement process in Riskesdas 2018 has been undertaken. This has an impact on controlling the data collection process that has already been conducted in line with SOP that had been previously agreed and helps to check whether Susenas also undertook field visits, since the same households will be visited by officials for Riskesdas 2018.

Figure 4: Susenas Supervisor Activity Scheme for Quality Assurance of Riskesdas Data Collection



Source: quality assurance mechanism of Riskesdas data collection (BPS-MoH integration) BPS, Jakarta, september 2017

Harmonisation Results

Riskesdas and Susenas are two surveys with different goals, yet each is expected to be mutually integrated, and their different results are also expected to complement each other. The two data collection periods in 2018 are expected to complement each other, although it also presents a risk that Susenas sample households will not be found by Riskesdas due to a relocation or a possible change in household structure caused by a household member who has moved. In addition, there is a difference in data collection between Riskesdas and Susenas, because BPS and Balitbangkes carried out their data processing in different places. of being different in the time of data collection will lead to the possibility of Susenas sample households that cannot be found due to relocation and the possibility of changes in the structure of the household because ART has moved.

Table 2: Comparison between Susenas and Riskesdas of 2018

Company's Legality	Susenas	Riskesdas
Result	Generate important indicators, particularly socioeconomic indicators.	Generate important indicators, particularly anthropometric measurement.
Period of data collection	March 2018	April-May 2018
Data Manager	Statistics Indonesia (BPS)	Balitbangkes-MoH
Sample	±300,000 sub-neighbourhoods (rukun tetangga: RT) in all regencies/cities, provinces across Indonesia.	Equal to Susenas

Source: Guideline for Susenas and Riskesdas of 2018.

Quality Control of Riskesdas Data

Quality control that is conducted jointly in Riskesdas 2018 is expected to create better results compared with internal quality control, be it by Balitbangkes or BPS. It is expected that the SOP for field data collection can be optimised effectively. The quality control process conducted by BPS focuses on field data collection through supervision or presence in the field, random spot-checks, and verification and validation of field data collection. Field visits by BPS are undertaken by the PML.

The duties and responsibilities of the Susenas PML include:
Participating in the quality assurance training for data collection of Riskesdas of 2018 which is integrated with training for regional instructors for Susenas of March 2018 in every province**;**

- **Coordinating with the health office in each regency/city to serve as a guide and conduct integrated supervision on the Riskesdas enumeration team;**
- **Discussing and coordinating the enumeration time with the Riskesdas team under his/her responsibility;**
- **Facilitating Riskesdas enumeration team to identify the work area and households that are sampled in Susenas March 2018;**
- **Carrying out an integrated supervision after anthropometric measurement by noting whether the enumerator of the Riskesdas questionnaire conducts any measurement;**
- **Filling out the Quality Assurance Worksheet (*Lembar Kerja Penjaminan Kualitas*: LKPK);**
- **Preparing a work report in accordance with the required format;**
- **Submitting the final report to the head of the local regency/city BPS on the supervision results; and**
- **Submitting the LKPK and work report to the Directorate of Community Welfare at BPS.**

Integrated supervision by the Susenas PML in March 2018 on Riskesdas 2018 is conducted by distributing the workload as follows: one PML is responsible for four census blocks to facilitate and conduct integrated supervision on the Riskesdas team for every household sample (40 household samples).

Harmonisation of Household Samples

Harmonisation of the household samples between Susenas and Riskesdas is conducted by the Riskesdas field enumerator by copying Blok IV VSEN18.K. This contains the information of Susenas sample households undertaken by BPS in March 2018. From the field data collection conducted by Riskesdas enumerators in April 2018, we expect to obtain samples that are aligned with the households and household members to be visited by Susenas officials in March 2018.

The two sets of data that are obtained by Susenas (by BPS) and Riskesdas (Balitbangkes) teams will then be harmonised. Throughout two weeks at the end of November 2018, data harmonisation is conducted by using the information in the Blok IV VSEN 19.K, by looking at data on the name, relationship with the household head, marital status, sex, and individual–which are specified in Susenas and Riskesdas 2018.

After being processed, 72.60 percent of variables from the two data sets could be matched. Based on the name and order of household member (yet different order of household), the result is 0.56 percent, and matching by name and order of household (yet different order of household member) resulted in 0.49 percent. For matching by name but different order of household and household member, the result is 0.001 percent. From all the results, 17.70 percent of the data had no name match, however, information in Blok IV does match; unmatched data by gender is 0.27 percent, unmatched on marital status is 0.23 percent, and unmatched in Blok IV VSEN18.K due to moving in/out is 7.95 percent.

Policy Recommendation

TNP2K suggests several policy recommendations regarding the harmonisation of Susenas and Riskesdas:

1. **Routine monitoring of health conditions through regular surveys.** The mini-anthropometry data collection should be integrated with Susenas annually if Riskesdas is not conducted.

2. **Data management and processing of results of two integrated surveys.** Some of the separate data processing risks are: (i) possible variable differences used (length, type); and (ii) possible changes in household member ordering due to change of household structure. It is, therefore, necessary to ensure that the variables used are the same and ensure the order of household members does not change, despite the change of household structure.

3. **Provision of a single identity as a link between the two surveys.** BPS has certain policies on Riskesdas 2018 data results, namely: (i) a one door system in data dissemination; and (ii) micro data will not be disseminated (Law on Statistics). The consequences of using Susenas data are: (i) Susenas data that can be accessed by data users comes from the data dissemination; (ii) the format of Susenas data is different because the microdata is not available; and (iii) data user will not be able to merge the Susenas-Riskesdas data. "Another identity" is, therefore, required before the data is disseminated, and the Susenas-Riskesdas data should have "one single identity" to enable the public to access the data that has been integrated between Susenas and Riskesdas of 2018. The use of Riskesdas 2018 data should be more transparent because it is now integrated with Susenas 2018, so that data on socioeconomic conditions and stunting can be obtained from the same household.

4. **Development of toddler health information through harmonisation of the Maternal and Child Health Book (Kesehatan Ibu dan Anak: KIA) and Growth Chart (*Kartu Menuju Sehat: KMS*).** To date, the survey result at national level on mother and child health still does not have any accurate population comparison. This also has implications for the availability of information on mothers and children that is needed to determine targets, particularly who and where the targets are that need intervention. There is a need to develop an instrument to monitor mothers and children by modifying the KIA and KMS to include information on length/height of children under five years of age. This is important to help achieve the national priority target for prevention of stunting.

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THE DEVELOPMENT OF NUTMAP (NUTRITION MAP) STATUS AND STUNTING PREVALENCE IN CHILDREN UNDER-FIVE

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Abstract

Indonesia still faces major challenges with chronic undernutrition among children under-five, which is evidenced by the high prevalence of stunting in children under-five. In order to measure the effectiveness and strengthen the targeting of stunting prevention efforts, the government needs information on the level and distribution of the prevalence of stunting in children under-five at the lower administrative level than the regency/municipality. This activity aims to provide information on the nutritional status of children under- five, including stunting prevalence, up to the village/ward level. The methodology selected to produce the Nutritional Status Map for children under-five was adopted from the Small Area Estimation (SAE) approach developed by Elbers et al. (2003). The estimation model of the nutritional status indicator was determined for each indicator: stunting, wasting, and underweight. The estimation model for each indicator used reference number of the nutritional status prevalence for z-scores of -2 and -3 at the regency/municipality level. In the initial stage, the development of this map was focused on five districts that are included in the 100 priority districts/cities for stunting prevention. Although the coverage area of this map is still limited to five districts, this nutritional status map is expected to be developed comprehensively, starting from priority districts for handling stunting to covering all districts/cities. It is expected that development of the nutritional status map and quantifying stunting prevalence will contribute to improving the system for targeting priority policies to reduce stunting.

Daftar Singkatan

Balitbangkes : *Badan Penelitian dan Pengembangan Kesehatan* (National Institute of Health Research and Development)

GLS : Generalised Least Squares

MoU : Memorandum of Understanding

PKS : *Perjanjian Kerja Sama* (Cooperation Agreement)

Podes : Potensi Desa (Village Potential Statistic)

PovMap : Poverty Map

Riskesdas : *Riset Kesehatan Dasar* (Basic Health Research)

SAE : Small Area Estimation

SP : *Sensus Penduduk* (Population Census)

TNP2K : *Tim Nasional Percepatan Penanggulangan Kemiskinan* (The National Team for The Acceleration of Poverty Reduction)

Background

Indonesia still faces a major challenge with chronic undernutrition among children under-five–which is evidenced by the high prevalence of stunting in children under-five. Stunting is a condition of impaired growth in children under-five due to chronic undernutrition–notably from the status of fetus until the child is 23 months of age. In 2018, the Basic Health Research (Riskesdas) unit of the Ministry of Health found 30.8 per cent of children under-five were stunted. Compared to neighboring countries, Indonesia has the second-highest prevalence of stunting in Southeast Asia after Cambodia.

Responding to these conditions, the Government of Indonesia took the initiative to strengthen efforts to reduce stunting based on the Five Pillars of Stunting Prevention since 2017: (i) the commitment, and vision of, leadership; (ii) national campaigns and communication on behavioural change; (iii) convergence, coordination, and consolidation of the national, regional, and community programs; (iv) food nutritional security; and (v) monitoring and evaluation. Implementation of the five pillars is expected to increase the effectiveness of an integrated nutritional intervention, including nutrition-specific and nutrition-sensitive actions. This integrated intervention needs to be carried out by targeting priority groups in priority locations and through priority interventions. Based on global experience, this is the key to success in improving nutrition and preventing stunting (Levinson and Balarajan 2013). The Government of Indonesia, therefore, determined priority areas for stunting prevention, starting from 100 priority districts/cities in 2018 and 160 priority districts/cities in 2019–with the objective of expanding to all districts/cities gradually until 2024.

In order to measure the effectiveness and strengthen the targeting of stunting prevention efforts, the government needs information on the level and distribution of the stunting prevalence in children under-five at a lower administrative level than the regencies/municipalities. This information can be useful for the government to synchronise various programs, especially the ones that are closely related to the role of subnational government and the role of the community at the subdistrict and village/ward levels. The data set used to identify the nutritional status of children under-five and stunting prevalence is currently the Basic Health Research (*Riset Kesehatan Dasar* or *Riskesdas*) that was published by the Ministry of Health. This data is, however, only valid to display nutritional status at the district/city level. To plan, monitor, and evaluate the success of stunting prevention programs, therefore, requires a database that is adequate to display nutritional status down to the village/ward level.

The Purpose of the Development of Children Under-Five Nutritional Status Map

To support the efforts to converge policies on stunting prevention in Indonesia, TNP2K cooperated with the National Institute of Health Research and Development (*Badan Penelitian dan Pengembangan Kesehatan*: Balitbangkes) of the Ministry of Health to initiate an activity to map the prevalence of nutritional status in children under-five. This activity aims to provide information regarding the nutritional status of children under-five, including stunting prevalence up to the village/ward level. With this information, the government is expected to strengthen the targeting up to the village/ward level, which becomes the priority areas of stunting prevention. In addition, the nutritional status map can also serve as baseline data, which can be a reference when performing the program monitoring and evaluation of stunting prevention.

The collaboration between the TNP2K and *Balitbangkes* was realised in a Memorandum of Understanding (MoU) or Collective Agreement which is applicable for four years from the date of signing of the agreement on 6 August 2018. This agreement serves as a legal umbrella that regulates the cooperation of the health research implementation in efforts to accelerate poverty reduction in Indonesia. The scope of this agreement includes the use of research data in the preparation of policy and planning, research implementation, dissemination and publication, as well as increased resource capacity.

As a follow-up to the Collective Agreement, TNP2K and *Balitbangkes* also compiled a Cooperation Agreement (*Perjanjian Kerja Sama*: PKS) which regulates the technical development of the nutritional status map of children under-five at the village/ward level in more detail. The collaboration with *Balitbangkes* was not just limited to the provision of the required data from both institutions, but also included increased human resource capacity as well as the implementation forum of scientific discussion and dissemination. One of the capacity-building activities that has been carried out was the Small Area Estimation (SAE) method training, which was held in August 2018.

The Methodology for the Development of the Children Under-Five Nutritional Status Map

The methodology selected to generate the Children Under-Five Nutritional Status Map was adopted from the Small Area Estimation (SAE) approach developed by Elbers et al. (2003). It was used to describe the level of poverty and inequality at the level of aggregation of administrative regions at the district level or village/ward. The SAE method has been reviewed by the World Bank and became the main reference of empirical research for the development of the Poverty Map (PovMap). The PovMap could estimate the regression based on consumption, z-score estimation, and others with the composition of selected explanatory variables. The PovMap could generate percentage distribution and a number of outcomes at a certain regional level based on a particular standard measurement as the calculation benchmark.

This method was later developed by Fujii (2005, 2010) to describe the distribution of undernourished and malnourished children in Cambodia at the lowest aggregate-administrative level. In developing this map, the outcome variables used included the nutritional status of children under-five as measured from z-scores or standardised values. The following are the indicators and their standardised values obtained from *Riskesdas*:

1. The ratio of weight-to-age or weight/age index that indicated nutritional problems in general. Children under-five were categorised as having undernutrition and malnutrition or underweight if the z-score of weight/age is lower than -2;
2. The ratio of height-to-age or height/age index that indicated chronic or acute nutritional problems as a result of a longstanding condition. Children under-five were categorised as short and stunted if the z-score of height/age is lower than -2; and
3. The ratio of weight-to-height or weight/height index that indicated acute nutritional problems as a result of a short-time condition. Children under-five were categorised as thin and wasted if the z-score of weight/height is lower than -2.

In addition to those indicators, development of children under-five nutritional status also requires other information, such as individual and household characteristics that can be obtained from the Population Census and Riskesdas, as well as community or environmental characteristics that can be obtained from administrative data on Village Potential Statistics (*Potensi Desa* or Podes).

Selection of Estimation Variables

The estimation model of nutritional status indicators was determined for each indicator: stunting, wasting, and underweight. The estimation model for each indicator applied the prevalence rate of nutritional status for z-scores of -2 and -3 at the regency/municipality level. Although the estimation of children under-five nutritional status could be carried out using a provincial-level estimation model, this study employed a district-level estimation model to capture the heterogeneity within districts/cities. Estimation was carried out for each nutritional status indicator at the regency/municipality level separately. This study determined six districts as initial models for mapping development throughout Indonesia. As a result, there were 18 models for estimating nutritional status indicators based on the

indicator types and districts/cities (three models for estimating indicators in each district/city). Each model should ideally produce an estimation of at least ± 5% relative difference to the reference point at the regency/municipality level. In addition, the model should also be consistent when the reference point used is changed, for instance, the z-score was less than -2 to -3, and vice versa.

The estimation was initially made when the z-score point was less than -2. If the difference in the aggregated estimation results at the regency/municipality level was still more than 5 per cent relative to the reference point at the regency level from the survey, the model will be adjusted by adding other census variables that were statistically equivalent to the survey variables. The estimation with the created model to determine the rate of nutritional status at point -2 was then carried out when the z-score was less than -3. At this stage, this model frequently had to readjust in the process of selecting both independent variables as well as location and household errors, because the difference in the estimation results could reach more than 5 per cent relative to the regency/municipality rate. It might be caused by sampling error–for instance, taking too large a sample size due to the small number of samples from the survey, so that the location and household errors from the census estimation were also higher.

In addition to considering the level of significance, independent variables in estimating nutritional status indicators were also selected based on the results of literature reviews. The selected variables were included in the following four characteristics:

1. Parents characteristics:
    a. Mother's education (Beal et al. 2018; Fernalda et al. 2012; Keino et al. 2014; and Mzumara et al. 2018).
    b. Mother's age (Mzumara et al. 2018). Based on the study of Efevbera et al. (2017), pregnancy at a young age is not the only cause of stunting. Early marriage can affect stunting through education and economic status.
    c. Mother's occupation (Keino et al. 2014).
    d. Father's education (Beal et al. 2018; Semba et al. 2008; Vollmer et al. 2016).
    e. Father's employment status (Beal et al. 2018).
2. Household characteristics:
    a. Welfare status (Beal et al. 2018; Fernalda et al. 2012; Keino et al. 2014; Mzumara et al. 2018; Torlesse et al. 2016); could be taken from the welfare index, which was prepared based on asset ownership.
    b. Sources of drinking water (Beal et al. 2018; Mzumara et al. 2018).
    c. Household sanitation (Beal et al. 2018; Keino et al. 2014).
    d. The interaction between sanitation facilities and access to clean water (Torlesse et al. 2016). Stunting risks increased three times higher in households that consumed non-potable water and used poor sanitation.
3. Children characteristics:
    a. Gender (Mzumara et al. 2018; Torlesse et al. 2016).
    b. Age (Beal et al. 2018; Mzumara et al. 2018; Torlesse et al. 2016).
4. Community characteristics:
    a. Lack of access to health facilities (Beal et al. 2018).
    b. Rural areas (Beal et al. 2018).

By applying the findings of this literature review, the independent variables related to the characteristics were selected to estimate the nutritional status indicators in the five districts/cities studied. The number of variables selected ranged from 5-25. Variables mostly selected at the household level included access to sanitation and clean water as well as parents' education. At the village level, the most selected variables were the parents' average education, access to sanitation and clean water, the presence of health infrastructure (Pos Pelayanan Terpadu: Posyandu or Integrated Health Post) and the number of midwives in the village.

The Procedure of Small Area Estimation

Basically, z-score based regression was used to estimate small areas, such as the index of weight/age, height/age, and weight/height. The z-score based regression generated a predicted value which was then used as the basis for calculating the malnutrition rate. In practice, the simulation process using the SAE method utilised population census data to strengthen the estimation power in generating malnutrition rates at the subdistrict or village/ward level.

The PovMap procedure was performed with a series of statistical tests. **The first stage** was the process of matching the categories, types, and variable values between *Riskesdas* and Population Census data. This process was also known as the matching process. Types of statistical tests on continuous variables and categorical variables were distinguished. The independent variables included in the model specification were limited to those that passed the statistical test. Variables constructed from household survey data should have the same operational definition as variables constructed from population census data.

The second stage of the Nutritional Map procedure was the specification of the z-score estimation model–that is, index of weight/age, height/age, and weight/height)–which also included aggregation at village/ward level in survey and census data. This model could be written as follows:

$$\ln y_{ch} = E[\ln y_{ch} | \mathbf{x}_{ch}] + u_{ch} \qquad (2.1)$$

or the model could also be written linearly as:

$$\ln y_{ch} = \mathbf{x}_{ch}{}'\boldsymbol{\beta} + u_{ch} \qquad (2.2)$$

dengan:

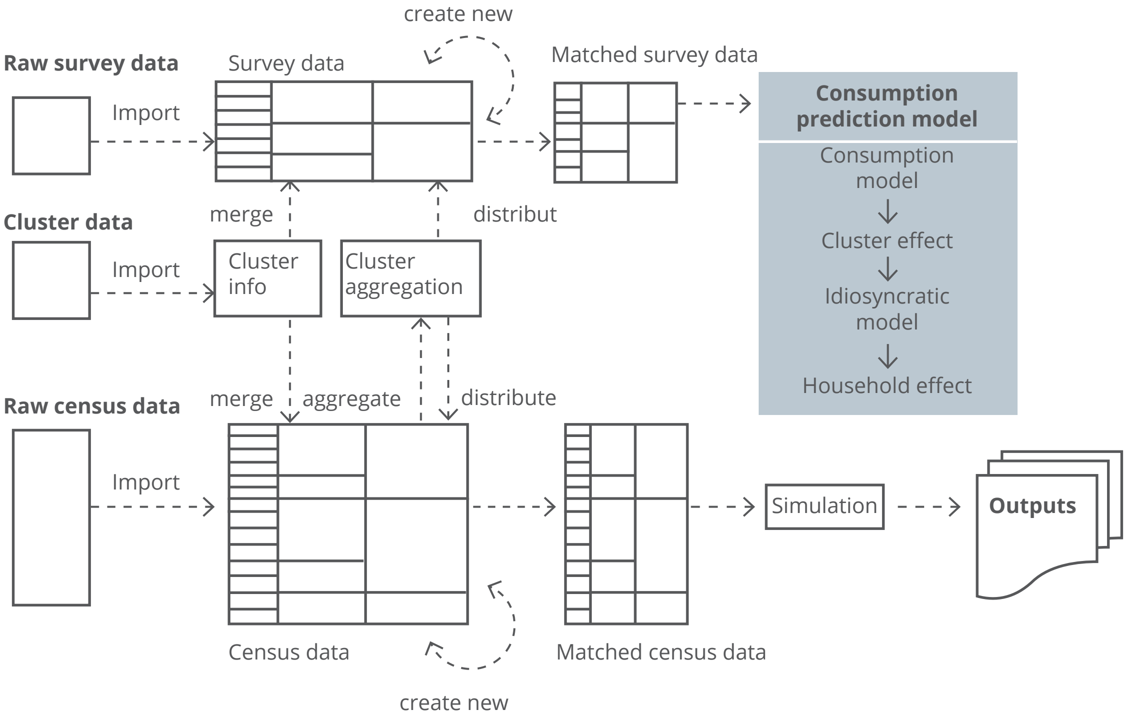
c = cluster representation (village/ward)

h = individual/household in cluster $_c$ (village/ward)

y_{ch} = individual z-score h in cluster $_c$ (village)

$\mathbf{x}_{ch}$ = characteristics of household h in cluster $_c$ (village/ward)

Figure 1: ELL Methodology Flowchart



Source: Zhao and Lanjouw 2006 using PovMap2: A User's Guide, (draft), The World Bank.

As mentioned earlier, this model referred to predictive power so that it was expected to obtain a statistically strong parameter coefficient. The first stage was a z-score based regression model which consisted of household characteristics–known as the **beta model**.

In the third stage, the error term estimation from the beta model was further processed to: (i) construct a variance-covariance matrix to fix the heteroscedasticity problem by decomposing household units and aggregation at the village/ward level. In principle, this approach was similar to the random effect model; and (ii) obtain the variance parameter value on the estimation of the household units and the aggregation of village/ward level for the bootstrap simulation.

The ELL method proposed a logistical transformation of the household units' error term in modeling heteroscedasticity, which was then referred to as the **alpha model**. In summary, it could be written as follows:

$$\ln\left[\frac{e_{ch}^2}{A - e_{ch}^2}\right] = \mathbf{z}_{ch}^T \hat{\boldsymbol{\alpha}} + r_{ch} \qquad (3.1)$$

The estimated variance of the beta model and alpha model was constructed to estimate the generalised least squares (GLS), where the variance-covariance matrix would be:

$$\begin{bmatrix} \sigma_{\eta c} + \sigma_{\varepsilon} & \sigma_{\varepsilon} & \sigma_{\varepsilon} & \sigma_{\varepsilon} \\ \sigma_{\varepsilon} & \sigma_{\eta c} + \sigma_{\varepsilon} & \sigma_{\varepsilon} & \sigma_{\varepsilon} \\ \sigma_{\varepsilon} & \sigma_{\varepsilon} & \sigma_{\eta c} + \sigma_{\varepsilon} & \sigma_{\varepsilon} \\ \sigma_{\varepsilon} & \sigma_{\varepsilon} & \sigma_{\varepsilon} & \sigma_{\eta c} + \sigma_{\varepsilon} \end{bmatrix} \quad (3.2)$$

The estimated GLS coefficient parameter was the initial value for the simulation process employing the bootstrap method. This process performed 100 replications to produce a poverty level at the cluster level. This simulation estimated each individual's z-score value of children under-five in the census.

The fourth stage was the outcome value prediction. At this stage, the prediction of outcome indicators was carried out at an aggregated level. This aggregation level was lower than the aggregation unit at the regional/municipal level by combining the census data information and estimation results at the regional/municipal level.

The fifth stage was Field Verification. Direct verification of the community was conducted in selected areas to ensure that the outcome estimation results mirrored the reality on the ground.

Table 1: Standard Procedure for Nutritional Mapping (NutMap) (2018)

Tahap	Proses
1	Estimating the Beta model according to the equation (2.1)
2	Calculating the cluster effect η_c
3	Calculating the variance estimator $\mathrm{var}(\sigma_{\eta}^{2})$
4	Preparing the residual term for the Alpha model estimation
5	Estimating the GLS model under the matrix description in (x.x)
6	Utilising singular value decomposition to break down the variance-covariance matrix from the previous step. It was used to generate a vector from normally distributed random variables so that the combined variance-covariance matrix would match the description in (3.2)
7	Analysing the census data, omitting the observations containing missing values, creating all census variables required for both Beta and Alpha models.
8	Saving all data for the simulation process, which was known as a "PDA" file

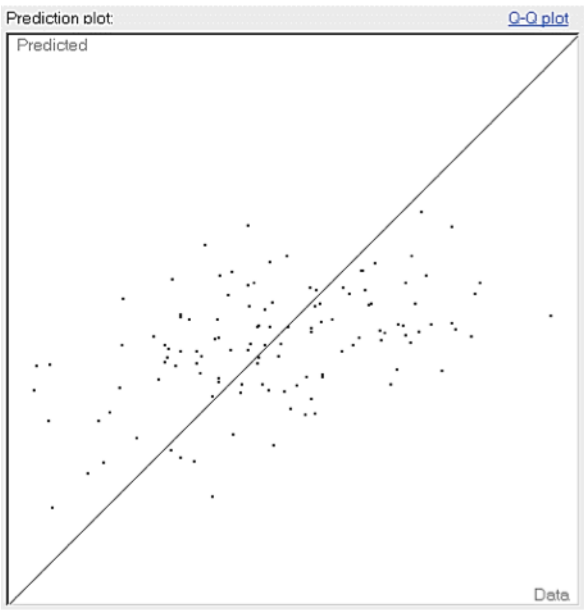
Source: World Bank, Manual PovMap.

SAE utilised other data resources to overcome the issue of estimating representation at smaller levels which became a constraint on survey data through a regression approach. Other data that could be used to increase the estimated representation ability at lower levels were: (i) population census data; and (ii) administrative data at the village/ward, or cluster levels.The information on z-score values and household characteristics was obtained from *Riskesdas*. Then, since the census data had the same household characteristic variables as *Riskesdas*, the estimation results of parameter coefficients obtained through regression with Basic Health Research data could be borrowed to predict the households' z-score contained in the census data. The predicted results for individual units of children under-five were aggregated to the desired level–in this case, the village/ward level. The next section describes an illustration of the process carried out in the SAE Nutrition Analysis at the regency/municipal level, namely the Lampung Tengah District.

As explained in the previous section regarding the variables selection that would be included in the model specification, in the initial test the procedure employed was statistical testing on the variables in the National Socioeconomic Survey (*Susenas*) and Population Census. At the model estimation stage, three types of models were performed, namely: beta model, alpha model, and GLS regression model.

In the beta model, the variables that passed from the preliminary testing stage were involved in the model specification. The regression estimation results were attempted to be statistically significant. The PovMap software package provided stepwise options with both backward and forward techniques. It was essential to consider the behaviour of variables by the type–for instance, whether the included variables were continuous variables or categorical variables (mostly binary variables), as this affected the final result.

Figure 2: Lampung Tengah District Beta Model, Actual and Predicted Plots



The evaluation of beta models could take advantage of the appropriate fit of statistics such as Adjusted-R2. Furthermore, the assessment could also be conducted by observing the graphic plot display. For instance, in the chart above, the plot of actual observations and the model's predicted results are around the 45-degree line. It indicated that the estimation results in the initial stage were quite good.

After estimating the beta model, the second step was decomposing the error-disturbance of the estimation results at the household and cluster levels (in this model, the cluster referred to the village/ward). The decomposition process aimed to obtain the estimation value of the variance in the household unit and village/ward unit. Table 2 indicates an example of the average error-disturbance display of the beta model for the Lampung Tengah District.

Table 2: The Example of Estimation Error-Disturbance in Lampung Tengah District

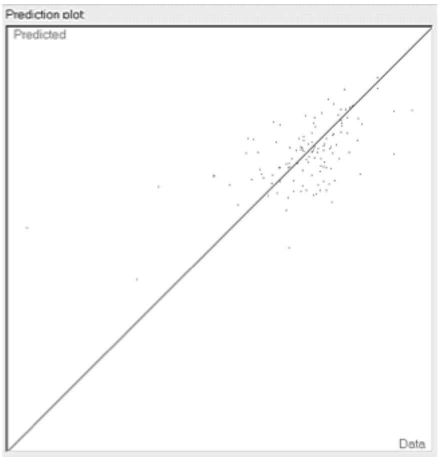
	Cluster ID	#HHLD	Mean	Std.Err.	Min	Median	Max	Weight Sum
1	1012003	4	-1.4406	2.8027	-2.7462	-0.3314	0.7246	2937.4534
2	1014002	5	-0.0674	6.2947	-4.1063	0.2448	2.9049	5169.5596
3	1030004	8	-0.6268	2.2358	-2.8638	-0.3351	1.6616	7779.9237
..	...	...	...	...	...	...	...	..
22	1121006	4	-0.1337	5.8614	-3.8645	0.4763	2.0293	3254.7997

Source: Riskesdas 2013; SP (Sensus Penduduk or Population Census) 2010. Results of the Nutritional Map prepared by the Drafting Team.

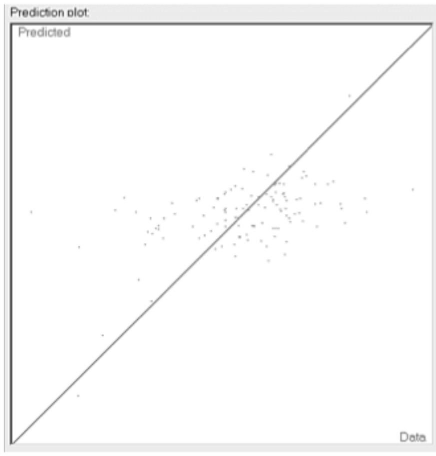
The next estimation process was establishing an alpha model, namely modeling the error-disturbance at the household level. The implication involving the alpha model allowed modeling with a variance that was not constant (experiencing heteroscedasticity). In alpha models, such as ELL (2002 and 2003), the error-disturbance at the household level in the form of a logistic transformation was specified as the dependent variable. Furthermore, the number of household characteristics and cluster-level variables were identified as independent variables.

In the alpha model, selection of the independent variables allowed the consumption prediction variable (yhat) to be used as a candidate. Besides, the interaction between yhat and characteristic variables was also an option to be included in the model. Technically, PovMap provided a stepwise approach to obtain estimation results where all the variables involved were statistically significant. The opportunity to estimate step-by-step allowed the use of both the backward and forward methods. The variance parameter obtained from this alpha model estimation would be used to form the variance-covariance matrix construction in the next GLS model. To evaluate the results, a graphical approach could provide an overview of random patterns in the alpha model prediction. For the alpha model that is still not well-fitted, graphically, there was a line pattern (patterned plot).

Figure 3: Graphic Plot of Alpha Model



a. Pattern Plot



b.Random Pattern Plot

Source: Susenas; SP 2010. PovMap results processed by the 2011 Integrated Database Drafting Team.

After estimating the alpha model, PovMap estimated the consumption model employing the GLS approach. It implied that the construction of the variance-covariance matrix in this GLS estimation had taken into account the estimated variance of household units and cluster units at the village/ward level. The implication was that the heteroscedasticity problem experienced by the early consumption model (beta model) could be overcome or corrected. The next implication was that the estimation results on the variance parameter could be utilised for bootstrap simulation. Estimation of the parameter coefficient on each household characteristic variable formed the parameter that would be used for the simulation.

The bootstrap simulation was the final stage to obtain an estimation of the extent of malnutrition or stunting among children under-five in the desired regional unit or cluster. In this context, the percentage estimation of individual children under-five in the village/ward unit which is in the regency/municipal z-score (weight/age index, height/age index, and weight/height index). The essential data or information to conduct simulations included the malnutrition rate or the stunting rate at the regency/municipal level. Technically, the bootstrap process was repeatedly carried out to predict the z-score value of children under-five through population census data (the process was carried out in 100 repetitions by default).

To every prediction of the weight/age, the height/age, and the weight/height index in each child under-five, confirmation was required whether the prediction value was above or below the weight/age, height/age, and weight/height index. The confirmation process was carried out by providing a value; if it were smaller than the weight/age index, height/age index, and weight/height index, it would be categorised as one. If the value was greater than the weight/age index, it would be classified as zero. After 100 replications, the number of times or how many proportions of the household in question would be counted below the weight/age index, height/age index, and weight/height index. Furthermore, a predictive simulation number or probability value of malnutrition would be obtained from each household. The aggregated value for each child under-five was calculated at the village/ward level so that an estimation of the number of malnourished children under-five at the subdistrict and regency/municipality levels was obtained. Appendix A reveals the examples of estimation results for the five districts at the subdistrict and village/ward levels.

Early Stage Development: The Map of Nutritional Status of Children Under-Five in Five Districts

In 2018, TNP2K initiated the development of the nutritional status map of children under-five in five districts/cities as a prototype for a more comprehensive mapping of the nutritional status of children under-five and stunting prevalence. In the early stages, development of the map was focused on five districts that were included in the 100 priority districts/cities for stunting prevention–Lampung Tengah, Tasikmalaya, Pemalang, Jember, and Timor Tengah Selatan. Table 3 indicates that these five districts are the districts with a prevalence of stunting among children under-five and a poverty rate that is higher than the national rate.

Table 3: Stunting Prevalence and Poverty Rates

District	Stunting Prevalence (2013) (%)	Number of Stunted Children Under-Five (2013) (headcount)	Poverty Rate (March 2018) (%)	Total Number of Villages
Lampung Tengah	52.68	59,838	13.28	307
Tasikmalaya	41.73	69,401	11.24	351
Pemalang	46.28	57,370	17.58	222
Jember	44.10	80,359	10.97	248
Timor Tengah Selatan	70.43	38,773	29.89	278
National	**37.21**		**9.82**	**74,957**

Source: Susenas 2018 and Basic Health Research (Riskesdas) 2013 (processed).

An essential step in the preparation of nutrition maps for five selected districts was the model validation testing by comparing the prevalence values generated by the SAE approach and field findings obtained from direct field surveys (*field verification*). The verification process was conducted with anthropometric surveys and interviews in three sample villages in each selected district. The survey collected directly the data of children aged 0-59 months in the sample villages. The data collected included not only anthropometric information but also the characteristics of households and household members.

The data from the primary survey results in the sample villages would then be compared with the estimation results using the SAE approach. The confidence interval measure was used as the basis for assessing whether the numbers generated were the same between the SAE approach and the field survey. The comparison of these two numbers produced three possibilities–*matched*, *inconclusive*, and *not matched*.

Policy Contribution

The development of a map of nutritional status and stunting prevalence among children under-five was very dependent on the support of, and coordination between, related institutions. The Health Research and Development Unit (Ministry of Health) and Statistics Indonesia played an essential role in providing access to data on Basic Health Research, Population Census, Susenas, Podes, and other relevant survey data used in the development of the nutritional status map.

Although the coverage area of this map was still limited to five districts, it is expected that this nutritional status map can be developed comprehensively–starting from priority districts for handling stunting to one covering all districts/cities. The development of the map of nutritional status and stunting prevalence was expected to contribute to improving the targeting system of priority policies to reduce stunting as follows:

1. It is expected that the nutritional status map can function as a reliable data baseline that can capture the condition of children under-five and household characteristics before the start of specific interventions based on the Five Pillars of Stunting Prevention;
2. It is expected that the nutritional status map can function as a planning guide for regional governments, at regency/municipality, subdistrict, and ward/village levels to allocate resources to priority areas; and
3. It is expected that the nutritional status map can help the process of monitoring and evaluating the impact of stunting prevention programs to identify the most effective programs for stunting prevention.

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Table 1A.1: Estimation Results with Beta Model in Small Area Estimation: Lampung Tengah District

	Coefficient	Std. Err	t	|Prob|>t
Beta Model				
_Intercept	-1.228	2.918	-0.421	0.675
Father's School Education Period	0.149	0.137	1.090	0.279
CV_AYAH_YOS	-0.229	0.345	-0.663	0.509
CV_AYAH_IBU	0.143	0.365	0.391	0.696
DWATER1_1	-1.099	1.500	-0.732	0.466
DWATER2_1	-0.660	0.915	-0.721	0.473
FDISPOSAL2_1	-0.966	0.952	-1.015	0.313
Mother's School Education Period	-0.011	0.153	-0.074	0.941
TOILET1_1	-0.318	1.436	-0.222	0.825
TOILET2_1	-0.923	1.763	-0.523	0.602
Age of Children Under-Five	-0.028	0.017	-1.626	0.108
Father's Age	0.093	0.076	1.227	0.223
Mother's Age	-0.091	0.091	-1.003	0.319
R-squared: 0,1149407, Adj.R-squared: -0,0085559409, Obs: 99				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.2: Estimation Results with Alpha Model in Small Area Estimation: Lampung Tengah District

	Coefficient	Std. Err	t	|Prob|>t
Alpha Model				
intercept	-6.785	1.313	-5.166	0.000
yhat	-2.961	1.207	-2.452	0.016
_yhat_*_yhat_	-0.448	0.246	-1.823	0.071
Age of Children Under-Five	-0.019	0.014	-1.379	0.171
R-squared: 0,11716618, Adj.R-squared: 0,08928722, Obs: 99				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.3: Estimation Results with the GLS Model in Small Area Estimation (SAE Nutritional Map-ELL) in Lampung Tengah

	Coefficient	**Std. Err**	**t**	**|Prob|>t**
GLS				
Intercept	12.7545	0.1951	65.3855	0.0000
H_ACCINTERNET_1	0.1137	0.0640	1.7756	0.0765
H_CELLPHONE_1	0.1805	0.0345	5.2299	0.0000
H_FCOOK_1	0.2656	0.0627	4.2391	0.0000
H_HHIND_1	0.1423	0.0849	1.6771	0.0942
H_HHMALE_1	0.1427	0.0410	3.4826	0.0005
H_HHSERV_1	0.1503	0.0447	3.3631	0.0008
H_HOUSE1_1	-0.0672	0.0512	-1.3111	0.1905
H_HOUSE2_1	-0.1616	0.0773	-2.0909	0.0371
H_NCHILDSD	-0.1025	0.0130	-7.8975	0.0000
H_NCHILDSMA	-0.0915	0.0188	-4.8742	0.0000
H_NCHILDSMP	-0.0856	0.0182	-4.6976	0.0000
H_PCFLOOR	0.0091	0.0017	5.2446	0.0000
H_SHHMEMPLOY	0.2299	0.0680	3.3808	0.0008
H_TFLOOR_1	0.1356	0.0444	3.0521	0.0024
H_TOILET1_1	0.1252	0.0428	2.9228	0.0036
PDS_APOTEK_1	-0.2091	0.2331	-0.8968	0.3703
PDS_DOCTOR_1	-0.2630	0.1135	-2.3167	0.0210
PDS_HHAGR	-0.0034	0.0019	-1.8074	0.0714

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.4: Nutritional Map Estimation Results at the District Level: Lampung Tengah District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	DISTRICT			
1805	Lampung Tengah District	108,491	56,762	52.32
(Target of Povmap percentage rate = 52.68 percent)				
	SUBDISTRICT			
1805010	Padang Ratu	4,520	2,530	55.97
1805011	Selagai Lingga	3,064	1,676	54.70
1805012	Pubian	4,063	2,085	51.32
1805013	Anak Tuha	3,352	1,827	54.51
1805014	Anak Ratu Aji	1,483	835	56.31
1805020	Kalirejo	5,731	2,860	49.91
1805021	Sendang Agung	3,491	1,641	47.00
1805030	Bangunrejo	5,127	2,599	50.69
1805040	Gunung Sugih	5,801	2,970	51.19
1805041	Bekri	2,281	1,171	51.34
1805042	Bumi Ratu Nuban	2,452	1,315	53.65
1805050	Trimurjo	4,239	2,021	47.68
1805060	Punggur	3,196	1,598	49.99
1805061	Gajah City	2,676	1,186	44.32
1805070	Seputih Raman	3,819	1,930	50.54
1805080	Terbanggi Besar	10,395	5,028	48.37
1805081	Seputih Agung	4,153	2,162	52.05
1805082	Way Pengubuan	3,825	1,942	50.76
1805090	Terusan Nunyai	4,518	2,440	54.00
1805100	Seputih Mataram	4,001	2,293	57.31
1805101	Bandar Mataram	7,045	4,060	57.63
1805110	Seputih Banyak	3,408	1,926	56.51
1805111	Way Seputih	1,486	813	54.70
1805120	Rumbia	2,928	1,589	54.26
1805121	Bumi Nabung	2,547	1,454	57.10
1805122	Putra Rumbia	1,663	953	57.31
1805130	Seputih Surabaya	4,037	2,226	55.13
1805131	Bandar Surabaya	3,190	1,628	51.05

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.5: Nutritional Map Estimation Results at the Village/Ward Level: Lampung Tengah District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	SUBDISTRICT			
1805010	Padang Ratu	4,520	2,530	55.97
	VILLAGE/WARD			
1805010006	Purwosari	263	147	55.89
1805010008	Mojokerto	271	145	53.50
1805010009	Sendang Ayu	446	258	57.84
1805010010	Surabaya	305	181	59.34
1805010011	Bandarsari	482	262	54.35
1805010012	Sri Agung	255	130	50.98
1805010013	Kota Baru	310	169	54.51
1805010014	Margorejo	389	242	62.21
1805010015	Karang Tanjung	220	138	62.73
1805010028	Kuripan	420	231	55.04
1805010029	Haduyang Ratu	302	182	60.26
1805010030	Padang Ratu	287	144	50.17
1805010051	Karang Sari	205	113	55.12
1805010061	Sumbersari	105	64	60.96
1805010062	Purworejo	260	122	46.92

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.6: Estimation Results with Beta Model in Small Area Estimation: Tasikmalaya District

	Coefficient	Std. Err	t	|Prob|>t
Beta Model				
_Intercept	-1.945	2.145	-0.907	0.366
Father's School Education Period	-0.048	0.043	-1.111	0.268
BBAKAR_LISTRIK_1	-0.785	0.616	-1.275	0.204
CV_AYAH_SLTP	-0.820	0.842	-0.973	0.332
CV_IBU_SD	0.864	0.766	1.128	0.261
CV_IBU_YOS	0.267	0.146	1.830	0.069
Mother's School Education Period	-0.031	0.059	-0.526	0.600
JMLANAK_06	1.479	0.792	1.867	0.064
JMLANAK_10	2.919	1.845	1.582	0.115
TOILET1_1	0.995	1.399	0.711	0.478
TOILET2_1	0.972	1.410	0.689	0.492
Age of Children Under-Five	-0.018	0.009	-2.067	0.040
Father's Age	-0.070	0.034	-2.081	0.039
Mother's Age	0.034	0.032	1.075	0.284
R-squared: 0,15097465, Adj.R-squared: -0,0085559409, Obs: 189				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.
Note: R-squared: 0,15097465, Adj.R-squared: -0,0085559409, Obs: 189

Table 1A.7: Estimation Results with Alpha Model in Small Area Estimation: Tasikmalaya District

	Coefficient	Std. Err	t	|Prob|>t
Alpha Model				
intercept	-4.863	1.409	-3.451	0.001
yhat	7.696	4.950	1.555	0.122
_yhat_*_yhat_	3.765	2.286	1.647	0.101
AYAH_YOS	0.001	0.138	0.007	0.995
AYAH_YOS*_yhat_	-0.087	0.195	-0.446	0.656
AYAH_YOS*_yhat_*_yhat_	-0.052	0.080	-0.641	0.523
BBAKAR_LISTRIK_1	-0.473	0.837	-0.565	0.573
CV_AYAH_SLTP	-0.755	1.131	-0.668	0.505
CV_AYAH_YOS*_yhat_*_yhat_	0.018	0.047	0.385	0.700
CV_IBU_YOS*_yhat_*_yhat_	0.010	0.055	0.173	0.863
IBU_YOS*_yhat_	0.180	0.146	1.237	0.218
IBU_YOS*_yhat_*_yhat_	0.071	0.076	0.940	0.348
JMLANAK_00	-0.876	1.117	-0.784	0.434
JMLANAK_10	-7.372	3.621	-2.036	0.043
TOILET1_1*_yhat_	-9.578	4.588	-2.087	0.038
TOILET1_1*_yhat_*_yhat_	-4.188	2.122	-1.973	0.050
TOILET2_1*_yhat_	-8.918	4.588	-1.944	0.054
TOILET2_1*_yhat_*_yhat_	-3.769	2.123	-1.775	0.078
UMURBALITA	0.059	0.049	1.202	0.231
UMURBALITA*_yhat_	0.033	0.063	0.531	0.596
UMURBALITA*_yhat_*_yhat_	-0.005	0.021	-0.220	0.826
R-squared: 0,22480814, Adj.R-squared: 0,1325234, Obs: 189				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.8: Estimation Results with the GLS Model in Small Area Estimation: Tasikmalaya District

	Coefficient	**Std. Err**	**t**	**|Prob|>t**
GLS				
Intercept	12.7545	0.1951	65.3855	0.0000
H_ACCINTERNET_1	0.1137	0.0640	1.7756	0.0765
H_CELLPHONE_1	0.1805	0.0345	5.2299	0.0000
H_FCOOK_1	0.2656	0.0627	4.2391	0.0000
H_HHIND_1	0.1423	0.0849	1.6771	0.0942
H_HHMALE_1	0.1427	0.0410	3.4826	0.0005
H_HHSERV_1	0.1503	0.0447	3.3631	0.0008
H_HOUSE1_1	-0.0672	0.0512	-1.3111	0.1905
H_HOUSE2_1	-0.1616	0.0773	-2.0909	0.0371
H_NCHILDSD	-0.1025	0.0130	-7.8975	0.0000
H_NCHILDSMA	-0.0915	0.0188	-4.8742	0.0000
H_NCHILDSMP	-0.0856	0.0182	-4.6976	0.0000
H_PCFLOOR	0.0091	0.0017	5.2446	0.0000
H_SHHMEMPLOY	0.2299	0.0680	3.3808	0.0008
H_TFLOOR_1	0.1356	0.0444	3.0521	0.0024
H_TOILET1_1	0.1252	0.0428	2.9228	0.0036
PDS_APOTEK_1	-0.2091	0.2331	-0.8968	0.3703
PDS_DOCTOR_1	-0.2630	0.1135	-2.3167	0.0210
PDS_HHAGR	-0.0034	0.0019	-1.8074	0.0714

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.9: Nutritional Map Estimation Results at the District Level: Tasikmalaya District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	DISTRICT			
3206	Tasikmalaya	151,301	60,732	40.14
(Target of Povmap percentage rate = 41.73 percent)				
	SUBDISTRICT			
3206010	Cipatujah	5,871	2,434	41.45
3206020	Karangnunggal	6,798	2,671	39.29
3206030	Cikalong	5,844	2,453	41.97
3206040	Pancatengah	4,356	1,815	41.66
3206050	Cikatomas	4,174	1,606	38.47
3206060	Cibalong	2,404	936	38.94
3206061	Parungponteng	2,700	1,067	39.52
3206070	Bantarkalong	3,084	1,206	39.11
3206071	Bojongasih	1,660	644	38.80
3206072	Culamega	2,124	834	39.28
3206080	Bojonggambir	3,689	1,727	46.81
3206090	Sodonghilir	5,683	2,402	42.27
3206100	Taraju	3,560	1,557	43.74
3206110	Salawu	4,844	2,220	45.84
3206111	Puspahiang	2,729	1,219	44.67
3206120	Tanjungjaya	3,848	1,515	39.38
3206130	Sukaraja	4,419	1,670	37.80
3206140	Salopa	4,907	1,935	39.44
3206141	Jatiwaras	4,507	1,811	40.18
3206150	Cineam	2,240	861	38.43
3206151	Karangjaya	886	367	41.42
3206160	Manonjaya	5,125	1,970	38.43
3206161	Gunungtanjung	2,590	1,040	40.17
3206190	Singaparna	5,965	2,241	37.57
3206191	Sukarame	3,403	1,270	37.31
3206192	Mangunreja	3,350	1,292	38.58

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	SUBDISTRICT			
3206200	Cigalontang	5,942	2,610	43.92
3206210	Leuwisari	3,337	1,310	39.26
3206211	Sariwangi	2,739	1,111	40.55
3206212	Padakembang	3,354	1,274	37.98
3206221	Sukaratu	4,116	1,572	38.19
3206230	Cisayong	4,362	1,743	39.95
3206231	Sukahening	2,418	917	37.94
3206240	Rajapolah	4,235	1,569	37.06
3206250	Jamanis	3,018	1,220	40.44
3206260	Ciawi	5,321	2,040	38.33
3206261	Kadipaten	3,514	1,431	40.71
3206270	Pagerageung	4,909	1,911	38.92
3206271	Sukaresik	3,276	1,254	38.29

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.10: Nutritional Map Estimation Results at the Village/Ward Level: Tasikmalaya District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	DISTRICT			
3206010	Cipatujah	5,871	2,434	41.45
	VILLAGE/WARD			
3206010001	Ciheras	526	240	45.63
3206010002	Cipanas	329	155	47.11
3206010003	Ciandum	486	203	41.77
3206010004	Cipatujah	480	178	37.08
3206010005	Sindangkerta	584	225	38.54
3206010006	Cikawungading	692	297	42.92
3206010007	Kertasari	394	166	42.13
3206010008	Padawaras	217	89	41.01
3206010009	Darawati	259	117	45.17
3206010010	Bantarkalong	427	164	38.41
3206010011	Tobongjaya	331	130	39.27
3206010012	Nangelasari	245	94	38.37
3206010013	Nagrog	364	173	47.53
3206010014	Pameutingan	304	114	37.54
3206010015	Sukahurip	233	86	36.91

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.11: Estimation Results with Beta Model in Small Area Estimation: Pemalang District

	Coefficient	Std. Err	t	|Prob|>t
Beta Model				
intercept	-1.558	1.755	-0.888	0.376
AYAH_SLTA_1	0.894	0.903	0.990	0.324
AYAH_SLTP_1	0.620	0.678	0.915	0.362
AYAH_YOS	-0.040	0.064	-0.624	0.533
BALITA_LAKI2_1	-0.366	0.382	-0.958	0.339
CV_AYAH_YOS	-0.112	0.119	-0.946	0.346
CV_IBU_SD	-0.676	0.874	-0.774	0.440
DWATER2_1	0.371	0.438	0.847	0.399
FDISPOSAL1_1	0.488	0.504	0.969	0.334
IBU_YOS	0.005	0.059	0.082	0.935
LANTAI_UBIN_1	-0.834	0.461	-1.809	0.073
TOILET1_1	0.570	0.612	0.931	0.353
TOILET2_1	-0.233	0.798	-0.292	0.771
UMURBALITA	-0.009	0.010	-0.825	0.411
UMUR_AYAH	0.028	0.036	0.789	0.431
R-squared: 0,10842519, Adj.R-squared: 0,022342109, Obs: 160				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.12: Estimation Results with Alpha Model in Small Area Estimation: Pemalang District

	Coefficient	Std. Err	t	|Prob|>t
Alpha Model				
intercept	0.804	12.638	0.064	0.949
yhat	9.578	14.194	0.675	0.501
_yhat_*_yhat_	3.332	3.947	0.844	0.400
AYAH_SLTA_1	15.127	8.956	1.689	0.094
AYAH_SLTA_1*_yhat_	18.494	12.622	1.465	0.145
AYAH_SLTA_1*_yhat_*_yhat_	6.015	4.619	1.302	0.195
AYAH_SLTP_1	6.990	5.450	1.283	0.202
AYAH_SLTP_1*_yhat_	4.435	6.927	0.640	0.523
AYAH_SLTP_1*_yhat_*_yhat_	0.657	2.213	0.297	0.767
AYAH_YOS	-0.777	0.539	-1.443	0.152
AYAH_YOS*_yhat_	-0.686	0.576	-1.191	0.236
AYAH_YOS*_yhat_*_yhat_	-0.126	0.153	-0.823	0.412
BALITA_LAKI2_1	-6.315	3.015	-2.095	0.038
BALITA_LAKI2_1*_yhat_	-5.756	3.490	-1.649	0.102
BALITA_LAKI2_1*_yhat_*_yhat_	-1.190	1.002	-1.187	0.238
DWATER2_1	1.346	3.921	0.343	0.732
DWATER2_1*_yhat_	2.442	4.411	0.554	0.581
DWATER2_1*_yhat_*_yhat_	1.170	1.232	0.950	0.344
FDISPOSAL1_1	-2.325	2.746	-0.847	0.399
FDISPOSAL1_1*_yhat_	-6.941	3.798	-1.827	0.070
FDISPOSAL1_1*_yhat_*_yhat_	-2.886	1.285	-2.246	0.027
IBU_YOS	-0.135	0.275	-0.493	0.623
IBU_YOS*_yhat_	-0.511	0.393	-1.299	0.196
IBU_YOS*_yhat_*_yhat_	-0.214	0.134	-1.588	0.115
LANTAI_UBIN_1	-0.215	3.034	-0.071	0.944
LANTAI_UBIN_1*_yhat_	3.024	3.767	0.803	0.424
LANTAI_UBIN_1*_yhat_*_yhat_	1.025	1.226	0.836	0.405
TOILET1_1	-1.504	6.763	-0.222	0.824

	Coefficient	**Std. Err**	**t**	**|Prob|>t**
TOILET1_1*_yhat_	-1.672	7.037	-0.238	0.813
TOILET1_1*_yhat_*_yhat_	-0.165	1.820	-0.091	0.928
TOILET2_1	4.992	8.767	0.569	0.570
TOILET2_1*_yhat_	5.192	9.834	0.528	0.598
TOILET2_1*_yhat_*_yhat_	1.810	2.586	0.700	0.485
UMURBALITA	-0.092	0.067	-1.370	0.173
UMURBALITA*_yhat_	-0.075	0.088	-0.846	0.399
UMURBALITA*_yhat_*_yhat_	-0.022	0.027	-0.794	0.429
UMUR_AYAH	-0.003	0.243	-0.013	0.990
UMUR_AYAH*_yhat_	-0.122	0.296	-0.412	0.681
UMUR_AYAH*_yhat_*_yhat_	-0.053	0.090	-0.592	0.555
R-squared: 0.34137871, Adj.R-squared: 0.13453897, Obs: 160				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.13: Estimation Results with the GLS Model in Small Area Estimation: Pemalang District

	Coefficient	Std. Err	t	|Prob|>t
GLS				
Intercept	12.7545	0.1951	65.3855	0.0000
H_ACCINTERNET_1	0.1137	0.0640	1.7756	0.0765
H_CELLPHONE_1	0.1805	0.0345	5.2299	0.0000
H_FCOOK_1	0.2656	0.0627	4.2391	0.0000
H_HHIND_1	0.1423	0.0849	1.6771	0.0942
H_HHMALE_1	0.1427	0.0410	3.4826	0.0005
H_HHSERV_1	0.1503	0.0447	3.3631	0.0008
H_HOUSE1_1	-0.0672	0.0512	-1.3111	0.1905
H_HOUSE2_1	-0.1616	0.0773	-2.0909	0.0371
H_NCHILDSD	-0.1025	0.0130	-7.8975	0.0000
H_NCHILDSMA	-0.0915	0.0188	-4.8742	0.0000
H_NCHILDSMP	-0.0856	0.0182	-4.6976	0.0000
H_PCFLOOR	0.0091	0.0017	5.2446	0.0000
H_SHHMEMPLOY	0.2299	0.0680	3.3808	0.0008
H_TFLOOR_1	0.1356	0.0444	3.0521	0.0024
H_TOILET1_1	0.1252	0.0428	2.9228	0.0036
PDS_APOTEK_1	-0.2091	0.2331	-0.8968	0.3703
PDS_DOCTOR_1	-0.2630	0.1135	-2.3167	0.0210
PDS_HHAGR	-0.0034	0.0019	-1.8074	0.0714

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.14: Nutritional Map Estimation Results at the Subdistrict Level: Pemalang District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	DISTRICT			
3327	Pemalang District	112,320	52,341	46.60
(Target of Povmap percentage rate = 46.28 percent)				
	SUBDISTRICT			
3327010	Moga	5,992	2,810	46.90
3327011	Moga	3,472	1,513	43.57
3327020	Pulosari	4,871	2,480	50.92
3327030	Belik	9,770	4,743	48.55
3327040	Watukumpul	6,378	2,975	46.65
3327050	Bodeh	4,462	2,181	48.88
3327060	Bantarbolang	6,085	2,483	40.80
3327070	Randudongkal	7,829	3,453	44.11
3327080	Pemalang District	14,899	7,132	47.87
3327090	Taman	14,074	6,484	46.07
3327100	Petarukan	12,580	5,896	46.87
3327110	Ampelgading	5,622	2,632	46.81
3327120	Comal	7,401	3,292	44.48
3327130	Ulujami	8,885	4,265	48.00

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.15: Nutritional Map Estimation Results at the Village/Ward Level: Pemalang District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	SUBDISTRICT			
3327010	Moga	5,992	2,810	46.90
	VILLAGE/WARD			
3327010001	Plakaran	363	146	40.22
3327010002	Mandiraja	534	233	43.63
3327010003	Walangsanga	636	317	49.85
3327010004	Sima	1,004	475	47.31
3327010005	Banyumudal	1,528	725	47.43
3327010006	Moga	753	337	44.75
3327010007	Wangkelang	212	117	55.19
3327010008	Kebanggan	156	70	44.87
3327010009	Pepedan	143	90	63.93
3327010010	Gendowang	663	301	45.40

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.16: Estimation Results with Beta Model in Small Area Estimation: Jember District

	Coefficient	Std. Err	t	|Prob|>t
Beta Model				
intercept	-1.113	0.983	-1.131	0.259
AYAH_PT_1	-0.662	1.239	-0.534	0.594
AYAH_SD_1	-0.546	0.432	-1.265	0.207
AYAH_SLTA_1	-0.598	0.915	-0.654	0.514
AYAH_SLTP_1	0.450	0.701	0.642	0.522
AYAH_TDKSEKOLAH_1	0.791	0.717	1.103	0.271
AYAH_YOS	0.036	0.070	0.505	0.614
BBAKAR_GAS_1	0.294	0.267	1.099	0.273
CV_AYAH_SD	1.232	0.643	1.916	0.056
CV_AYAH_TDKSEKOLAH	0.681	1.307	0.521	0.603
CV_AYAH_YOS	0.095	0.082	1.167	0.244
CV_IBU_SD	-1.584	0.711	-2.226	0.027
CV_IBU_YOS	-0.118	0.093	-1.279	0.202
DWATER1_1	0.822	0.301	2.735	0.007
IBU_PT_1	1.148	0.715	1.605	0.110
IBU_SLTA_1	0.161	0.480	0.336	0.737
IBU_TDKSEKOLAH_1	-0.951	0.698	-1.361	0.175
IBU_YOS	-0.036	0.047	-0.777	0.438
UMURBALITA	-0.017	0.006	-2.835	0.005
UMUR_IBU	0.014	0.017	0.803	0.423
R-squared: 0.17898775, Adj.R-squared: 0.11781428, Obs: 275				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.17: Estimation Results with Alpha Model in Small Area Estimation: Jember District

	Coefficient	Std. Err	t	|Prob|>t
Alpha Model				
intercept	-3.570	0.594	-6.012	0.000
yhat	1.134	0.787	1.441	0.151
_yhat_*_yhat_	0.366	0.252	1.450	0.148
R-squared: 0.17898775, Adj.R-squared: 0.11781428, Obs: 275				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.18: Estimation Results with the GLS Model in Small Area Estimation: Jember District

	Coefficient	**Std. Err**	**t**	**|Prob|>t**
GLS				
Intercept	12.7545	0.1951	65.3855	0.0000
H_ACCINTERNET_1	0.1137	0.0640	1.7756	0.0765
H_CELLPHONE_1	0.1805	0.0345	5.2299	0.0000
H_FCOOK_1	0.2656	0.0627	4.2391	0.0000
H_HHIND_1	0.1423	0.0849	1.6771	0.0942
H_HHMALE_1	0.1427	0.0410	3.4826	0.0005
H_HHSERV_1	0.1503	0.0447	3.3631	0.0008
H_HOUSE1_1	-0.0672	0.0512	-1.3111	0.1905
H_HOUSE2_1	-0.1616	0.0773	-2.0909	0.0371
H_NCHILDSD	-0.1025	0.0130	-7.8975	0.0000
H_NCHILDSMA	-0.0915	0.0188	-4.8742	0.0000
H_NCHILDSMP	-0.0856	0.0182	-4.6976	0.0000
H_PCFLOOR	0.0091	0.0017	5.2446	0.0000
H_SHHMEMPLOY	0.2299	0.0680	3.3808	0.0008
H_TFLOOR_1	0.1356	0.0444	3.0521	0.0024
H_TOILET1_1	0.1252	0.0428	2.9228	0.0036
PDS_APOTEK_1	-0.2091	0.2331	-0.8968	0.3703
PDS_DOCTOR_1	-0.2630	0.1135	-2.3167	0.0210
PDS_HHAGR	-0.0034	0.0019	-1.8074	0.0714

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.19: Nutritional Map Estimation Results at the Subdistrict Level: Jember District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	DISTRICT			
3509	Jember	176,858	76,067	43.01
(Target of Povmap percentage rate = 44.10 percent)				
	SUBDISTRICT			
3509010	Kencong	4,390	1,826	41.60
3509020	Gumuk Mas	5,566	2,590	46.54
3509030	Puger	8,807	3,612	41.01
3509040	Wuluhan	8,411	3,734	44.39
3509050	Ambulu	7,503	3,220	42.92
3509060	Tempurejo	5,424	2,441	45.00
3509070	Silo	8,392	3,849	45.86
3509080	Mayang	3,646	1,706	46.79
3509090	Mumbulsari	4,870	2,329	47.82
3509100	Jenggawah	6,078	2,792	45.93
3509110	Ajung	5,775	2,649	45.87
3509120	Rambipuji	5,940	2,564	43.17
3509130	Balung	5,532	2,159	39.02
3509140	Umbulsari	5,112	2,211	43.26
3509150	Semboro	3,301	1,318	39.93
3509160	Jombang	3,539	1,523	43.04
3509170	Sumber Baru	8,103	3,318	40.95
3509180	Tanggul	6,551	2,518	38.43
3509190	Bangsalsari	8,685	3,975	45.77
3509200	Panti	4,694	2,119	45.15
3509210	Sukorambi	2,992	1,417	47.36
3509220	Arjasa	2,986	1,287	43.09
3509230	Pakusari	3,311	1,545	46.65
3509240	Kalisat	5,609	2,711	48.33

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	SUBDISTRICT			
3509250	Ledokombo	4,853	2,333	48.08
3509260	Sumberjambe	4,678	2,082	44.51
3509270	Sukowono	4,169	2,014	48.31
3509280	Jelbuk	2,503	1,049	41.92
3509710	Kaliwates	9,069	3,034	33.45
3509720	Sumbersari	9,301	3,496	37.59
3509730	Patrang	7,068	2,641	37.37

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.20: Nutritional Map Estimation Results at the Village/Ward Level: Jember District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	SUBDISTRICT			
3509010	Kencong	4,390	1,826	41.60
	VILLAGE/WARD			
3509010001	Paseban	481	197	40.95
3509010002	Cakru	672	284	42.26
3509010003	Kraton	590	256	43.39
3509010004	Wonorejo	986	390	39.55
3509010005	Kencong	1,661	700	42.14

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.21: Estimation Results with Beta Model in Small Area Estimation: Timor Tengah Selatan District

	Coefficient	Std. Err	t	|Prob|>t
Beta Model				
intercept	-0.111	1.234	-0.090	0.929
AYAH_YOS	0.041	0.036	1.142	0.255
BALITA_LAKI2_1	-0.555	0.269	-2.060	0.041
CV_AYAH_SD	-0.380	1.345	-0.283	0.778
CV_AYAH_SLTA	-1.439	2.472	-0.582	0.561
CV_AYAH_SLTP	0.782	2.140	0.366	0.715
CV_AYAH_YOS	-0.120	0.177	-0.677	0.499
CV_IBU_SD	-1.143	1.278	-0.894	0.372
CV_IBU_SLTA	-3.010	1.735	-1.734	0.084
CV_IBU_SLTP	-1.651	1.522	-1.085	0.279
CV_IBU_YOS	0.169	0.124	1.365	0.173
DWATER1_1	-0.381	0.672	-0.567	0.571
DWATER2_1	-0.577	0.301	-1.914	0.057
FDISPOSAL1_1	0.074	0.618	0.120	0.905
IBU_YOS	-0.042	0.037	-1.129	0.260
TOILET1_1	-1.271	0.622	-2.044	0.042
TOILET2_1	-0.955	0.810	-1.179	0.240
UMURBALITA	-0.043	0.008	-5.452	0.000
UMUR_IBU	0.058	0.024	2.478	0.014
R-squared: 0.2708789, Adj.R-squared: 0.21430916, Obs: 251				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.22: Estimation Results with Alpha Model in Small Area Estimation: Timor Tengah Selatan District

	Coefficient	Std. Err	t	|Prob|>t
Alpha Model				
intercept	-3.701	1.676	-2.208	0.028
yhat	2.208	0.851	2.594	0.010
_yhat_*_yhat_	0.164	0.163	1.009	0.314
AYAH_YOS	-0.132	0.056	-2.348	0.020
BALITA_LAKI2_1	1.358	0.520	2.612	0.010
CV_AYAH_SD	2.955	1.422	2.079	0.039
CV_AYAH_SLTA	7.968	3.518	2.265	0.024
CV_AYAH_SLTP	0.310	2.773	0.112	0.911
CV_AYAH_YOS	-0.129	0.275	-0.468	0.640
CV_IBU_YOS	-0.020	0.138	-0.146	0.884
DWATER1_1	0.512	0.855	0.599	0.550
DWATER2_1	0.292	0.541	0.539	0.590
FDISPOSAL1_1	-0.478	0.913	-0.524	0.601
IBU_YOS	0.037	0.060	0.618	0.537
TOILET1_1	0.763	0.795	0.960	0.338
UMURBALITA	0.038	0.032	1.187	0.236
UMUR_IBU	-0.011	0.055	-0.209	0.835
R-squared: 0.16063379, Adj.R-squared: 0.10324123, Obs: 251				

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

Table 1A.23: Estimation Results with the GLS Model in Small Area Estimation: Timor Tengah Selatan District

	Coefficient	Std. Err	t	|Prob|>t
GLS				
Intercept	12.7545	0.1951	65.3855	0.0000
H_ACCINTERNET_1	0.1137	0.0640	1.7756	0.0765
H_CELLPHONE_1	0.1805	0.0345	5.2299	0.0000
H_FCOOK_1	0.2656	0.0627	4.2391	0.0000
H_HHIND_1	0.1423	0.0849	1.6771	0.0942
H_HHMALE_1	0.1427	0.0410	3.4826	0.0005
H_HHSERV_1	0.1503	0.0447	3.3631	0.0008
H_HOUSE1_1	-0.0672	0.0512	-1.3111	0.1905
H_HOUSE2_1	-0.1616	0.0773	-2.0909	0.0371
H_NCHILDSD	-0.1025	0.0130	-7.8975	0.0000
H_NCHILDSMA	-0.0915	0.0188	-4.8742	0.0000
H_NCHILDSMP	-0.0856	0.0182	-4.6976	0.0000
H_PCFLOOR	0.0091	0.0017	5.2446	0.0000
H_SHHMEMPLOY	0.2299	0.0680	3.3808	0.0008
H_TFLOOR_1	0.1356	0.0444	3.0521	0.0024
H_TOILET1_1	0.1252	0.0428	2.9228	0.0036
PDS_APOTEK_1	-0.2091	0.2331	-0.8968	0.3703
PDS_DOCTOR_1	-0.2630	0.1135	-2.3167	0.0210
PDS_HHAGR	-0.0034	0.0019	-1.8074	0.0714

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.24: Nutritional Map Estimation Results at the District Level: Timor Tengah Selatan District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	DISTRICT			
5304	Timor Tengah Selatan	58,765	38,650	65.77
(Target of Povmap percentage rate = 70.43 percent)				
	SUBDISTRICT			
5304010	Mollo Utara	3,209	2,076	64.70
5304011	Fatumnasi	878	584	66.51
5304012	Tobu	1,232	853	69.23
5304013	Nunbena	508	369	72.64
5304020	Mollo Selatan	1,890	1,340	70.90
5304021	Polen	1,729	1,109	64.14
5304022	Mollo Barat	1,019	649	63.68
5304023	Mollo Tengah	961	640	66.60
5304030	Kota Soe	4,457	3,367	75.55
5304040	Amanuban Barat	2,957	2,123	71.80
5304041	Batu Putih	1,654	1,068	64.57
5304042	Kuatnana	2,111	1,357	64.29
5304050	Amanuban Selatan	3,555	2,256	63.45
5304051	Noebeba	1,618	1,021	63.09
5304060	Kuanfatu	2,628	1,639	62.35
5304061	Kualin	3,032	1,983	65.39
5304070	Amanuban Tengah	1,880	1,281	68.14
5304071	Kolbano	2,373	1,640	69.10
5304072	Oenino	1,433	880	61.40
5304080	Amanuban Timur	2,248	1,427	63.48
5304081	Fautmolo	1,004	674	67.13
5304082	Fatukopa	658	388	58.97
5304090	Kie	2,949	1,918	65.04
5304091	Kotolin	1,574	1,056	67.09

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	SUBDISTRICT			
5304100	Amanatun Selatan	2,248	1,432	63.71
5304101	Boking	1,401	793	56.60
5304102	Nunkolo	1,876	1,168	62.26
5304103	Noebana	591	392	66.33
5304104	Santian	767	458	59.72
5304110	Amanatun Utara	2,182	1,367	62.65
5304111	Toianas	1,721	1,082	62.88
5304112	Kokbaun	422	261	61.85

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by Drafting Team.

Table 1A.25: Nutritional Map Estimation Results at the Village/Ward Level: Timor Tengah Selatan District

Code	Name of District/ Subdistrict	Number of Children Under-Five (headcount)	Estimated Number of Stunted Children Under-Five (headcount)	Prevalence of Stunting in Children Under-Five (%)
	SUBDISTRICT			
5304010	Mollo Utara	3,209	2,076	64.70
	VILLAGE/WARD			
5304010003	Leloboko	190	110	57.89
5304010004	Nefokoko	236	146	61.86
5304010005	Lelobatan	293	189	64.50
5304010006	Netpala	231	153	66.23
5304010007	Obesi	246	182	73.98
5304010008	Eon Besi	490	348	71.02
5304010009	Bosen	274	153	55.84
5304010010	Sebot	167	96	57.48
5304010011	Ajaobaki	233	167	71.67
5304010012	Bijaepunu	233	142	60.94
5304010014	Halme	83	48	57.83
5304010016	Tunua	215	141	65.58
5304010017	Fatukoto	318	202	63.52

Source: *Riskesdas* 2013, SP 2010. Results of the Nutritional Map prepared by the Drafting Team.

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THE CHALLENGES OF UNIVERSAL HEALTH INSURANCE IN DEVELOPING COUNTRIES: EVIDENCE FROM A LARGE-SCALE RANDOMISED EXPERIMENT IN INDONESIA*

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Abstract

To assess ways to achieve widespread, financially sustainable health insurance coverage in developing countries, we designed a randomised experiment involving almost 6,000 households in Indonesia who are subject to a nationally mandated government health insurance program (*Jaminan Kesehatan Nasional*: JKN). We assessed several interventions that simple theory and prior evidence suggest could increase coverage and reduce adverse selection: (i) substantial temporary price subsidies (which had to be activated within a limited time window and lasted for only a year); (ii) assisted registration; and (iii) information. Both temporary subsidies and assisted registration increased initial enrolment. Temporary subsidies attracted lower-cost enrolees, in part by eliminating the practice observed in the no-subsidy group of strategically timing coverage for a few months during health emergencies. As a result, while subsidies were in effect, they increased coverage more than eightfold at no higher unit cost. Even after the subsidies ended, coverage remained twice as high–again at no higher unit cost. However, the most intensive (and effective) intervention, however–assisted registration and a full one-year subsidy–resulted in only a 30 percent initial enrolment rate, underscoring the challenges to achieving widespread coverage.

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***TNP2K: Tim Nasional Percepatan Penanggulangan Kemiskinan: National Team for the Acceleration of Poverty Reduction.*

Section One:

Introduction

As developing countries emerge from extreme poverty and enter middle-income status, many aim to expand their government-run social safety net systems (Chetty and Looney 2006). An important part of this process is the creation of universal health insurance policies which have expanded to many lower- and middle-income countries over the past decade (Lagomarsino et al. 2012). In expanding health insurance, however, emerging countries may face particularly vexing versions of the challenges faced by many developed countries because of the large informal sector operating outside the tax net (Jensen 2019).

Some countries–such as Thailand–have sought a single-payer health insurance system funded entirely out of tax revenues and supplemented by small copayments at the time of service (Gruber, Hendren, and Townsend 2014) which has been shown to improve health but faces substantial funding challenges. Many other countries, such as Ghana, Kenya, the Philippines and Vietnam and Indonesia–which is the focus of our study–have sought to create a contributory system with an individual mandate to reduce the financial burden on the government. In these systems, the very poor are subsidised by tax revenues but everyone else is required to pay a premium that is collected through a payroll tax for formal sector workers and directly from individuals for everyone else.

The challenge with contributory systems, however, is that enforcing the insurance mandate for those who must pay premiums directly is difficult. While the political and administrative challenges of enforcing mandates are not unique to developing countries–for example, the Patient Protection and Affordable Care Act 2010 (commonly known as "Obamacare") legislation did not achieve universal coverage in the United States (Berchick 2018)–they are particularly difficult for them, again because the majority of their citizens are outside the tax net. This means that the types of penalties for noncompliance used initially in the United States under Obamacare–fines collected through the personal income tax system–are not an option.

Since developing countries have shown little appetite for enforcing the few possible remaining sanctions on the noncompliant population (for example, by denying delinquent households the ability to enrol their children in school), perhaps rightly, what they are left with is a toothless mandate. In theory, a toothless mandate can create two related challenges for governments that are trying to achieve universal or near-universal coverage: (i) low program enrolment; and (ii) adverse selection, where the least healthy are more likely to enrol, thereby raising program costs above the population average (Akerlof 1970; Einav and Finkelstein 2011). In practice, like other nations that have experimented with these policies, Indonesia has experienced both: despite the fact that mandatory, universal health insurance was launched in 2014, the contributory portion of the program, known as *JKN Mandiri*, had enroled only 20 percent of the targeted population a year after its introduction, and its claims exceeded premiums by a ratio of 6.45 to 1.[1] These facts motivate the question of whether and how developing country governments can design supplemental policies to mitigate these challenges—to boost national health insurance enrolment, while also reining in the financial costs to the tax-funded government budget—in the context of mandatory, but weakly enforced, contributory health insurance programs. The aim is not necessarily for the government to break even—it is clear that some subsidies may be needed to make sure that there is enough social protection against health shocks—but to limit government spending while insuring as many people as possible.

With this perspective in mind, in 2015, in cooperation with the Indonesian Government, we designed a large-scale, multiarm experiment—involving almost 6,000 households—to assess three interventions that simple economic theory suggested could increase enrolment and reduce adverse selection in JKN. First, we examined the role of large, temporary subsidies: we randomised households to receive subsidies of either 50 percent ("half subsidy") or 100 percent ("full subsidy") for the first year of enrolment. To be eligible for the subsidy, households had to enrol within two weeks after they were offered it, akin to governments offering a large, time-limited registration incentive. Second, we examined the role of transaction costs by randomly offering some households at-home assistance with the online registration system, rather than traveling to a far-off insurance office to enrol. Third, we tested for information constraints by randomly advertising three different types of basic insurance information: (i) the financial costs of a health episode and how they relate to insurance prices; (ii) the two-week waiting period from enrolment to coverage (so that one could not wait to get sick to sign up); and (iii) the fact that insurance coverage is legally mandatory.

To assess the impacts of these interventions, we utilise a number of new data sources to examine the impact on enrolment and coverage. These data include the government's administrative insurance data on registration, premiums paid, and all claims made by program enrolees for up to 32 months after the intervention. We first use these data to examine the impact of the interventions on *enrolment* which we define as completing the initial registration process. As the decision to stay enroled is a dynamic one in which households need to pay a monthly premium, we also examine the impact of the interventions on *insurance coverage* which we define as having paid the premium for a given month to ensure insurance coverage for that month.

Given the extensive and detailed administrative data on claims, we then examine questions relating both to adverse selection and to the ultimate government costs per household insured under the various policy treatments. Finally, we supplement these administrative data with a short baseline assessment survey in which we collected data on demographics and self-reported health status prior to the intervention. Among other things, this baseline survey allows us to measure preintervention "health status" for all study participants, regardless of whether they subsequently enroled in the insurance program.

In the context of a toothless mandate, our findings reveal both opportunities and challenges for increasing coverage in contributory health insurance programs in developing countries. On the one hand, we find that temporary subsidies and assisted registration can both increase

[1] Enrolment rates are from authors' calculations based on official membership numbers and the national sample survey, Susenas 2015 (BPS 2015). Claims to premium ratios are from LPEM-UI (2015).

enrolment. Moreover, temporary subsidies attract a much lower-cost population, enabling substantial increases in coverage at no higher cost per covered unit. This increased coverage persists (albeit at a lower rate) after the subsidies end. On the other hand, even our most intensive (and effective) intervention–assisted registration and a full one-year subsidy–resulted in only a 30 percent initial enrolment rate. This was a substantial increase on the status quo enrolment rate of 8 percent but still a far cry from universal coverage. Our analysis reveals specific obstacles to achieving widespread coverage stemming from limited state capacity to facilitate enrolment and to prevent strategic short-term coverage.

Our study explicitly builds on the literature on participation in public health insurance systems and in social protection programs more broadly. We not only test the impact of these individual policy tools on enrolment but also test the relative magnitudes of relieving different participation constraints against one another in a common real-world context.[2]

Theory suggests that the three constraints that we examine could each increase enrolment in various types of public programs including health insurance. In fact, the empirical evidence is consistent with this theory: the findings (Thornton et al. 2010; Asuming 2013; Fischer et al. 2018; Finkelstein, Hendren and Shepard 2019) from both developed and developing settings indicate that subsidies, reductions in transaction costs (Alatas et al. 2016; Bettinger et al. 2012; Dupas et al 2016), and information (Gupta 2017; Bhargava and Manoli 2015) all have the potential to increase participation in a variety of social insurance programs, motivating our experimental design. Importantly, our extensive high-frequency administrative data allow us to build upon this literature because we can precisely study whether these different types of interventions have persistent results over time as individuals make dynamic, and possibly strategic, decisions over insurance coverage each month.[3] This is particularly important for the temporary subsidies if “experience” with the health care system leads households to increase their perceived value of insurance and stay covered after the subsidies expire.[4]

We then go further to examine not only the impacts on overall enrolment but also whether these interventions affect the *type* of individual who enrols–as well as remains enroled–and thus whether it is possible to increase enrolment of low-utilisation individuals enough to reduce the per-participant cost of insurance. In the standard textbook models in which individuals differ only in their risk type, the interventions that we test could all potentially mitigate adverse selection since the marginal enrolees will be lower-cost than the average enrolees (Akerlof 1970). In the presence of multiple dimensions of heterogeneity, however, the impact of these

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2 This study, in particular, is related to Thornton et al. (2010) which examined the impact of whether informal workers, recruited through a health insurance registration booth in the market, are randomised to receive a subsidy for contributory insurance through Nicaragua’s social security system offices or through a microfinance organisation which could potentially have been more convenient for informal workers. Their study finds impacts of subsidies on enrolment and, therefore, on utilisation but does not study how the treatments affect the degree to which the market is adversely or advantageously selected, as we do here.

3 In the developing world, there is little known about the longer-run impacts of improving health insurance take-up and selection through interventions. One notable exception is Asuming et al. (2018) which uses survey data to assess the impact of one-time subsidies on enrolment and subsequent health behaviours in Ghana, three years post-intervention. Our high-frequency, administrative data allow us to further unpack the dynamics of selection and show how differential retention affects our understanding of these health insurance markets. The only related paper that we know that explores these issues does so in a developed country setting, studying California’s Affordable Care Act (Diamond et al. 2018).

4 Delavallade (2017) provides evidence that a related “experience” effect could be important by showing that randomly providing households with a free preventive health visit increased their hypothetical willingness to pay for insurance in a subsequent survey.

interventions on adverse selection is theoretically ambiguous (Einav and Finkelstein 2011) and, indeed, existing evidence from health insurance studies indicates that while such interventions can ameliorate adverse selection (Fischer et al. 2018; Finkelstein, Hendren, and Shepard 2019), they can also, in different contexts, exacerbate it (Asuming et al. 2018; Handel 2013). It is, therefore, an empirical question whether varying the different insurance constraints, holding constant the setting, leads to a different type of enrolment, and in particular one that makes a meaningful difference in terms of participant costs.

More specifically, our three interventions produce three distinct sets of findings.

First, we find that the one-year full subsidies significantly boosted enrolment and improved selection leading to more people insured at the same cost to the government, even after the subsidies expired. Those offered the full subsidy were 20.9 percentage points (almost seven times) more likely to enrol than were those in the no-subsidy group during the active subsidy period. This increase was not driven simply by households who would have purchased insurance anyway ("harvesting") but rather represents a real net increase in enrolment. While some of these households did not elect to pay premiums at the end of the one-year subsidy, many did. As a result, in the year after the subsidy ended, insurance coverage in the full-subsidy group remained over twice as high as coverage in the no-subsidy group–consistent with the idea of health insurance as an experience good.

Despite the fact that more households enroled under the full-subsidy treatment, the net cost to the government per covered person–that is, the difference between revenues from premiums and payments to providers and, therefore, the amount that would need to be covered from the general government budget–was similar with and without the full subsidy. Remarkably, this was true *even* in the first year, when the subsidy was active and hence when the full-subsidy group brought in essentially no revenue. This is because the subsidies brought in substantially lower-cost enrolees. Relative to enrolees in the no-subsidy group, those receiving the full subsidy reported better health at baseline and had fewer claims (and, notably, fewer claims for chronic conditions) during their first year of enrolment. This cost difference may also, in part, reflect strategic timing decisions by the no-subsidy group, rather than fixed health differences alone. In fact, the no-subsidy enrolees submitted more claims than did full-subsidy enrolees in the first three months after enrolment, after which the difference between the two groups attenuates. Many enrolees in the no-subsidy group subsequently ceased paying premiums and dropped coverage after a few months. Such strategic enrolment timing was less of an option for full-subsidy enrolees because the subsidy offer was time-limited and, once enroled, they stayed covered for the full first year. When the full-subsidy group had to begin paying premiums in the second year, they brought in slightly more revenue to the government since more people were enroled (due to the experience effect highlighted above), but the value of their claims appears similar to the value of those in the control group.

In contrast, the half-subsidy offer was less effective than the full subsidy, enroled fewer people than the full subsidy–the treatment effect was about one-half that of the full subsidy–and did not appear large enough to generate an experience effect in the second year. Nor do we observe a large selection effect on claims. Taken together, in the first year, despite bringing in more revenue than the full subsidy, the half-subsidy treatment led to fewer households covered than the full subsidy at a higher per enrolee cost.

Second, while the subsidy treatments highlight that the financial cost of insurance is a barrier to enrolment, we find that hassle costs also appear to be a real barrier to participation, and one that we were not able to fully solve. Reducing hassles by assisting with Internet-based registration increased enrolment by 3.5 percentage points (41 percent). Importantly, however, many more people attempted to enrol than were actually able to do so: in fact, nearly as many people attempted to enrol in the assisted Internet-based registration as in the full-subsidy group. When offered *both* a full subsidy and assisted Internet registration, nearly 60 percent of households tried to enrol, but only about one-half were successfully able to do so.

Households' enrolment efforts were substantially muted by technical and administrative challenges with the government's online enrolment system. While also reminiscent of the issues with Healthcare.gov in the United States, this particular challenge stemmed from a problem common to many developing countries–Indonesia's underlying state civil registry. Registry data on who is in each family is often inaccurate (Sumner and Kusumaningrum 2014) and, since whole families must be enroled at once to help mitigate adverse selection, these problems in the civil registry meant that people needed to visit an office to fix errors and sign up correctly. Since imperfect civil registries are common throughout the developing world (Mikkelsen et al. 2015), these types of challenges are likely to be encountered in other contexts as well.

We also find that those who enroled in the assisted-Internet registration group stopped paying premiums at a faster rate than those who enroled under the status quo registration. This is possibly because those who selected in under this treatment might also be those who are easily discouraged by the hassle costs involved in making payments each month. Not surprisingly, given their high dropout rate, we do not observe any differences in the claims of the assisted-registration group as compared to the status quo registration group.

Third, none of the information treatments affected enrolment into the system. The fact that our various information treatments had no impact suggests that lack of information may not be a key barrier, although we cannot rule this out definitively. It does suggest, however, that while information and 'nudge' campaigns are often an attractive policy option given their low cost (Thaler and Sunstein 2009), this does not seem to be the primary constraint in this context.

Taken together, the most important takeaway from our results is that large, temporary subsidies can work. A common concern with offering a "free" trial period is that individuals may become used to receiving insurance without paying, thus decreasing payments in the long term. We find the opposite: temporary registration incentives, featuring limited periods of free coverage before requiring premiums to be paid, actually increase coverage and premiums paid in the subsequent year while reducing adverse selection. This may be because many households in developing countries lack experience with insurance (Aacharya et al. 2012), suggesting an important role for registration drives featuring temporary subsidy periods to give people experience with insurance as part of campaigns to increase enrolment.

Despite the fact that we find that these large temporary subsidies can substantially boost enrolment, particularly among lower-cost enrolees, we did not find an immediate and effective solution that would lead to universal (or even close to universal) enrolment. Even the most intensive intervention–assisted registration plus free insurance for one year–only resulted in a 30 percent initial enrolment rate. While this is substantially higher than the status quo initial enrolment rate of 8 percent, it is still a long way from universal enrolment; moreover, many newly enroled households dropped coverage over time.

Nevertheless, our findings offer important insights into how to further improve these types of programs on the margin:

- **First, a trial period of free insurance had significant positive effects–increasing enrolment rates while substantially mitigating adverse selection–at no additional cost to the government.**
- **Second, our results suggest that the dynamics of coverage decisions can exacerbate adverse selection.** A key administrative challenge, therefore, lies not just in enforcing the enrolment mandate–which was the premise for our interventions–but also in designing insurance regulations to prevent the strategic timing of gaining and dropping coverage.
- **Finally, as the assisted Internet registration treatment demonstrated, without substantial long-term investments in overall administration and infrastructure (for example, improved identification systems and better Internet connections), there will continue to be substantial hassles that prevent universal insurance coverage.**

The remainder of the paper is organised in four sections. Section Two presents the setting, the experimental design, and the data used in the analysis. Section Three presents the enrolment effects of the intervention as well as its impacts on coverage over time. Section Four presents the selection effects and discusses their implications for government costs, while Section Five provides the conclusions.

Section Two:

Setting, Experimental Design and Data

2.1 Setting: The JKN Mandiri Program

In January 2014, the Government of Indonesia launched *Jaminan Kesehatan Nasional* (JKN), a national, contributory health insurance program aimed at providing universal coverage by 2019. JKN comprises different subprograms based on income and employment status. Non-poor informal workers who represent 30 percent of the country are covered through a subprogram called *JKN Mandiri*. Under *JKN Mandiri*, households must complete an initial registration process and then pay monthly premiums.[5] While insurance enrolment is legally mandatory, the mandate is hard to enforce in practice and there are currently no penalties imposed on households that do not enrol.

Households may register for *JKN Mandiri* at any time of the year, either in person at the *Badan Penyelenggara Jaminan Sosial - Kesehatan* (Social Security Administration for Health, or BPJS) office or through the social security administration website. Households are required to register all nuclear family members (for example, father, mother, and children) listed on their official Family Card (*Karta Keluarga*) which is maintained in the civil registry by another ministry (Department of Home Affairs).

The monthly premium per person for basic coverage (known as Class III) is IDR 25,500 (US$2.00) which corresponds to 3.5 percent of average monthly total expenditures for eligible households.[6] The premium that a household pays to have JKN coverage for a year is lower than the reported yearly out-of-pocket (OOP) health expenditures for 12 percent of all non-poor informal households without health insurance. This percentage reaches 66 percent, however, for households that had an inpatient episode in the last year, in which case the median “savings” from having health insurance are large (IDR 231,341 per month).[7]

The premium can be paid at any BPJS office, ATM, or equipped convenience store. Paying the premium by the 10th of a given month ensures coverage for that calendar month. If no payment is made, coverage is deactivated after a one-month grace period. For coverage to reactivate at a later

5 Those below the poverty line (about the bottom 40 percent) receive fully subsidised insurance. Formal workers are covered jointly by employers and the employee’s own contributions that are withheld by the tax system.

6 There are three different classes that cover the same medical procedures but offer different types of accommodation should an inpatient procedure be required. The monthly premium per person during the period of the study was IDR 42,500 (~US$3.00) for class II (3-5 beds per room) and IDR 59,500 (~US$4.50) for class I (2-3 beds per room). Class III (more than 5 beds) is the most common insurance among our population of interest–with 72 percent of households in the control group enroling in Class III insurance.

7 For each household, we compute what would have been the yearly JKN premium based on household size and compare this with the yearly OOP expenditures reported in the survey using Susenas 2015 data (BPS 2015).

date, the household must pay arrears which are capped at a maximum of six months.[8] After the program's introduction, the government became concerned that individuals might only enrol in JKN when they had a health emergency. To limit this, in September 2015, the government introduced a two-week waiting period after enrolment, only after which households could submit an insurance claim.

An active membership provides coverage for health care costs incurred at public or affiliated clinics and hospitals with no copayments, although specific procedures (for example, cosmetic surgery, infertility treatments, and orthodontics) are excluded. Primary care clinics are reimbursed under a capitation system based on the total number of practitioners, the ratio of practitioners to beneficiaries, and operating hours. Hospitals are reimbursed by case following a tariff system called INA-CBG (Indonesia Case Based Groups) in which amounts are determined jointly by primary diagnosis and severity of the condition.

2.2 Sample

We carried out this project in two large Indonesian cities: Kota Medan in North Sumatra and Kota Bandung in West Java. We focused on an urban setting to abstract from supply-side issues that are likely to depress demand in rural areas. We chose Medan and Bandung because a significant proportion of their population was uninsured.[9] Moreover, selecting cities both on- and off-Java helps ensure representativeness of Indonesia's heterogeneity in culture and institutions (Dearden and Ravallion 1988).

Working with the government, we implemented the interventions in two subdistricts in Medan in February 2015 and in eight subdistricts in Bandung in November and December 2015. The subdistricts were selected from among those with the highest concentration of non-poor informal workers; within those subdistricts we randomly selected neighbourhoods for the study.[10] To identify JKN-eligible households within the sampled areas, we targeted uninsured, informal workers by administering a rapid eligibility survey to all listed households. We excluded households that already had at least one member covered by health insurance and those that were officially below the poverty line (and thus qualified for free insurance). Of the 52,584 listed households, 14.5 percent (7,629) satisfied the target population criteria.

When we matched our survey data with the government's administrative data, we discovered that some households were already covered by health insurance, even if they reported that they were not. This was mostly an issue for Medan where the local government had recently expanded the set of poor households who qualified for free insurance but had not yet communicated this to the newly insured. Since households with at least one insured member were not eligible for the study, we excluded those already enroled, resulting in a sample of 5,996 households.

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[8] If no inpatient claims are submitted within 45 days from re-activation, there are no additional fees. Otherwise, the household has to pay a penalty equal to 2.5 percent of the treatment cost times the number of inactive months, up to a maximum of 12 months or IDR 30 million.

[9] Other large cities, such as DKI Jakarta, Surabaya and Makassar, introduced free local health insurance programs covering a large fraction of the population. Neither Bandung nor Medan had local programs of this type during the study period.

[10] Using the 2010 census, we chose subdistricts with a high fraction of non-poor informal workers. We excluded subdistricts with universities, large factories, or malls to avoid areas with a high concentration of temporary residents. We then randomly selected 12 kelurahan (urban municipal units) in the two subdistricts in Medan (out of 16 possible *kelurahan*) and four kelurahan in each subdistrict in Bandung (out of 41 possible *kelurahan*). Within each kelurahan, we randomly selected the neighbourhoods (rukun warga, also known as RW) to enumerate.

2.3 Experimental design

Upon identifying an eligible household, we administered a short baseline survey (see below for details). At the end of this survey the household was randomly assigned to three fully cross-treatment arms affecting the insurance price, the hassle cost of registration, and the information available (Figure 1).

2.3.1 Temporary subsidy treatments

Households were randomly selected to be in one of three groups: a control group, a full-subsidy group covering the premiums for all family members for one year, and a half-subsidy group covering one-half of a family's premiums for one year.[11] After the offer, the subsidy was valid for up to two weeks in Bandung and two weeks in Medan. To be conservative and ensure we captured all households that enroled during the subsidy period and to account for data lags, our definition of households enroled during the subsidy period includes all households that enroled within eight weeks of the offer date.

For logistical reasons, we could not pay one-half of each person's premium. Instead, we implemented the half subsidy through a "buy-one-get-one-free" scheme in which we paid the full premiums for one-half of the family members for one year and the household was then required to pay for the other half.[12] Households chose which family members were subsidised. In theory, the government regulated that all immediate household members be registered, so subsidising one-half of the household members was roughly equivalent to providing a 50 percent discount. The subsidy received for the subsidised members was conditional on payment for the non-subsidised members for the first month but unconditional thereafter in practice. Households in the full-subsidy period were not required to make any payments during the subsidy period.

2.3.2 Assisted Internet registration treatment

Registering for *JKN Mandiri* usually requires traveling to the BPJS office in the district capital so, to reduce the hassle costs of registration, we offered one-half of the study households the opportunity to complete the registration process online at home with the assistance of the study enumerator. The enumerators had Internet-enabled laptops that they used to access the official social security website. They then assisted the household with gathering the correct documentation, taking pictures and filling in all of the forms on the website. Upon successful registration, the enumerators provided information on payment procedures. If households wanted to think more about their options, wanted to enrol but needed time to assemble the documentation, or had technical registration problems, the enumerators returned within a few days to continue the enrolment process.

[11] In Medan, households with a positive subsidy offer were randomised to receive a one-week deadline, a two-week deadline, or the ability to choose either a one- or two-week deadline to enrol using the subsidy. In Bandung, we additionally offered a fourth subsidy subtreatment in which households that enroled but did not submit an inpatient claim within a 12-month period were reimbursed 50 percent of the premiums that they had paid. Since these subtreatments only took place in one of the two cities, we exclude them from the main analysis but we discuss these findings below and show the results in the accompanying appendix.

[12] If a family had an odd number of members, we randomly assigned the household to receive a subsidy for or members with equal probability. If there was only one member, the member received a full subsidy.

2.3.3 Information treatments

All study households received basic information about the insurance service coverage, the premiums, and the procedure for registration. For randomly selected households in each city, we provided additional types of information to test whether various forms of knowledge constrained enrolment.

In Medan, we randomly assigned a group of households to receive additional information on the financial costs of a health episode ("extra information treatment"). Using a script and an accompanying booklet, we detailed the average OOP expenditures for Indonesia's most common chronic health conditions, as well as the cost of having a heart attack.

In Bandung, all households received basic insurance information and a discussion of the OOP expenditures associated with accessing care. Based on discussions with the government, however, we then randomly assigned households to the following two treatments: (i) a "waiting period" treatment in which we informed households about the new two-week waiting period between enrolment and the start of coverage; and (ii) a "mandate penalties" treatment in which we reminded households that enrolment is mandatory, and that there was a possibility that the government would soon introduce regulations requiring proof of insurance to be able to renew government documents such as passport and driver's license.

2.4 Randomisation design and timing

The study occurred in February 2015 in Medan and in November and December 2015 in Bandung. Subsidies were administered for 12 months after the offer for those who enroled within two weeks of the offer. Figure 1 shows the experimental design for Medan and Bandung separately,[13] while Figure 2 provides the experimental timeline.

2.5 Data and variable definitions

We compiled two new data sets for this project.

First, we conducted a short baseline survey in conjunction with an independent and established survey firm (SurveyMeter). We administered the baseline survey immediately following the listing questionnaire to determine eligibility. The baseline survey collected information on the demographic characteristics of family members, self-reported health and previous health care utilisation, and existing knowledge of the program.[14] Self-reported health was measured on a four-point scale from 1 (unhealthy) to 4 (very healthy); we analyse average self-reported health across household members. The survey was identical in Bandung and Medan with the one exception being that we added questions on income and employment in Bandung.

[13] The number of households differs in each treatment for two reasons. First, while in Medan we maximised power to detect differences in enrolment, in Bandung we maximised power to detect differences in claims conditional on take-up. Since we expected greater take-up with a larger subsidy, we randomised more households into groups with smaller subsidy amounts. Second, a coding error meant that while the overall treatment probabilities were as assigned, some combinations of treatments were more likely to be randomly assigned to households than others (this coding error was corrected partway through the Bandung experiment). We include in the analysis a dummy for whether the old or new randomisation was used and reweight observations to obtain the intended cross-randomisation weights so that each main treatment group has the same mix of each crossed additional treatment.

[14] To minimise priming, the questions related to knowledge of the program were asked after the information on health status. The consent form only mentioned SurveyMeter and Indonesia's National Development Planning Agency (Bappenas), the other partner in the study, but not BPJS or JKN.

Second, we use uniquely detailed government administrative data from February 2015 to August 2018 to measure enrolment outcomes, coverage, and health care utilisation.[15] We track all participants for 32 months after the baseline survey. We matched the study participants to the administrative data using individuals' unique national identification number (*Nomor Induk Kependudukan* or NIK).[16]

We define *enrolment* to be the household's successful completion of the registration process for the national insurance program. Since a household may enrol but not actually pay any premiums, we then also define *coverage* in a given month to mean that the enroled household's premiums were paid that month. We use the administrative data on registration date to measure enrolment. We use the administrative premium payment data which report the date and value of each payment to measure coverage.

To measure health care utilisation, we analyse administrative data on all claims that are covered by JKN in both hospitals and clinics. The hospital claim data report start and end date, diagnosis, reimbursement value, and facility where the claim was made.[17] We are able to distinguish between outpatient and inpatient hospital claims. In contrast, all clinic claims are for outpatient procedures. The clinic claims data report similar information to the hospital claims data, except that–due to capitation–claim values are not available. In addition to overall claims, we report two other types of information. First, since claims data are often noisy, we also examine the number of days until the first claim was submitted. Second, we use the diagnoses to code whether the claim was for a chronic condition.[18]

2.6 Balance

Appendix Table 1 provides a check on the randomisation by regressing various household characteristics measured in the baseline survey on treatment dummies. Only six out of the 54 coefficients are significantly different from zero at the 10 percent level, in line with what we would expect by chance.

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[15] The administrative data quality is good and has been improving over time, but some inconsistencies still arise. To ensure that we identify the correct individuals, we exclude matches when the year of birth reported in the baseline and that reported in the administrative database differ by more than one year. When the same NIK links to two different membership numbers, we consider both observations as a match. When two different NIKs link to the same membership number, we exclude the observation. When enrolment date or membership type changes in subsequent extracts, we retain the information as reported in the first extract in which the individual appears.

[16] About 23 percent of the individuals surveyed did not have a NIK at baseline and cannot be matched to the administrative data. We show in Column 1 of Appendix Table 1 that the probability that a household reports the NIK of at least one of its members is not differential across treatment. Given that a NIK is a requirement of enrolment, those without a NIK are likely to not be enroled in JKN.

[17] A claim corresponds to an outpatient or inpatient event. Each event is associated with a series of diagnoses. The hospital is reimbursed for the amount that corresponds to the primary diagnosis according to the INA-CBG tariff. All exams and treatment needed for an event gets reimbursed under the same claim.

[18] We build our chronic classification from the Chronic Condition Indicator for the International Classification of Diseases from the Healthcare Cost and Utilization Project. This database provides information on whether diagnoses included in the ICD-10-CM: 2018 can be classified as chronic conditions. We link conditions in the ICD-10-CM: 2018 to conditions in the ICD-10: 2008–the classification system followed by BPJS using the first three digits of the diagnosis code. This is the lowest classification that straightforwardly corresponds across the two systems. We consider a diagnosis as chronic if it belongs to a three-digit code group with more than 75 percent chronic diagnoses.

Section Three:

Impacts on Enrolment and Subsequent Coverage

3.1 Enrolment

Table 1 and Table 2 examine the impacts of the various treatments on enrolment–that is, successfully completing the registration process. We measure enrolment over the first year after the intervention date–that is, the date the baseline survey occurred. We estimate the following regression:

$y_i = \beta_0 + \beta_1\ HALF\ SUBSIDY_i + \beta_2\ FULL\ SUBSIDY_i + \beta_3 INTERNET_i + INFO^{i\prime}\ \beta_4 + X_i\delta + \varepsilon_i$ (1) where *HALF SUBSIDY*$_i$, *FULL SUBSIDY*$_i$ *and INTERNET*$_i$, are dummy variables equal to *1* if household 1 was randomly assigned to the respective treatment, and *INFO* is a vector of dummies equal to *1* if household *i* was randomly assigned to a particular information intervention. X_i is a matrix of household-level controls that includes dummy variables for the assignment to the other treatments (see footnote 11), a dummy for the randomisation procedure (see footnote 13) and a dummy variable for city of residence. Regressions are weighted to reflect the desired cross-treatment randomisation design (see footnote 13). Given the household-level randomisation, we report robust standard errors.[19]

Table 1 presents the coefficients for *HALF SUBSIDY*$_i$, *FULL SUBSIDY*$_i$, *and INTERNET*$_i$ from equation (1), as well as the *p*-values from a test that shows the half and full subsidy have the same treatment effect (that is, $\beta_1=\beta_2$) and from a test that the full subsidy and the assisted Internet registration have the same effect (that is, $\beta_1=\beta_3$). Column 1 examines whether the household was enroled within the 12 months that the subsidies were active. In Column 2, we examine whether households initiated the enrolment process, regardless of whether they successfully enroled.[20] In Column 3, we examine enrolment within eight weeks of offer date (that is, when the subsidy offer was valid plus some margin for error).[21] In Column 4, we consider enrolment after the subsidy offer expired but throughout the subsidy period (up to one year from the offer date).

[19] Note that to facilitate comparisons, we separate out interventions reported in tables. Nevertheless, the full set of indicator variables is always included.

[20] For households assigned to the assisted Internet registration treatment, we set attempted enrolment equal to 1 if they stated that they wanted to enrol during the visits. For households assigned to follow the status quo registration procedures, we recorded whether they showed up to the office, regardless of whether they were successful in enroling. Since only households with a voucher had to contact the study assistant at the social security office, we do not know whether households assigned to the no-subsidy group attempted to enrol if they were not ultimate ly successful in enroling. For these households, attempted enrolment is set equal to actual enrolment, a choice justified by the fact that the failure rate for households assigned to the status quo registration in the subsidy treatments was negligible.

[21] For all groups (including the control group), the offer date is that of the baseline survey. For subsidy group households, we consider house holds who have a signup date in the administrative data within eight weeks from the offer date as having enroled using the subsidy to allow for potential delays in the data.

Subsidies substantially increased the probability of enrolment during the 12 months after the offer date, while assisted registration had a positive but smaller impact (Panel A, Column 1). Only about 9 percent of the no-subsidy group enroled within the 12-month period. Relative to this, offering the full subsidy increased enrolment by 18.6 percentage points (216 percent), while offering the half subsidy increased enrolment by 10 percentage points (116 percent). In contrast, the assisted Internet registration treatment only increased enrolment by 3.5 percentage points (40 percent).[22]

The enrolment measure by itself masks the fact that many more households–particularly those in the assisted Internet treatment–attempted to enrol than were successful. Assisted Internet registration led to a 23.8 percentage point increase in attempted enrolment during the first eight weeks (Column 2), but only a 4.3 percentage point increase in successful enrolment during that period (Column 3). This indicates that less than one-fifth of the households induced by the registration assistance to attempt enrolment were actually successful in doing so. The most common reason for unsuccessful enrolment was an inaccurate Family Card, the official identification document (see Appendix Table 3). To combat adverse selection, the government required that households enrol all nuclear family members as listed in this document which was automatically sourced from the digital records held by the Ministry of Home Affairs. This was problematic if the family composition had changed but the document had not been updated. In practice, updating the card is challenging–it cannot be updated online and requires at least one trip to a Home Affairs-linked administrative office, and can often incur delays and other additional costs. During in-person enrolment, social security administration officials use discretion to overrule the system for cause (for example, if households had documentation that the Home Affairs record was inaccurate) but the lack of flexibility in the online system made web enrolment nearly impossible for many.

The evidence in Column 3 of impacts on enrolment within the first eight weeks also raises the question of whether the interventions merely shifted forward in time an enrolment decision that would have occurred anyway (so-called "harvesting"). This seems particularly plausible given that both the offer of registration assistance and the subsidy offers were time-limited. Column 4, therefore, shows the probability of enroling after the subsidy offer expired–specifically, after eight weeks post-offer but within one year of the offer date. The results indicate that the subsidy interventions reduced the probability of enroling in this period but the decline is significantly smaller than the increase due to the subsidies in the initial period (shown in Column 3). Harvesting is, therefore, relatively small–accounting for no more than about 10 percent of the total additional enrolment we observed in the first eight weeks.

3.2 Barriers to universal enrolment

The results in Table 1, Panel A, show enrolment impacts from the intervention but also indicate that even with a full subsidy for one year, most people do not enrol. One explanation is that the hassle costs of enrolment discussed above are large enough to provide a barrier even when the insurance has no monetary costs. To investigate this, Panel B of Table 1 shows estimates from an enhanced version of equation (1) that also includes a full set of interactions between

22 Appendix Tables 2a and 2b replicate Table 1 but disaggregate the data by city. Overall, subsidies had similar effects on actual enrolment in the two cities.

the (cross-randomised) subsidy treatments and the assisted intervention treatment. Column 1 shows that, even with a full subsidy and assisted Internet registration, enrolment only reached 30 percent. Column 2 shows that less than 60 percent of households even *tried* to enrol when offered both free insurance for the year and assistance with registration. This suggests that while hassle costs provide a significant barrier–even when the insurance is free–they do not fully explain why people do not enrol.

We, therefore, explored other potential barriers such as information barriers (Table 2). We report the results separately by city because we tested different information treatments in different cities, providing detailed information on heart attack costs in Medan (Panel A) and about the nature of insurance (that is, that enrolment is mandatory and that households must enrol in advance of a health shock) in Bandung (Panel B). We find no statistically significant effect of any of these information treatments. We can rule out effect sizes bigger than 8.5 percentage points (information on heart attack costs), 2.5 percentage points (information on mandates), and 3.2 percentage points (information on waiting period).[23]

3.3 Coverage dynamics

Insurance coverage is not a one-time decision–after the initial decision to enrol, households must decide whether to continue to pay their monthly premiums to remain covered at any given point in time. We now turn to the administrative data on premium payments to examine these monthly payment decisions. Figure 3 plots coverage by month and subsidy group since the offer date. Coverage for a household is defined as the premium having been paid in full for all its members that month. Payment may be made either independently by the household or by the study. All households in the full subsidy group who successfully enrol are, therefore, covered for 12 months.

In the no-subsidy group, coverage slowly increased over time–from 0.61 percent in the first month of the experiment to 6.66 percent almost two years later. Many enrolees quickly dropped coverage, however, as one-quarter of enroled control group households had stopped paying their premiums three months after enrolment, and nearly one-half of the enrolees in the no-subsidy group had stopped paying their premiums a year post-enrolment (Appendix Figure 1). The steady increase in coverage for the no-subsidy group in Figure 3 implies that the rate of new enrolments was large enough so that net coverage rates continued to increase despite the dropout effect.[24]

Interestingly, the different subsidy groups exhibited quite different levels and patterns of coverage, both before and after the subsidies expired. In the full-subsidy group, roughly 25 percent of those offered the full subsidy enroled in the first two months after the offer and their coverage remained constant during the first year when the subsidies were active.[25]

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[23] In Medan, we also tested whether individuals would want the offer but procrastinate on it. Specifically, households with a positive subsidy offer were cross-randomised into different deadlines: one-week, two-week, or the possibility to choose between a one- and a two-week deadline to enrol using the subsidy. As shown in Appendix Table 4, this treatment also had effects that were indistinguishable from zero.

[24] The steady increase in enrolment of the no-subsidy group throughout the study period is in line with the number of enrolees going from ap proximately 10 million in January 2015 to more than 15 million in January 2016.

[25] The slight increase in coverage shown in Figure 3 for the full-subsidy group during months 4-12 comes from the fact that a small number of households in this group enroled after the subsidy period was over.

While the full-subsidy group also had a high dropout rate after the subsidy ended (at about month 13-14), their coverage levels continued to remain higher than the no-subsidy group, even at 20 months after the offer date.[26] The fact that those brought in with the temporary full subsidy stayed enroled in the second year suggests a strong "experience effect," that is, that these individuals may not have understood the benefits of insurance until they experienced it. This implies that temporary subsidies can help boost enrolment past their expiration date and may be an important tool in boosting insurance coverage in low-enrolment settings.

As one may expect from theory, results for the half-subsidy group are somewhere between the no-subsidy and full-subsidy results. Their coverage rate in the first year was higher than the no-subsidy group but far below the full-subsidy group. They also experienced a drop in coverage when the subsidy ended and, while their coverage level was roughly flat in the second year, the no-subsidy group slowly caught up to them. By the 20-month mark, their coverage rates appear similar.

Table 3 summarises the coverage patterns in Figure 3.[27] In Column 1, we report the percentage of households that enroled and had coverage for at least one month in the first year after the offer. Columns 2 and 3 decompose those with coverage in Column 1 into those who no longer had coverage by month 15 ("the dropouts") and those who did ("the stayers"); Column 4 provides the *p*-value of the difference in the dropout vs. stayer shares. Column 5 reports the percentage who had coverage in month 15, after the subsidies ended, relative to all households in the sample; note that the interpretation in this column differs from Column 3 since we do not condition on the household having enroled within one year of the offer date. Column 6 reports *p*-values for tests of whether coverage rates were the same during the subsidy period (Column 1) and at 15 months (Column 5). Finally, Columns 7 and 8 report the same information for month 20 since offer date. In the final three rows of the table, we provide the *p*-values for tests of whether the full- and half-subsidy coverage rates each differ from the no-subsidy coverage rates (β_1=0 and β_2=0), as well as whether the assisted-registration coverage rates differ from the status quo registration (β_3=0). Appendix Table 5 provides the underlying regression estimates for the p-values reported in this table.

Table 3 quantifies the magnitude of several important patterns observed in Figure 3.

First, the full-subsidy group retained substantially higher coverage than the no-subsidy group, even after the subsidies were withdrawn. Those offered the full subsidy were 4.6 percentage points (86 percent; *p*-value < 0.001) more likely than the no-subsidy group to have coverage at month 15 (Column 5), and 3.9 percentage points (58 percent; *p*-value 0.001) more likely than the no-subsidy group to have coverage at month 20. This again suggests that health insurance is an experience good–those who were covered for free for a limited time were much more likely to pay for coverage afterwards than those who were never offered free insurance.

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[26] Appendix Figure 1 shows the coverage rate for the sample of those who enroled in the first year, by month of enrolment. There is a continuous decline in payments for those in the no- and half-subsidy groups. In contrast, there is a sharp decline for those in the full-subsidy group at month 13, the exact time when households had to start paying premiums.

[27] We report means in each treatment group in this and subsequent tables to facilitate comparisons both across time and across treatment groups. The means for each cell are calculated using the weights described in footnote 13, so that each treatment group shown has the same (weighted) combination of subtreatments; that is, half subsidy has the same weighted mix of status quo vs. assisted Internet registration as full subsidy, and so on.

Second, despite the experience effect, we still document statistically significant declines in coverage in the subsidy treatments. As shown in Figure 3, we observe significantly higher coverage rates for both the full-subsidy and half-subsidy group in the first year when the subsidy was still active (Column 1). By 20 months, after all subsidies had expired, coverage had fallen substantially and the coverage rates at 20 months were no longer statistically distinguishable between the half-subsidy and no-subsidy group. Even for the full-subsidy group, where we document the persistence of coverage above, comparing Columns 1 and 7 shows that about 61 percent of those who ever had coverage in the first year had dropped coverage by month 20 (10.6 percent in month 20 covered compared to 27.7 percent covered at some point in the first year; p-value < 0.001). These results suggest that, while temporary subsidies can lead to substantial increases in coverage even after the subsidies are over, only about 40 percent of those subsidised continue to retain coverage.

Finally, it is important to note that, while the assisted-registration group saw a slight increase in coverage initially (Column 1), their coverage rate quickly converged to that of the control group. This suggests that some of the households brought into the insurance system by reducing hassles may have been particularly sensitive to the hassles of paying each month, leading to the increased dropout rate. One possible reason is that, while the assisted-Internet registration made registration easier, it did not resolve the hassles of paying one's premium which still needed to be done at an office, ATM, or convenience store.

Section Four:

Selection Impacts and Their Implications for Government Costs

4.1 Impacts on selection

Subsidies are a textbook response to concerns about adverse selection since in standard models they will induce lower-cost individuals to enrol. To examine the types of people who enrol under different intervention arms, we draw on two sources of data: (i) self-reported health from the baseline survey; and (ii) administrative claims data among those who enroled. While these two measures capture different objects–namely, health and health care usage–perhaps, not surprisingly, enrolees with better self-reported health indeed tend to have fewer claims (see Appendix Table 6).

Table 4 shows various measures of health and health care use for those who enroled and had coverage for at least one month during the first year (that is, as measured in Column 1 of Table 3).[28] Column 1 indicates that the marginal household that received coverage in response to the subsidies had a higher level of self-reported health at baseline than enrolees in the no-subsidy group. Those enroling with the subsidies had an average self-reported health score that is about 4.5 percent higher than that of no-subsidy enrolees, with both subsidy treatment effects significant at the 5 percent level. The effects of assisted-Internet registration were smaller but in the same direction and statistically significant at the 10 percent level.[29]

The remaining columns of Table 4 examine health care usage of households that enroled and had coverage for at least one month during the first year. We examine all claims for the 12 months after the enrolment date. By examining a fixed number of months since enrolment date regardless of when households enroled, we can abstract from the feature that temporary subsidies may drive households to enrol earlier in a calendar year, thereby mechanically affecting length of insurance coverage. We focus on three main indicators: (i) whether the household had any claim (Column 2); (ii) the total number of visits made (Column 6); and (iii) the total value of claims paid (Column 10). We then subdivide claims into outpatient, inpatient, and chronic. We also examine the number of days to first claim which can provide greater precision than the value of claims which tend to have a large right tail (Aron-Dine et al. 2015).

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[28] The regressions that calculate these p-values are provided in Appendix Table 7.

[29] Appendix Table 8 shows that the results also hold if self-reported health is measured as the self-reported health of the least healthy family member. In addition, households that enroled under the full-subsidy treatment were also less likely to have a family member over 60 years of age.

Consistent with the results on self-reported health in Column 1, the claims analysis in the remaining columns also indicates that those who enroled under the full subsidy were healthier and lower-cost. Households in the full-subsidy group were also less likely to submit claims. For example, in the no-subsidy group, 62 percent had any claim compared to 48 percent in the full-subsidy group (Column 2; *p*-value 0.040). Those in the full-subsidy group were also less likely to have had a claim for a chronic, ongoing condition: 27 percentage points for the no-subsidy group compared to 17 percentage points for the full-subsidy group (Column 5; *p*-value 0.082). Results for the half-subsidy group are mostly qualitatively similar to the full-subsidy group but smaller in magnitude and never statistically significantly different from the no-subsidy group. The same is true of the results for the assisted-Internet registration group.

In addition to having fewer overall claims, the full-subsidy group were less likely to lodge "large claims" that suggest a substantial health emergency. This is shown in Figure 4 that reports the probability distribution function of the value of inpatient claims submitted within 12 months since enrolment by treatment status for those who enroled within one year since offer date and paid for at least one month. The distribution of values of claims for the full-subsidy group is markedly left-shifted relative to the no-subsidy group. Again, the same is true–although less pronounced–in comparing the half-subsidy and no-subsidy groups. The differences across groups are statistically significant according to a Kolmogorov-Smirnov test for equality of distribution functions (p=0.012 for the test of equality between the distribution of the half-subsidy and no-subsidy groups and p=0.001 for the test of equality between the distribution of the full-subsidy and no-subsidy groups). In short, when they use the health care system, those whose coverage was heavily subsidised have less expensive health incidents.

On net, the fact that the full-subsidy group had fewer claims and that these claims were small results in substantial reductions in claims expenditures from the insurer. In particular, the full-subsidy group had average claims that were 40 percent lower in value than those in the no-subsidy group (Column 10 of Table 4; *p*-value 0.095) and, on average, waited 30 percent longer before submitting their first claim (Column 11; *p*-value 0.006).

4.2 Dynamics and selection

An important question is whether the fact that households can time enrolment and dropout decisions exacerbates adverse selection. We investigate both: (i) whether households in the no-subsidy group who do not face a time-limited enrolment period are more likely to time enrolment to when they are likely to have a claim; and (ii) how those who choose to retain coverage differ from those who drop. Figure 5 begins by plotting the number of claims by month since enrolment, separately by subsidy treatment groups among households who enroled within one year since offer and had coverage for at least one month over that period, along with 95 percent confidence intervals.

Those who enroled without the subsidy appear to have submitted more claims in the first few months upon enrolment than did the households in the full-subsidy group. Over time this difference became less stark, however, and by the end of the period they displayed similar patterns in number of claims. Households in the half-subsidy group also submitted more claims than households in the full-subsidy group and even submitted claims for a higher value than the no-subsidy group in a handful of months.[30] Combined with the payments findings in the previous section (that is, Figure 3), this suggests that no-subsidy households may have had large claims once they enroled but then stopped paying premiums (that is, dropped coverage). In contrast, the subsidy groups brought in healthier people who kept paying premiums longer in the first year while the subsidies were active (see Figure 3) and had smaller claims throughout the year (Figure 5).

Table 5 investigates differential selection in terms of who retained coverage and several results are worth highlighting. For each treatment, we divide those who enroled in the first year into "dropouts"–those who did not still have coverage in month 15–and "stayers"–those who did. The coverage rates of these two groups are shown in Table 3.

In the full-subsidy group, those who retained coverage had *higher* baseline self-reported health than those who did not (Column 1; *p*-value 0.068). On the other hand, the stayers were also more likely to have had claims (Column 2; *p*-value 0.005) and to have had more visits (Column 6; *p*-value 0.002). These were particularly likely to be outpatient claims/visits and those for chronic conditions, rather than inpatient claims. The half-subsidy group showed a similar pattern of claims.[31] The pattern for the no-subsidy group is more ambiguous, with the dropouts more likely to have had an inpatient claim but having had fewer overall visits.

The results from the subsidy treatments continue to suggest an experience effect: those who stayed were those who made use of the system, even for smaller outpatient or chronic conditions. They also raise the possibility that allowing relatively small payments from a plan (as opposed to a high-deductible plan that only covers catastrophic expenses) may be important for continuing to entice healthy people to remain covered.

4.3 Implications for government costs

The selection patterns indicate that the subsidies brought in healthier enrolees, while the coverage dynamics indicate that not only were no-subsidy enrolees sicker and higher-cost but that they strategically timed enrolment to coincide with major health expenditures and were quicker to drop coverage (that is, stopped paying premiums) after a few months. In Table 6, we examine the implications of these results for the net costs to the government. The results indicate that the subsidies covered more households at similar cost per covered household.[32]

[30] Appendix Table 9 formally confirms this result. In the first three months that the households were enroled in insurance (Panel A), full-subsidy households were less likely to submit inpatient or outpatient claims, had fewer overall claims than the control group, and their inpatient claims were, on average, for lower values. The coefficient on the half-subsidy group is generally negative but the difference is not always statistically significant. Months four through 12 after enrolment (Panel B) show that, over time, the difference disappears: all of the treatment groups display a very similar pattern of claims although the coefficient for the full-subsidy group is overall still negative.

[31] Appendix Table 10 presents the equivalent results broken down by the assisted-Internet registration treatment and finds a similar pattern: stayers were more likely to have had claims, particularly inpatient and outpatient claims. Appendix Table 11 presents the regressions from which we calculate the p-value of the difference in means reported in Table 5 and in Appendix Table 10.

[32] Appendix Table 12 presents equivalent results split by assisted-Internet registration vs. status quo registration and finds no substantial differences in net costs to the government. Appendix Table 13 reports the regressions that correspond to the p-values reported in Table 6 and Appendix Table 12.

Table 6 shows net revenues with and without accounting for capitation payments by month, which can be decomposed into revenues[33] from premiums and government expenditures as a result of claims.[34] Claims expenditures are defined as the value of claims paid. In Columns 2 to 5, we focus on revenues and expenditures per household-month covered. This provides us with estimates of the additional revenue and expenditure for each additional household covered in a given month. As an alternative way of presenting the same results, Columns 6 through 9 report the results for all households in the sample regardless of whether they enroled, thus providing us the total revenues and costs of offering the policy. These estimates reflect the corresponding cells in Columns 2 through 5, scaled by the number of covered households in that group.

While the subsidy was active, on net the government lost around IDR 125,000 (~US$9.00) per household-month covered in the no-subsidy group (Column 5, Panel A). By comparison, over this same period, on net the government lost only about IDR 50,000 (~US$3.50) per household-month covered in the full-subsidy group. In other words, the net cost to the government per covered household-month in the subsidy group was no higher than in the no-subsidy group (p-value = 0.19), *even taking into account that the government received essentially no revenue from the subsidy group*. This is because the decline in average claims between the full-subsidy and no-subsidy groups (Column 3: decline of IDR 152,000 per covered household-month; p-value 0.026) was even larger than the forgone revenue from not collecting premiums (Column 2: decline of IDR 71,000 per covered household-month; p-value <0.001).[35] As a result, the full subsidy resulted in over eight times more covered household-months (Column 1) at no higher cost to the government per household-month covered (Column 5).

Of course, there are more people covered so this policy does entail an increase in the total amount spent by the government. Looking over the entire sample (that is, not conditioning on enrolment), Column 9 indicates that in the no-subsidy group the government cost was IDR 3,000 (~US$0.20) per eligible household per month, while with the full-subsidy the government cost was IDR 6,000 (~US$0.40) per eligible household per month.

Panel B explores what happened in the year *after* the subsidies were withdrawn–as shown in Table 3, there was a persistent increase in coverage in the full-subsidy group. Table 5 shows, however, that despite being healthier initially, households in the full-subsidy group that retained coverage (that is, paid premiums) after the subsidy ended were more likely to have had a claim during the first year than those who dropped coverage after the subsidy ended. As a result, those who retained coverage had similar average claims after the subsidy ended to those in the no-subsidy group.

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33 Revenues are defined as premiums paid by enrolees. They should, therefore, be mechanically zero for the full-subsidy group while the subsidy is in effect but are not literally zero since a few households in this group enroled after the time period the subsidy offer was in effect and, therefore, had to pay premiums.

34 Capitation payments depend on the number of enrolees who declare the facility as their primary provider, the total number of practitioners, the ratio of practitioners to beneficiaries, and operating hours. These range between IDR 3,000-6,000 per enrolee for puskesmas and IDR 8,000-10,000 for clinics. Given that approximately 80 percent of JKN Mandiri enrolees declare puskesmas and 20 percent declare clinics as their primary health facility, for these calculations we assume capitation payments to be IDR 6,800 per enrolee per month. Capitation payments are only paid to health care facilities in months in which the household paid the premium.

35 For household-months covered in the half-subsidy group, the net losses are similar to those in the no-subsidy group (about IDR 160,000 per covered household-month); again, the fact that net revenue losses are only slightly larger for the half-subsidy group than for the no-subsidy group–despite mechanically lower revenues reflects the healthier composition of the half-subsidy pool.

On net, government costs were not statistically different per covered household-month for the no-subsidy group and the full-subsidy group in the period after the subsidy ended (Table 6, Panel B, Column 5). Nevertheless, the point estimates suggest that the government lost about half as much per covered household-month in the full-subsidy group compared to the no-subsidy group (IDR 47,000 in net government costs per covered household-month in the full-subsidy group; IDR 102,000 in net government costs per covered household-month in the no-subsidy group). In the year after the temporary full subsidy ended, we, therefore, estimate that twice as many household-months were covered (Panel B, Column 1), at no higher cost per covered household-month (Panel B, Column 5). Looking over the entire sample (that is, not conditioning on enrolment), Column 9 indicates virtually identical government expenditures (about IDR 5,000 per person) in the year after the subsidies end for the full-subsidy group compared to the no-subsidy group.

Putting this all together, one can calculate the bottom-line implications for the government by offering a temporary full subsidy to a given population. In the year the subsidy was in effect, the government doubled its net budgetary contribution for this population (from IDR 3,000 to IDR 6,000 per person offered). During that year, coverage expanded dramatically–from 6.3 percent of the population to 27.7 percent of the population. In the subsequent year, the bottom line for the government was the same–about IDR 5,000 per person in the population–regardless of treatment. But the full-subsidy group had, on net, 58 percent more people covered, with the same *total* government expenditure. This is very far from universal coverage–the full-subsidy group had 10.6 percent covered at 20 months after the project started, compared to 6.7 percent in the no-subsidy group–but it represents meaningfully more people covered with no additional ongoing cost to the government.

Section Five:

Conclusions

As incomes have risen in emerging economies, there has been a growing move to increase coverage of social insurance programs, however, insurance mandates can be difficult to enforce. We examine the impact of temporary insurance subsidies–which must be taken up within one month of offer and only last one year–reduced hassle costs, and information provision on insurance coverage in a mandated insurance setting.

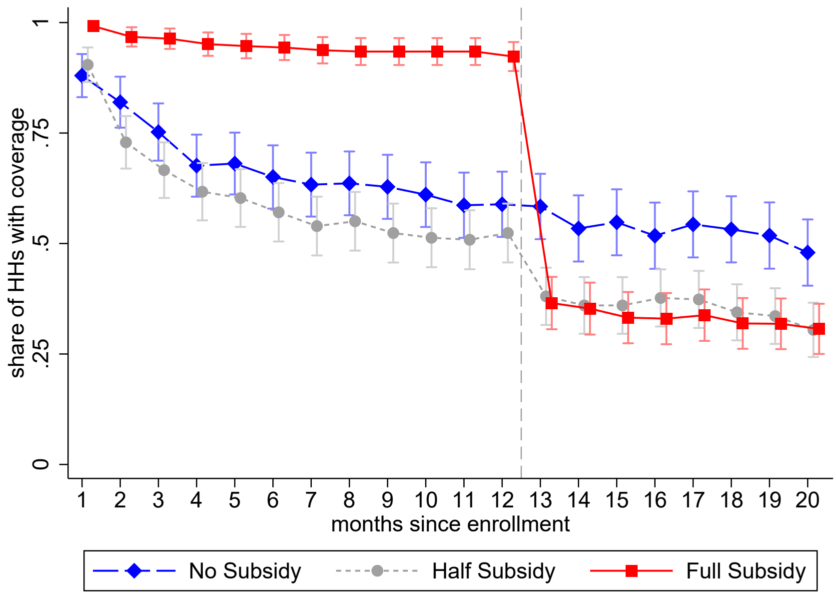
We find that offering a full, but temporary, subsidy was effective at increasing enrolment and helped to attract healthier enrolees. Because of the healthier selection and also the strategic dynamic adjustment of coverage and claims in the no-subsidy group–the no-subsidy group timed its enrolment to coincide with high expenditures and quickly dropped coverage a few months later–the net cost to the government per covered household-month of the full subsidy is no higher, *even despite the cost of the subsidies*. Importantly, subsidies induced higher enrolment even after they expired, in line with health insurance being an experience good. As a result, after the subsidy period was over, the government was able to cover substantially more people at a roughly similar net cost.

At the same time, however, our findings also highlight challenges that governments face when aiming to achieve universal health coverage through a contributory system.

While both subsidies and assisted enrolment increased enrolment rates, even the most aggressive interventions–a full subsidy for a year and Internet-assisted enrolment–only led to 30 percent enrolment. This is a substantial increase from the 8 percent enrolment in the status quo group but is far short of universal enrolment. Some of this reflects administrative challenges: almost 60 percent of households in the full subsidy, Internet-assisted registration treatment tried to enrol–double the numberr who actually did so. This underscores how weak social insurance infrastructure (in this case, the underlying social registry) can create obstacles to universal enrolment and suggests that long-term solutions to universal coverage are only feasible through strengthening overall administrative structures.

Appendix

Appendix Figure 1: Insurance Coverage, by Month since Enrollment and Subsidy Treatment



Note: This figure shows mean insurance coverage by month since enrollment for households who enrolled under different subsidy treatments, with 95% confidence intervals for the mean. Means are weighted to reflect the intended randomization. Coverage for a household is defined as the premium having been paid in full for all its members that month. The sample is restricted to households who enrolled within a year since offer date and had coverage for at least one month over the same time period. The sample size is 749 households.

Appendix Table 1: Randomization Balance

	Has NIK	Self-reported health	Outpatient	Inpatient	Any chronic	Family member 60+	HH finished highschool	HH employed	HH size
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Full subsidy	-0.001	0.028	0.009	0.010	0.021	-0.029	-0.008	-0.001	0.155**
	(0.017)	(0.024)	(0.022)	(0.012)	(0.022)	(0.019)	(0.023)	(0.013)	(0.067)
Half subsidy	0.021	0.015	-0.022	0.008	0.016	0.006	0.031	-0.014	0.002
	(0.014)	(0.020)	(0.019)	(0.010)	(0.019)	(0.016)	(0.019)	(0.012)	(0.055)
Assisted internet registration	0.001	-0.011	0.007	0.011	0.002	-0.003	-0.004	0.000	0.002
	(0.011)	(0.015)	(0.014)	(0.008)	(0.014)	(0.012)	(0.014)	(0.009)	(0.042)
Information on cost of	-0.001	-0.030	-0.002	0.005	0.021	0.034	-0.035	0.040*	0.006
treatment for heart attack	(0.026)	(0.037)	(0.034)	(0.020)	(0.033)	(0.031)	(0.035)	(0.021)	(0.111)
Information on possible	-0.003	-0.015	-0.021	-0.002	-0.009	0.004	0.040***	-0.012	0.014
mandate penalties	(0.011)	(0.016)	(0.015)	(0.008)	(0.015)	(0.012)	(0.015)	(0.009)	(0.042)
Information on two weeks	0.004	0.039**	-0.004	-0.008	-0.026*	0.004	-0.014	0.009	0.085**
waiting period	(0.011)	(0.016)	(0.015)	(0.008)	(0.015)	(0.012)	(0.015)	(0.009)	(0.042)
Observations	5996	5964	5964	5964	5964	5996	5964	5996	5964

Note: This table shows covariate balance across subsidies, registration and information treatment assignment. We regress each of the outcomes on indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for the study location (equation (1)). All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses. All data is from the baseline survey. The smaller sample size for some outcomes is explained by households participating in the listing and treatment assignment, but refusing to complete the baseline survey. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 2a: Effect of Temporary Subsidies and Assisted Internet Registration on Year 1 Enrollment, Medan

		Decomposition		
	Enrolled within 1 year	Attempted to enroll within 8 weeks of offer date	Enrolled within 8 weeks of offer date	Enrolled after 8 weeks, but within 1 year of offer date
	(1)	(2)	(3)	(4)
Panel A: Main effects				
Full subsidy	0.200***	0.319***	0.228***	-0.027
	(0.040)	(0.040)	(0.036)	(0.022)
Half subsidy	0.131***	0.199***	0.130***	0.002
	(0.033)	(0.040)	(0.028)	(0.020)
Assisted internet registration	0.019	0.371***	0.024	-0.005
	(0.028)	(0.029)	(0.025)	(0.016)
No subsidy mean	0.075	0.140	0.017	0.058
P-value of test of hypothesis				
Half subsidy = full subsidy	0.085	0.004	0.008	0.169
Assisted internet registration = full subsidy	0.001	0.328	0.000	0.451
Panel B: Interacted specification				
Full subsidy and assisted internet registration	0.195***	0.649***	0.222***	-0.027
	(0.049)	(0.044)	(0.042)	(0.029)
Full subsidy and status quo registration	0.228***	0.247***	0.240***	-0.013
	(0.055)	(0.049)	(0.047)	(0.033)
Half subsidy and assisted internet registration	0.176***	0.555***	0.175***	0.002
	(0.057)	(0.063)	(0.048)	(0.036)
Half subsidy and status quo registration	0.106**	0.100***	0.089***	0.017
	(0.042)	(0.034)	(0.032)	(0.030)
No subsidy and assisted internet registration	0.022	0.258***	0.007	0.015
	(0.030)	(0.028)	(0.015)	(0.027)
No subsidy, status quo registration mean	0.064	0.013	0.013	0.051

Note: This table shows the effect of subsidies and assisted internet registration on enrollment in year 1 in Medan. The sample size is 1446 households. In Panel A, we regress each outcome on indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for the study location (equation (1)). The omitted category is no subsidy for the subsidy treatments and status quo registration for the assisted internet registration treatment. The p-values reported are from a test of the difference between the half subsidy and full subsidy treatments ($\beta_1 = \beta_2$) and assisted internet registration and full subsidy treatments ($\beta_1 = \beta_3$). Panel B shows the effect of the interacted treatments on enrollment in year 1. The omitted category is no subsidy and status quo registration treatment. All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 2b: Effect of Temporary Subsidies and Assisted Internet Registration on Year 1 Enrollment, Bandung

		Decomposition		
	Enrolled within 1 year	Attempted to enroll within 8 weeks of offer date	Enrolled within 8 weeks of offer date	Enrolled after 8 weeks, but within 1 year of offer date
	(1)	(2)	(3)	(4)
Panel A: Main effects				
Full subsidy	0.188***	0.263***	0.202***	-0.014
	(0.022)	(0.023)	(0.021)	(0.011)
Half subsidy	0.091***	0.153***	0.112***	-0.021***
	(0.016)	(0.017)	(0.014)	(0.008)
Assisted internet registration	0.040***	0.194***	0.049***	-0.010
	(0.011)	(0.011)	(0.009)	(0.007)
No subsidy mean	0.088	0.090	0.033	0.055
P-value of test of hypothesis				
Half subsidy = full subsidy	0.000	0.000	0.000	0.560
Assisted internet registration = full subsidy	0.000	0.006	0.000	0.739
Panel B: Interacted specification				
Full subsidy and assisted internet registration	0.241***	0.494***	0.265***	-0.024
	(0.033)	(0.034)	(0.031)	(0.015)
Full subsidy and status quo registration	0.145***	0.163***	0.163***	-0.018
	(0.030)	(0.026)	(0.026)	(0.018)
Half subsidy and assisted internet registration	0.121***	0.345***	0.160***	-0.039***
	(0.026)	(0.029)	(0.024)	(0.010)
Half subsidy and status quo registration	0.075***	0.101***	0.091***	-0.016
	(0.018)	(0.015)	(0.015)	(0.012)
No subsidy and assisted internet registration	0.014	0.140***	0.027***	-0.013
	(0.012)	(0.012)	(0.008)	(0.010)
No subsidy, status quo registration mean	0.081	0.019	0.019	0.062

Note: This table shows the effect of subsidies and assisted internet registration on enrollment in year 1 in Bandung. The sample size is 4550 households. In Panel A, we regress each outcome on indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for the study location (equation (1)). The omitted category is no subsidy for the subsidy treatments and status quo registration for the assisted internet registration treatment. The p-values reported are from a test of the difference between the half subsidy and full subsidy treatments ($\beta_1 = \beta_2$) and assisted internet registration and full subsidy treatments ($\beta_1 = \beta_3$). Panel B shows the effect of the interacted treatments on enrollment in year 1. The omitted category is no subsidy and status quo registration treatment. All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 3: Reasons for Failing to Enroll

	N	%
	(1)	(2)
No reason reported	6	1.060
Technical reasons (internet, website)	21	3.710
Family card issues	468	82.686
Family card not registered in the online system	11	2.350
Family already has insurance according to the online system	80	17.094
Family card does not match the family members listed in the online system	91	19.444
Other family card issues	286	61.111
Other issues	71	12.544

Note: The sample includes households assigned to assisted internet registration treatment that attempted to enroll within six weeks from offer date but failed to complete the registration process. Data is from the enumerator forms that capture the enrollment process.

Appendix Table 4: Effect of Additional Treatments on Year 1 Enrollment, by City

		Decomposition		
	Enrolled within 1 year	Attempted to enroll within 8 weeks of offer date	Enrolled within 8 weeks of offer date	Enrolled after 8 weeks, but within 1 year of offer date
	(1)	(2)	(3)	(4)
Panel A: Medan				
Two week deadline	0.048	0.012	0.047	0.001
	(0.045)	(0.047)	(0.044)	(0.020)
Choice between one or two week deadline	0.031	0.023	0.001	0.030
	(0.048)	(0.051)	(0.043)	(0.028)
No subsidy mean	0.075	0.140	0.017	0.058
Panel B: Bandung				
Bonus subsidy	0.037***	0.061***	0.040***	-0.003
	(0.013)	(0.013)	(0.010)	(0.009)
No subsidy mean	0.088	0.090	0.033	0.055

Note: This table shows the effect of the deadline and the bonus subsidy treatment on enrollment in year 1, by city. The sample size is 1446 households in Medan and 4550 households in Bandung. We regress each of the enrollment measures on indicator variables for treatment assignment and an indicator variable for the randomization procedure used (equation (1)). The omitted category is one week deadline for the deadline treatment and no subsidy for the bonus subsidy treatment. All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 5: Insurance Coverage, by Temporary Subsidies and Assisted Internet Registration

	Enrolled within 1 year of offer date							
		Dropouts	Stayers					
	Had coverage for at least 1 month	Did not have coverage in month 15	Had coverage in month 15	P-Value (2) vs (3)	Had coverage in month 15	P-Value (1) vs (5)	Had coverage in month 20	P-Value (1) vs (7)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full subsidy	0.200***	0.142***	0.058***	0.153***	0.048***	0.208***	0.045***	0.210***
	(0.019)	(0.017)	(0.012)	(0.015)	(0.013)	(0.018)	(0.013)	(0.018)
Full subsidy interaction				-0.105***		-0.168***		-0.174***
				(0.020)		(0.016)		(0.016)
Half subsidy	0.100***	0.073***	0.027***	0.078***	0.022**	0.104***	0.010	0.106***
	(0.014)	(0.011)	(0.009)	(0.011)	(0.010)	(0.014)	(0.010)	(0.014)
Half subsidy interaction				-0.057***		-0.087***		-0.101***
				(0.016)		(0.014)		(0.015)
Assisted internet registration	0.022**	0.022***	-0.000	0.022***	0.001	0.022**	-0.008	0.022**
	(0.010)	(0.008)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)	(0.010)
Assisted internet registration interaction				-0.023**		-0.021**		-0.030***
				(0.011)		(0.009)		(0.010)
Observations	5996	5996	5996	11992	5996	11992	5996	11992
No subsidy mean	0.063	0.024	0.038	0.031	0.053	0.058	0.067	0.065

Note: This table shows insurance coverage by temporary subsidies and assisted internet registration. A household is considered as having insurance coverage if the premium was paid for all its members. In Columns (1), (2), (3), (5), and (7) we regress each outcome on indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for study location (equation (1)). Column (4), Column (6), and (8) report coefficients from regressions in which we stack the outcomes being compared and regress them on indicator variables for treatment assignment, the interaction of these indicators with an indicator for the outcome the observation refers to, an indicator variable for the randomization procedure used and an indicator variable for study location. All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses in Columns (1)-(3), (5), and (7) and standard errors clustered at the household level are reported in parentheses in Columns (4), (6), and (8). *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 6: Relationship between Self-Reported Health and Year 1 Health-Seeking Behavior

	Had a claim				Total # of visits				Claims	
	Of any type	Outpatient	Inpatient	Chronic	Of any type	Outpatient	Inpatient	Chronic	Value of claims	Days to first claim
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Self-reported health	-0.091**	-0.096**	-0.054*	-0.090**	-1.040	-0.884	-0.156	-0.093*	-0.885*	22.701*
	(0.040)	(0.040)	(0.033)	(0.037)	(0.696)	(0.645)	(0.097)	(0.054)	(0.503)	(12.561)
R2	0.035	0.040	0.027	0.027	0.028	0.027	0.032	0.025	0.035	0.044

Note: This table shows the coefficients from a regression of claims in months 1 to 12 since enrollment date on self-reported health. For self-reported health, higher values correspond to better self-reported health. The sample is restricted to households who enrolled within a year from offer date and had coverage for at least one month over the same time period. The sample size is 749 households. The value of claims in Column (8) is winsorized at the 99% level and only refers to hospital claims. Each regression additionally controls for indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for the study location (equation (1)). All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 7: Self-Reported Health and Claims in 12 Months since Enrollment, by Temporary Subsidies and Assisted Internet Registration

	Self-reported health	Had a claim				Total # of visits				Claims	
		Of any type	Outpatient	Inpatient	Chronic	Of any type	Outpatient	Inpatient	Chronic	Value of claims	Days to first claim
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Full subsidy	0.138**	-0.118**	-0.119**	-0.051	-0.089*	-2.115**	-2.022**	-0.092	-0.146**	-0.706*	47.159***
	(0.057)	(0.058)	(0.058)	(0.047)	(0.051)	(0.940)	(0.898)	(0.083)	(0.069)	(0.423)	(17.185)
Half subsidy	0.146**	-0.084	-0.080	0.028	-0.024	-0.986	-1.043	0.057	-0.030	0.237	28.996
	(0.060)	(0.059)	(0.059)	(0.046)	(0.051)	(1.082)	(1.044)	(0.081)	(0.071)	(0.484)	(17.963)
Assisted internet registration	0.076*	-0.033	-0.036	-0.026	0.009	-1.000	-0.984	-0.016	-0.010	-0.173	14.433
	(0.044)	(0.044)	(0.044)	(0.033)	(0.033)	(0.636)	(0.610)	(0.059)	(0.044)	(0.309)	(13.018)
No subsidy mean	3.099	0.622	0.612	0.181	0.272	6.167	5.906	0.262	0.339	1.637	176.259

Note: This table shows self-reported health and claims submitted in months 1 to 12 since one's enrollment date by temporary subsidies and assisted internet registration. The sample is restricted to households who enrolled within a year from offer date and had coverage for at least one month over the same time period. The sample size is 749 households. In Column (1), higher values of the outcome correspond to better self-reported health. The value of claims in Column (10) is winsorized at the 99% level and only refers to hospital claims. Each regression additionally controls for indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for the study location (equation (1)). All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 8: Self-Reported Health and Family Composition of Enrolled Households, by Subsidy and Assisted Internet Registration Treatments

	Self-reported health, min	Family member over 60
	(1)	(2)
Full subsidy	2.895	0.182
	[0.651]	[0.386]
Half subsidy	2.956	0.281
	[0.697]	[0.451]
No subsidy	2.801	0.259
	[0.750]	[0.440]
Assisted internet registration	2.927	0.231
	[0.686]	[0.422]
Status quo registration	2.821	0.244
	[0.714]	[0.430]
P-value of test of hypothesis		
Full subsidy = no subsidy	0.060	0.073
Half subsidy = no subsidy	0.019	0.770
Assisted internet registration = status quo	0.051	0.709

Note: This table shows the effect of subsidies and assisted internet registration on the minimum self-reported health across household members and family composition. Means are weighted to reflect the intended randomization. Standard deviations are in brackets. The sample is restricted to households who enrolled within a year since offer and had coverage for at least one month over the same time period. The sample size is 749 households. In Column (1), self-reported health is defined as the minimum self-reported health of all family members and higher values of the outcome correspond to better self-reported health. We regress each outcome on indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for study location (equation (1)). All regressions are estimated by OLS and weighted to reflect the intended randomization. The p-values reported are from a test of the difference between the no subsidy and full subsidy treatments ($\beta_2 = 0$), between the no subsidy and half subsidy treatments ($\beta_3 = 0$) and between the status quo and assisted internet registration treatments ($\beta_4 = 0$). All regressions are estimated by OLS and weighted to reflect the intended randomization.

Appendix Table 9: Effect of Temporary Subsidies and Assisted Internet Registration on Claims, Disaggregated by First Quarter versus Rest of the Year

	Had a claim				Total # of visits				Claims	
	Of any type	Outpatient	Inpatient	Chronic	Of any type	Outpatient	Inpatient	Chronic	Value of claims	Days to first claim
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Months 1 to 3 since enrollment date										
Full subsidy	-0.166***	-0.169***	-0.035	-0.047	-0.965***	-0.896***	-0.069	-0.047	-0.380	13.883***
	(0.055)	(0.054)	(0.028)	(0.035)	(0.357)	(0.334)	(0.053)	(0.041)	(0.233)	(3.759)
Half subsidy	-0.132**	-0.127**	0.001	0.010	-0.229	-0.255	0.026	0.034	0.050	9.373**
	(0.055)	(0.055)	(0.029)	(0.035)	(0.375)	(0.354)	(0.047)	(0.042)	(0.241)	(3.903)
Assisted internet registration	-0.044	-0.043	-0.018	-0.001	-0.318	-0.327*	0.009	0.003	0.066	3.459
	(0.040)	(0.039)	(0.020)	(0.022)	(0.216)	(0.197)	(0.040)	(0.028)	(0.166)	(2.797)
No subsidy mean	0.452	0.448	0.080	0.108	1.782	1.687	0.095	0.113	0.597	59.021
Panel B: Months 4 to 12 since enrollment date										
Full subsidy	-0.072	-0.051	-0.021	-0.078	-1.150	-1.126	-0.023	-0.110**	-0.237	
	(0.058)	(0.058)	(0.042)	(0.048)	(0.752)	(0.726)	(0.060)	(0.054)	(0.284)	
Half subsidy	-0.063	-0.052	0.027	-0.037	-0.757	-0.788	0.031	-0.047	0.120	
	(0.058)	(0.058)	(0.041)	(0.049)	(0.863)	(0.838)	(0.063)	(0.058)	(0.345)	
Assisted internet registration	-0.061	-0.061	-0.021	-0.003	-0.682	-0.657	-0.025	-0.016	-0.278	
	(0.042)	(0.041)	(0.029)	(0.031)	(0.518)	(0.501)	(0.041)	(0.035)	(0.203)	
No subsidy mean	0.527	0.498	0.127	0.236	4.385	4.219	0.166	0.274	1.012	

Note: This table shows the effect of subsidies and assisted internet registration on claims submitted for months 1 to 3 since enrollment date (Panel A) and from month 4 to 12 since enrollment date (Panel B). The sample is restricted to households who enrolled within a year since offer date and had coverage for at least one month over the same time period. The sample size is 749 households. The value of claims in Column (9) is winsorized at the 99% level and only refers to hospital claims. We regress each outcome on indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for study location (equation (1)). All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 10: Year 1 Claims by Retention in Year 2, by Assisted Internet Registration Treatment

	Self-reported health	Had a claim				Total # of visits				Claims	
		Of any type	Outpatient	Inpatient	Chronic	Of any type	Outpatient	Inpatient	Chronic	Value of claims	Days to first claim
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Assisted internet registration											
Dropouts	3.233	0.405	0.376	0.185	0.148	2.639	2.369	0.270	0.169	1.419	241.731
	[0.504]	[0.492]	[0.485]	[0.390]	[0.356]	[5.101]	[4.768]	[0.686]	[0.427]	[3.847]	[145.876]
Stayers	3.193	0.697	0.685	0.146	0.338	6.556	6.317	0.239	0.388	1.289	176.465
	[0.551]	[0.461]	[0.466]	[0.354]	[0.474]	[9.366]	[9.153]	[0.711]	[0.590]	[3.426]	[141.792]
P-value of test of hypothesis											
Dropouts = stayers	0.491	0.000	0.000	0.359	0.000	0.000	0.000	0.716	0.000	0.769	0.000
Panel B: Status quo registration											
Dropouts	3.173	0.485	0.461	0.167	0.184	3.069	2.867	0.201	0.221	0.932	227.274
	[0.467]	[0.501]	[0.500]	[0.374]	[0.388]	[5.456]	[5.277]	[0.499]	[0.498]	[2.637]	[144.664]
Stayers	3.125	0.627	0.614	0.230	0.245	7.330	6.983	0.347	0.313	2.118	173.817
	[0.542]	[0.485]	[0.488]	[0.422]	[0.432]	[12.985]	[12.620]	[0.800]	[0.657]	[4.719]	[152.519]
P-value of test of hypothesis											
Dropouts = stayers	0.424	0.016	0.008	0.173	0.187	0.000	0.000	0.062	0.156	0.005	0.002

Note: This table shows mean self-reported health and claims in the first year since enrollment, separately by registration treatment and by whether households kept or dropped coverage at month 15 since offer date. Means are weighted to reflect the intended randomization. Standard deviations are in brackets. The sample is restricted to households who enrolled within a year since offer and paid for at least one month over the same time period. The sample size is 749 households. In Column (1), higher values of the outcome correspond to better self-reported health. The value of claims in Column (10) is winsorized at the 99% level and only refers to hospital claims. The p-values are from an interacted specification where the outcome is regressed on indicator variables for treatment assignment interacted with an indicator variable for whether the household has coverage in month 15, an indicator variable for the randomization procedure used and an indicator variable for study location. All regressions are estimated by OLS and weighted to reflect the intended randomization. Appendix Table 11 provides the regression estimates behind the numbers reported in this table.

Appendix Table 11: Year 1 Claims by Retention in Year 2, by Temporary Subsidy and Assisted Internet Registration Treatment

	Self-reported health	Had a claim				Total # of visits				Claims	
		Of any type	Outpatient	Inpatient	Chronic	Of any type	Outpatient	Inpatient	Chronic	Value of claims	Days to first claim
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Full subsidy	0.028	-0.093	-0.099	-0.143**	-0.069	-0.711	-0.544	-0.167*	-0.165	-1.188**	45.628*
	(0.079)	(0.079)	(0.079)	(0.071)	(0.074)	(0.964)	(0.903)	(0.097)	(0.110)	(0.594)	(23.850)
Full subsidy interaction	0.239**	0.038	0.050	0.182**	-0.013	-1.370	-1.544	0.173	0.066	0.989	-17.912
	(0.107)	(0.108)	(0.108)	(0.089)	(0.095)	(1.702)	(1.625)	(0.141)	(0.132)	(0.777)	(32.717)
Half subsidy	0.075	-0.080	-0.077	-0.044	-0.056	-0.357	-0.368	0.012	-0.110	-0.282	33.343
	(0.088)	(0.084)	(0.084)	(0.075)	(0.074)	(1.009)	(0.938)	(0.113)	(0.111)	(0.699)	(26.055)
Half subsidy interaction	0.122	0.098	0.101	0.118	0.135	0.638	0.566	0.073	0.237	0.960	-32.530
	(0.122)	(0.121)	(0.121)	(0.096)	(0.108)	(2.030)	(1.942)	(0.176)	(0.154)	(1.014)	(36.749)
Assisted internet registration	0.070	-0.087	-0.092	0.018	-0.031	-0.528	-0.592	0.064	-0.048	0.416	17.612
	(0.056)	(0.060)	(0.060)	(0.044)	(0.042)	(0.599)	(0.562)	(0.076)	(0.055)	(0.385)	(17.767)
Assisted internet registration interaction	0.017	0.170*	0.178**	-0.089	0.126*	-0.089	0.070	-0.158	0.133	-1.139*	-20.585
	(0.087)	(0.088)	(0.088)	(0.062)	(0.071)	(1.325)	(1.273)	(0.115)	(0.089)	(0.590)	(26.106)

Note: This table shows the difference in self-reported health and claims by treatment and by whether households kept or dropped coverage at month 15 since offer date. The sample is restricted to households who enrolled within a year since offer and had coverage for at least one month over the same time period. The sample size is 749 households. In Column (1), higher values of the outcome correspond to better self-reported health. The value of claims in Column (10) is winsorized at the 99% level and only refers to hospital claims. We regress each outcome on indicator variables for treatment assignment, the interaction of these indicators with an indicator whether the household retained coverage at month 15, an indicator variable for the randomization procedure used and an indicator variable for study location. All regressions are estimated by OLS and weighted to reflect the intended randomization. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 12: Expenditures and Revenues, by Assisted Internet Registration

		Per covered household-month				Per household-month			
	Coverage	Revenues	Claims expenditures	Net revenues	Net revenues including capitation	Revenues	Claims expenditures	Net revenues	Net revenues including capitation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Months 1 to 12 since offer date									
Assisted internet registration	1.065	0.032	0.083	-0.051	-0.072	0.003	0.007	-0.004	-0.006
	[3.094]	[0.042]	[0.723]	[0.723]	[0.723]	[0.016]	[0.217]	[0.216]	[0.216]
Status quo registration	0.862	0.033	0.126	-0.093	-0.113	0.003	0.009	-0.006	-0.008
	[2.759]	[0.046]	[1.248]	[1.243]	[1.243]	[0.016]	[0.336]	[0.334]	[0.334]
Observations	5996	5558	5558	5558	5558	71952	71952	71952	71952
P-value of test of hypothesis									
Status quo = assisted	0.032	0.230	0.357	0.394	0.407	0.128	0.616	0.504	0.586
Panel B: Months 13 to 20 since offer date									
Assisted internet registration	0.586	0.070	0.161	-0.091	-0.110	0.006	0.012	-0.006	-0.007
	[1.901]	[0.047]	[1.517]	[1.516]	[1.516]	[0.023]	[0.413]	[0.411]	[0.411]
Status quo registration	0.606	0.067	0.110	-0.043	-0.061	0.005	0.008	-0.003	-0.004
	[1.926]	[0.055]	[0.904]	[0.903]	[0.904]	[0.024]	[0.251]	[0.249]	[0.249]
Observations	5996	3565	3565	3565	3565	47968	47968	47968	47968
P-value of test of hypothesis									
Status quo = assisted	0.669	0.397	0.198	0.222	0.210	0.505	0.371	0.418	0.411

Note: This table shows mean revenues and expenditures by assisted internet registration, for months 1 to 12 from offer (Panel A) and for months 13 to 20 from offer (Panel B). Column (1) reports mean number of months with insurance coverage. Means are weighted to reflect the intended randomization. Standard deviations are in brackets. Observations are at the household level. Columns (2) to (5) and (6) to (9) show mean net revenues, net revenues including capitation payments, revenues (premiums paid by enrollees) and expenditures (total value of claims) in millions IDR for household-months in which households had coverage and for all household-months. Observations are at the household-month level. The value of claims in Columns (5) and (9) is winsorized at the 99% level and only refers to hospital claims. The p-values are from regressions of each outcome on indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for study location (equation (1)). In Column (1) standard errors are robust, while in Columns (2) to (9) standard errors are clustered at the household level. The p-values reported are from a test of the difference between the status quo and assisted internet registration treatments ($\beta_3 = 0$). All regressions are estimated by OLS and weighted to reflect the intended randomization. Appendix Table 13 provides the regression estimates behind the numbers reported in Appendix Table 12. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 13: Expenditures and Revenues, by Temporary Subsidies and Assisted Internet Registration

		Per covered household-month				Per household-month			
	Coverage	Net revenues	Net revenues including capitation	Revenues	Claims expenditures	Net revenues	Net revenues including capitation	Revenues	Claims expenditures
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Months 1 to 12 since offer date									
Full subsidy	0.200***	0.111	0.105	-0.071***	-0.182**	-0.001	-0.006	-0.001***	-0.001
	(0.019)	(0.081)	(0.081)	(0.004)	(0.081)	(0.005)	(0.005)	(0.000)	(0.005)
Half subsidy	0.100***	-0.026	-0.028	-0.032***	-0.006	-0.009*	-0.010**	0.002***	0.011**
	(0.014)	(0.090)	(0.090)	(0.005)	(0.091)	(0.005)	(0.005)	(0.000)	(0.005)
Assisted internet registration	0.022**	0.039	0.037	-0.003	-0.042	0.002	0.002	0.001	-0.002
	(0.010)	(0.045)	(0.045)	(0.003)	(0.045)	(0.003)	(0.003)	(0.000)	(0.003)
Observations	5996	5558	5558	5558	5558	71952	71952	71952	71952
No subsidy mean	0.063	-0.108	-0.125	0.075	0.183	-0.003	-0.003	0.002	0.005
Panel B: Months 13 to 20 since offer date									
Full subsidy	0.045***	0.019	0.014	0.003	-0.016	-0.002	-0.004	0.005***	0.007
	(0.013)	(0.056)	(0.056)	(0.006)	(0.055)	(0.004)	(0.004)	(0.001)	(0.005)
Half subsidy	0.010	-0.068	-0.071	0.005	0.073	-0.006	-0.006	0.002***	0.008
	(0.010)	(0.083)	(0.083)	(0.005)	(0.083)	(0.006)	(0.006)	(0.001)	(0.006)
Assisted internet registration	-0.008	-0.063	-0.064	0.003	0.066	-0.003	-0.003	0.000	0.003
	(0.008)	(0.051)	(0.051)	(0.004)	(0.051)	(0.004)	(0.004)	(0.001)	(0.004)
Observations	5996	3565	3565	3565	3565	47968	47968	47968	47968
No subsidy mean	0.067	-0.085	-0.102	0.068	0.153	-0.005	-0.006	0.004	0.009

Note: This table shows the difference in revenues, coverage, and expenditures by subsidies and assisted internet registration. Column (1) reports mean number of months with insurance coverage. Observations are at the household level. Columns (2) to (5) and (6) to (9) show mean net revenues, net revenues including capitation payments, revenues (premiums paid by enrollees) and expenditures (total value of claims) in millions IDR for household-months in which households had coverage and for all household-months. Observations are at the household-month level. The value of claims in Columns (5) and (9) is winsorized at the 99% level and only refers to hospital claims. We regress each outcome on indicator variables for treatment assignment, an indicator variable for the randomization procedure used and an indicator variable for study location (equation (1)). All regressions are estimated by OLS and weighted to reflect the intended randomization. In Column (1) standard errors are robust, while in Columns (2) to (9) standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

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ESTIMATING THE STOCK OF HIGHLY SKILLED INDONESIANS

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Abstract

The most talented individuals organise production processes, discover, and innovate. As a result, talented individuals contribute more to economic growth than ordinary labour. This paper is the first step to understanding talented individuals in Indonesia. First, we use an international benchmark to estimate the number of students who could be considered as highly skilled. We then examine their background and the schools that they attend. We use three rounds of the Programme for International Student Assessment (PISA).

We find that Indonesia has a minuscule proportion of highly skilled individuals. Out of a cohort of 3.1 million 15-year-old students, Indonesia only had around 0.46 percent or 14,300 individuals with high mathematics skills and 0.06 percent or 1,900 individuals with high literacy skills in 2015. Our analysis shows that skills are associated with having tertiary-educated mothers and a favourable socioeconomic status. These skilled individuals cluster in a handful of schools that have a higher proportion of certified teachers. Students within these schools have similar characteristics, indicating the strong influence of parental choice. Our findings point to the need for Indonesia, and perhaps other similar middle-income countries, to have an active policy to identify and nurture talent.

Section 1

Introduction

The typical worker is an input to the production process while the most talented individuals organise the production processes and discover productivity-enhancing technologies that lead to higher output growth. Benzell and Brynjolfsson (2019) state that digital technology cannot replace talent. Inelastically supplied, a scarcity in the number of talented individuals would constrain growth and firms would be unable to make full use of digital abundance. This notion is related to the interaction between talent and scale (Rosen 1981; Kaplan and Rauh 2013). Benzell and Brynjolfsson (2019), therefore, consider geniuses to be more important than ordinary labour. The skills of the brightest individuals are even more critical as economies become knowledge based (Pritchett and Viarengo 2009).

Cross-country empirical studies find that highly intelligent individuals have a greater impact on economic growth than individuals of average intelligence (Burhan et al. 2014; Rindermann et al. 2015). The occupations chosen by talented individuals are also important. Murphy et al. (1989) note that countries realise the full benefit of talented individuals when they become entrepreneurs. Social benefits would be suboptimal if talented individuals become workers or, even worse, rent seekers. According to Rosen (1981), talented individuals should work in occupations with low diminishing returns to scale.

This literature has two consequences: (i) countries must have enough talented individuals. This calls for a focus on identifying and nurturing talent; and (ii) talented individuals need to be in occupations where their talents will have the greatest social impact. To achieve this, the private returns for these individuals must be highest in occupations that would produce the highest social impact. Being an entrepreneur is one way. Another way is to ensure that contracts are set to allow talented individuals to extract almost their full quasi-rents (Murphy et al. 1989).

Achieving the two objectives above is challenging–on nurturing talent, Card and Giuliano (2016) find that gifted education has no impact on the scores of gifted students. A meta-analysis of 26 studies found, however, that summer residential programs have a positive effect on the academic outcomes of gifted students (Kim 2017).

On optimal occupations, recent studies examined the determinants of becoming an inventor which is, arguably, an ideal occupation for talented individuals. Aghion et al. (2017) analysed data from Finland that found, while IQ has a positive and significant effect on the probability of becoming an inventor, parental income remains crucial. The correlation is particularly steep at higher levels of parental income. Lack of parental support also prohibits many high IQ individuals from becoming an inventor. Inefficiencies, therefore, happen even where education is high quality and completely free.

In the United States, Bell et al. (2019) find that the chance of becoming an inventor depends on gender, race, and parental socioeconomic class. They find that environment is a more important determinant than ability to innovate. The finding implies that many talented individuals, especially women and minority groups, fail to fulfill their potential to be inventors and, as a whole, society loses.

The literature on talented individuals has almost exclusively focused on rich countries. An exception is Pritchett and Viarengo (2009), who focus on Mexico. They found that Mexico produces too few highly talented individuals–between 3,500 and 6,000 individuals from a cohort of 2 million 15-year-olds. In comparison, the Republic of Korea produces 125,000, the United States 250,000, and India 100,000. The study also found that the 95th percentile Mexican student is about as smart as the average Korean student.

In this paper, we take the first step to understanding talented individuals in Indonesia by firstly estimating their number and then examining their background and the schools that they attend. We use the latest three rounds of PISA, focusing on performance in mathematics and reading tests. Given that PISA tests the skills of 15-year-olds, for the rest of this paper we prefer to use the term 'skilled' rather than talented as the latter term is closer to something one is born with. Skills, on the other hand, are a result of both talent and nurture.[1]

We find that Indonesia has a minuscule proportion of skilled individuals. In 2015, only five out of 1,000 Indonesians (0.5 percent) achieved the PISA threshold for high skills in mathematics.[2] Across the whole PISA sample, 7.6 percent passed the threshold. The rate is even smaller for reading. In 2015, only six out of 10,000 Indonesians (0.06 percent) passed the PISA threshold for high skills. In absolute numbers, Indonesia only had 14,300 individuals with high mathematics skills and 1,900 individuals with high literacy skills in 2015. The number of 15-year-old students that year was 3.1 million. While still extremely low, PISA indicates that the trend is positive between 2009 and 2015.

The small number of highly skilled individuals in Indonesia results in a very small sample size in PISA. To further understand the background of skilled individuals, therefore, we have included the sample that passed the PISA threshold for competence in mathematics or reading.[3] Only around 1-2 percent of Indonesian students are placed at this level, compared to 14-16 percent across the whole PISA sample.

Our analysis shows that skills are strongly associated with having tertiary-educated mothers and a favourable socioeconomic status. Skilled students spent more than one year in early childhood education. They live in large cities, not small villages. Rather than being uniformly distributed across schools, these skilled individuals tend to cluster in a handful of schools that have a higher proportion of certified teachers. Students within these schools have similar characteristics, indicating the strong influence of parental choice.

Section Two describes the PISA dataset and results for all countries, Section Three examines Indonesia's overall PISA performance, while Section Four contains our analysis of Indonesia's skilled individuals. We provide the conclusions in Section Five.

[1] We could find no dataset that records the IQ of Indonesians.
[2] Specifically, Levels 5 and 6 in PISA. See Section Two for further details.
[3] Level 4 in PISA.

Section 2

The PISA Data

PISA is a triennial international survey that tests the skills and knowledge of 15-year-old students. Administered by the OECD, PISA started in 2000 and, until 2015, has been undertaken six times. In total, 88 countries and economies (for example, China and Shanghai participate separately) have participated at least once. The PISA test is representative at the national level.

The skills and knowledge tested by PISA are in numeracy, science, reading, collaborative problem solving, and financial literacy, however, only the numeracy, science, and reading tests have been undertaken since the first PISA. The focus of PISA is on the application of knowledge and skills for tasks relevant in adult life, as opposed to memorisation. This is appropriate given our purpose is to measure skills that are relevant in the labour market.

To measure reading literacy, the assessment focuses on measuring students' ability to use written information in real-life situations, while in mathematics it aims to measure how well students can use and interpret mathematical concepts and apply their knowledge in real-life contexts (OECD 2016). PISA defines seven proficiency levels in reading. These proficiency levels are based on three required skills which are ability to find and collect information ("access and retrieve"), ability to process the information to make sense of a text ("integrate and interpret"), and ability to draw on knowledge, ideas, and values beyond the text ("reflect and evaluate") (OECD 2016 p.161).

In mathematics, PISA's six proficiency levels are based on three levels of cognitive demand or depth of knowledge (OECD 2016 p.55). The low depth of knowledge can be defined as ability to carry out a simple task such as recalling a fact or concept. The medium level refers to more advanced skills such as applying conceptual knowledge to explain real-life phenomena, organising data, or interpreting simple data sets. Lastly, the high depth of knowledge can be defined as an ability to analyse complex information, evaluate evidence, and develop a plan to approach a problem.

In both reading and mathematics, Level 2 is considered as a basic level of proficiency, meaning that students who achieved at this level or above are expected to demonstrate the literacy and numeracy skills that will enable them to participate productively in a knowledge-based society. PISA defines students who performed below Level 2 as low performers and those who performed at Level 5 and 6 as top performers.

Across all participating countries and economies, around 65 percent of 15-year-old students met or exceeded the basic proficiency level in mathematics (Figure 1) and around 70 percent in reading (Figure 2) in 2015. Around one-third of students scored below Level 2. These students pose a higher risk in terms of their participation in tertiary education and labour market outcomes at age 19 (OECD 2010). In 2015, around one in five students achieved Level 4 or above in either reading or mathematics.

Figure 1: Percentage of Students by Mathematics Proficiency Level

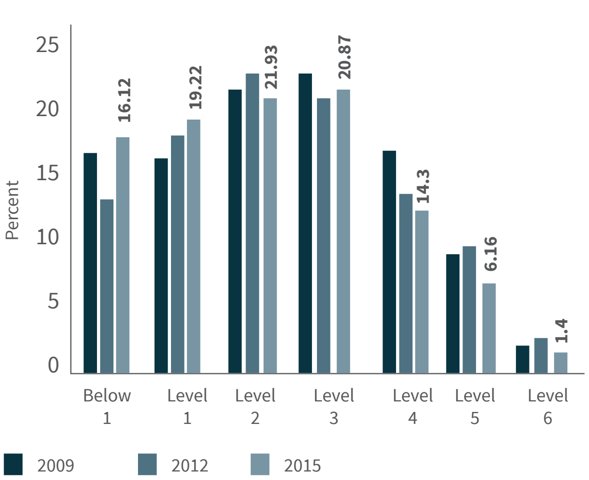
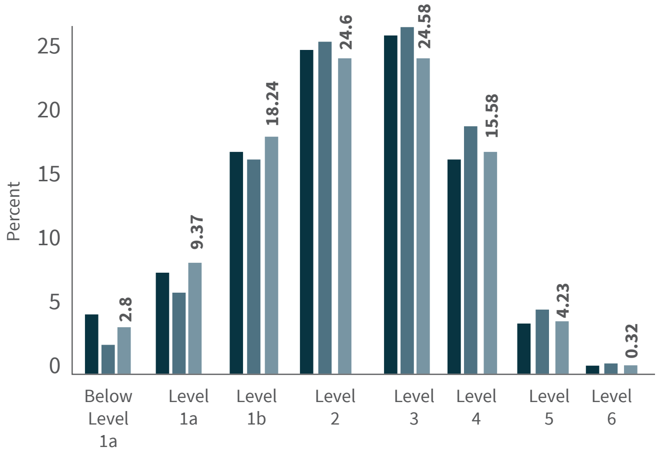


Figure 2: Percentage of Students by Reading Proficiency Level



Source: PISA 2009-2015 (authors' analysis).

Disaggregating participants into OECD and non-OECD countries, we observe a substantial difference in the distributions of student performance between the two groups (Figures 3-6). While the share of low performers (below Level 2) in mathematics in OECD countries is around 22 percent, the share in non-OECD countries is very high at 49 percent. We find the same outcomes in reading (19 percent and 42 percent respectively). When it comes to high performers, there is also a large gap between these two groups. The share of Level 4 and above in mathematics in OECD countries (28 percent) is almost double that of non-OECD countries (15 percent). In reading, the share in OECD countries (28 percent) is more than double that in non-OECD countries (12 percent). These patterns are consistent from 2009 to 2015.

Figure 3: Student Performance in Mathematics (OECD Countries)

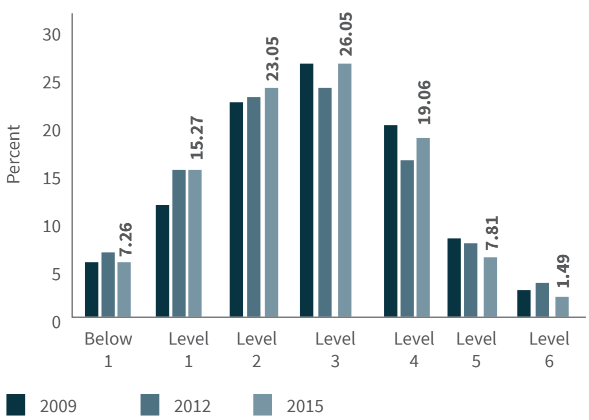
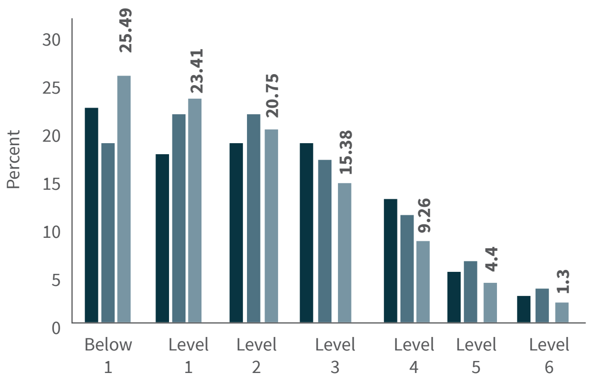


Figure 4: Student Performance in Mathematics (Non-OECD Countries)



Source: PISA 2009-2015 (authors' analysis).

Figure 5: Student Performance in Reading (OECD Countries)

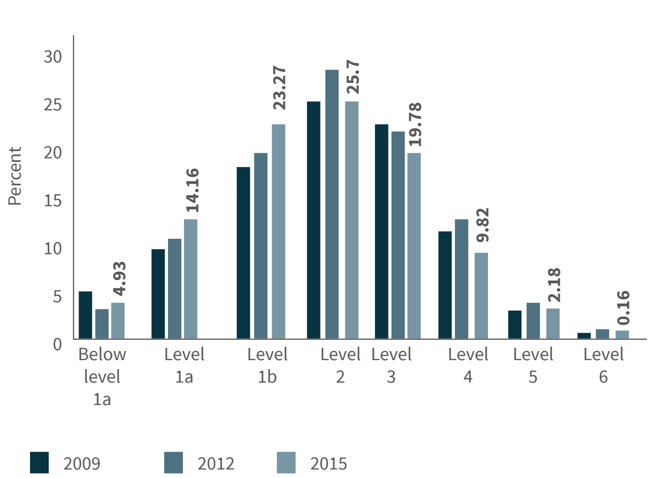
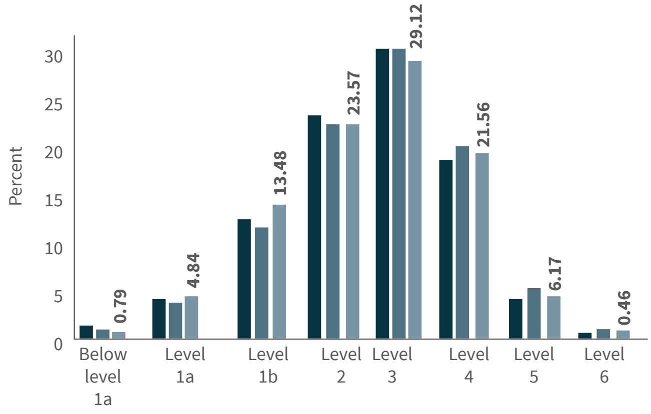


Figure 6: Student Performance in Reading (Non-OECD Countries)



Source: PISA 2009-2015 (authors' analysis).

It is also important to note that, among non-OECD countries, there is a major difference in student performance distribution between high-performing countries or economies–such as China (People's Republic of), Chinese Taipei, Hong Kong-China, Macao-China, and Singapore–and the remaining non-OECD countries (Figures 7-10). For example, in 2015 less than 10 percent of students in high-performing countries or economies did not achieve the basic level in mathematics, while 56 percent of students in all other non-OECD countries scored below this level. In high-achieving countries, around 53 percent and 35 percent of the students reached at least Level 4 in mathematics and reading respectively. By contrast, only around 8 percent of students in the other non-OECD countries achieved this threshold in either mathematics or reading.

Figure 7: Student Performance in Mathematics (Non-OECD: High-Performing Countries)

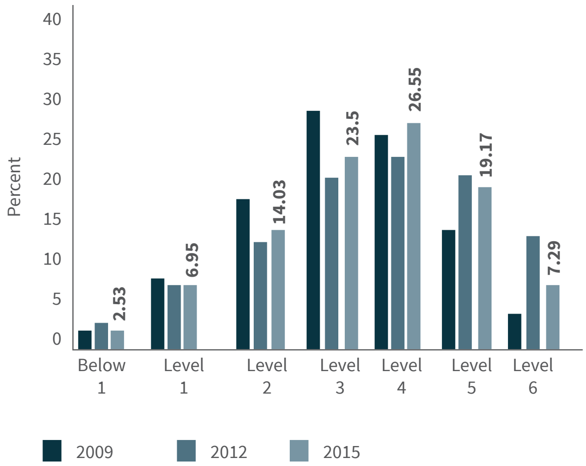
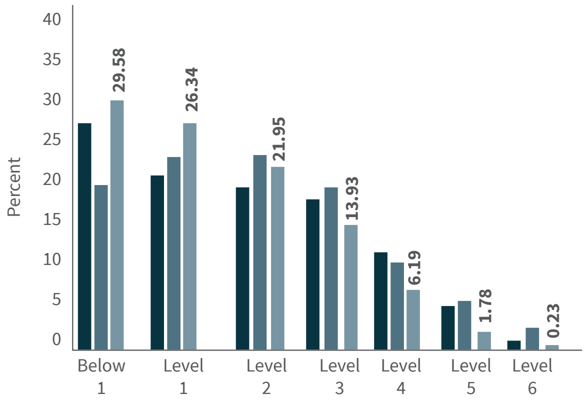


Figure 8: Student Performance in Mathematics (Non-OECD: Other Countries)



Source: PISA 2009-2015 (authors' analysis).

Figure 9: Student Performance in Reading (Non-OECD: High-Performing Countries)

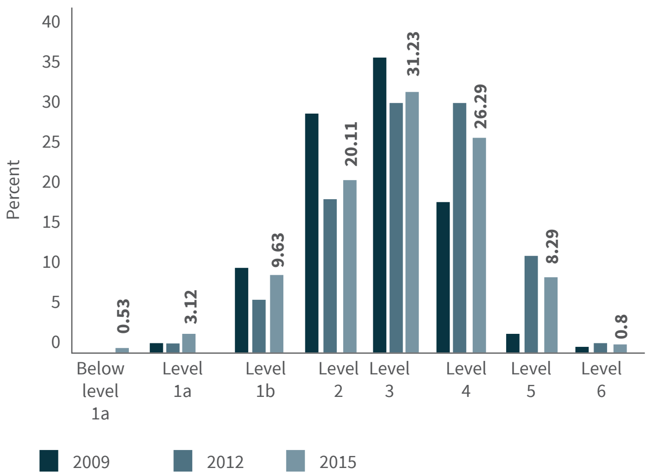
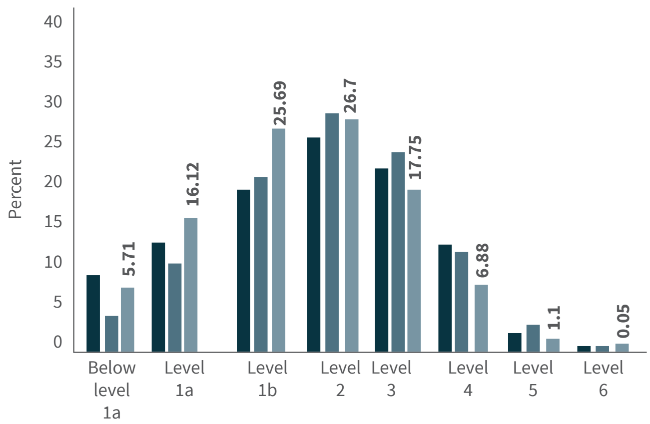


Figure 10: Student Performance in Reading (Non-OECD: Other Countries)



Source: PISA 2009-2015 (authors' analysis).

Section 3

Indonesia’s Overall PISA Performance

The 2009, 2012, and 2015 PISA datasets on Indonesia contain around 17,000 15-year-olds studying in 628 schools. We merge student performance data in reading and mathematics with the characteristics of the school that they are enrolled in and their family background.

Overall Indonesian Student Performance in PISA

Indonesia has a very low share of skilled students in both mathematics and reading (Figures 11 and 12). In 2009, only 54 out of 10,000 Indonesians reached Level 4 and four reached Level 5 in mathematics. The share of reading was slightly higher–around 76 out of 10,000 Indonesian students reached Level 4 but only two people out of 10,000 reached Level 5. Conditions improved by 2015. Although the vast majority, 72 percent in mathematics, were still below PISA Level 2, the proportion of Indonesians that could reach Level 4 has increased almost four-fold, to 208 per 10,000, while the rate of those who could reach at least Level 5 was around 46 out of 10,000. The increase in the proportion of Level 4 and above in reading between 2009 and 2015 was, however, lower–from 76 to 114 out of 10,000. Despite this improvement, the shares remain extremely low for both reading and mathematics.

Figure 11: Indonesian Students Mathematics Performance by Proficiency Level

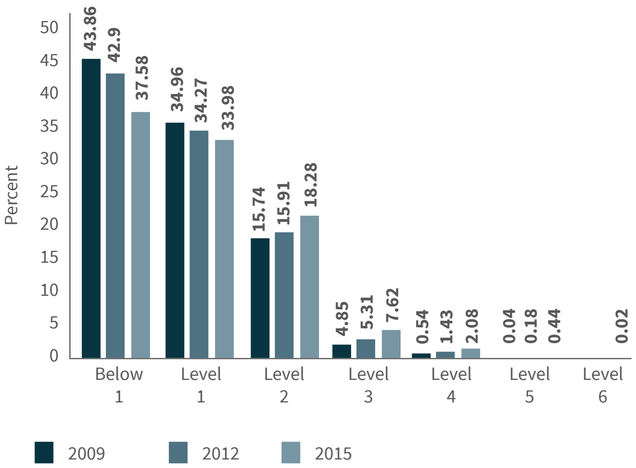
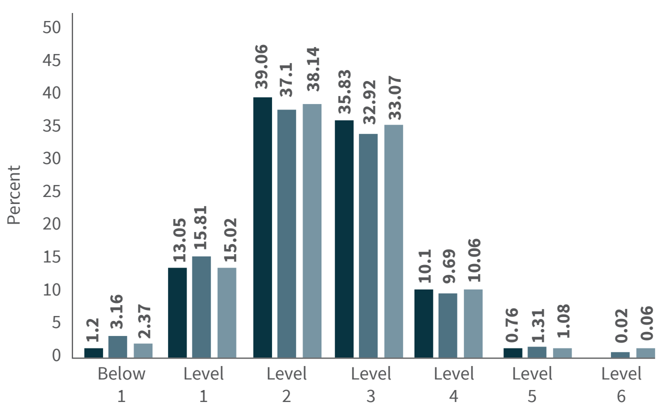


Figure 12: Indonesian Students Reading Performance by Proficiency Level

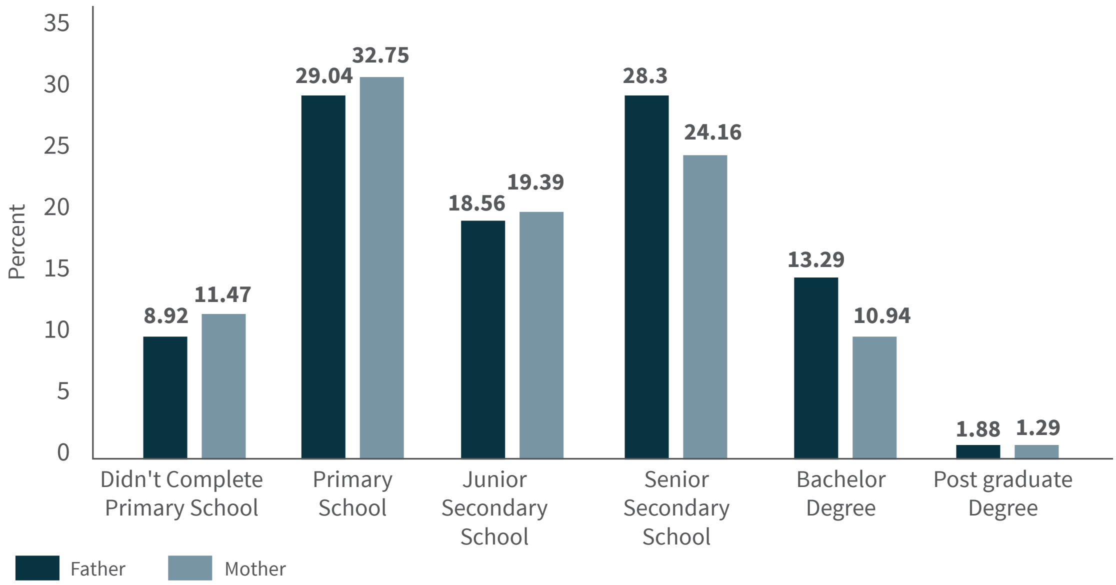


Source: PISA 2009-2015 (authors’ analysis).

Indonesian Students' Background Characteristics

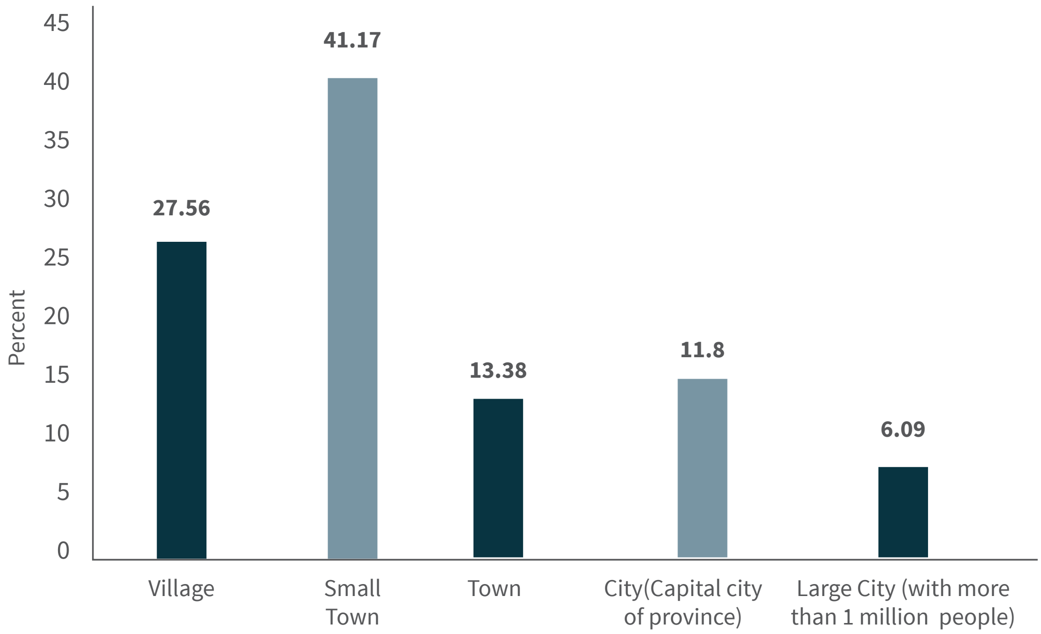
The study has disaggregated the data by gender, place of residence and parents' educational achievement level. One-half of Indonesian students participating in PISA 2009–2015 are female (51 percent). Figure 13 shows that across all students, around 60 percent of their parents only have nine years of schooling or lower. Around four out of ten students have parents who attended senior secondary school or higher. Figure 14 shows that 68 percent of students are living in villages or small towns.

Figure 13: Distribution of Parental Education Attainment (2009-2015)



Source: PISA 2009-2015 (authors' analysis).

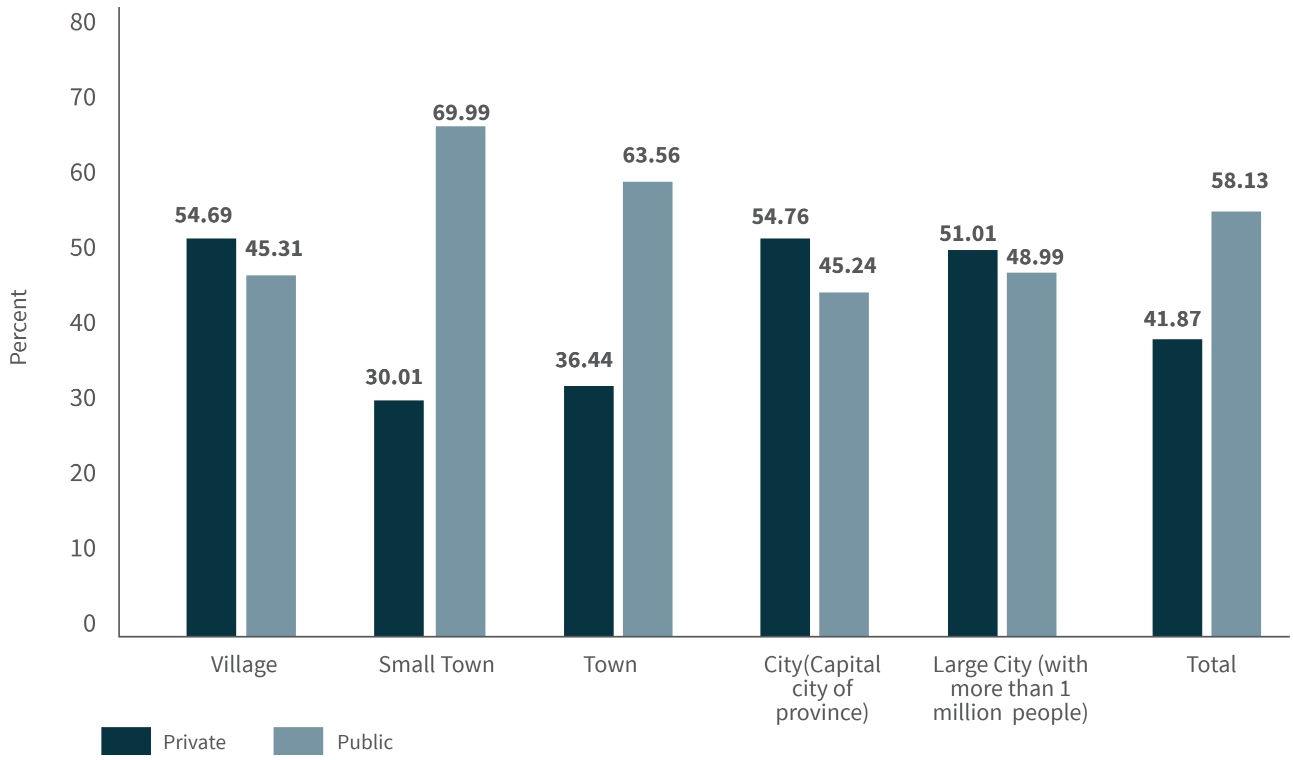
Figure 14: Indonesian Students by Residence (2009-2015)



Source: PISA 2009-2015 (authors' analysis).

With regards to school type, around 58 percent of the sampled students were enrolled in a public school, with higher rates in small towns and towns (70 percent and 64 percent respectively) (Figure 15). In villages and cities, more than one-half of the students were enrolled in private schools.

Figure 15: Indonesian Students by Residence and School Type (2009-2015)



Source: PISA 2009-2015 (authors' analysis).

Regarding the students' attendance in kindergarten, 45 percent of all students did not attend early childhood education (kindergarten).[4] Only one in four students attended kindergarten for longer than one year. The proportion of students attending kindergarten varies by region. In villages and small towns, around 59 percent and 46 percent of the sampled students respectively did not attend early-childhood education, whereas in cities less than one-third did not attend kindergarten.

[4] In the PISA questionnaire, Indonesian students were asked whether they attended a *Taman Kanak-Kanak* (kindergarten). A reference in this document to early childhood education, therefore, refers to kindergarten and does not include playgroups (*Taman Bermain*).

Section 4

Stock of Skills in Indonesia

In this section, we conduct separate analyses at the student and school levels for mathematics and reading. First, we examine characteristics of schools that have a relatively high proportion of skilled students. To obtain a sufficient sample size, we consider students to be skilled if they scored at Level 4 or above. Schools are categorised as high-performing schools if more than 10 percent of students are skilled. Second, we investigate factors that are correlated with the probability of being skilled in reading or mathematics by examining the effect of family background characteristics on the probability of being skilled. To increase the sample size, we combine PISA 2009, 2012, and 2015 in this section.

Descriptive Analysis

Schools Where Skilled Students are Enrolled

We find that skilled students in mathematics and/or reading are highly concentrated in a small proportion of schools. The proportion of skilled students in mathematics in a school ranges from zero to 63.6 percent, with an average of 0.6 percent. In reading, the proportion ranges from zero to 42.4 percent, with an average of 0.4 percent. Of all the schools in the sample, 94 percent have no skilled students in mathematics, while 96 percent have no skilled students in reading.

We categorise the schools into three types: schools with no skilled students (Type 1); schools where at most 10 percent of students are skilled (Type 2); and schools where more than 10 percent of students are skilled (Type 3). Schools are the most concentrated for reading skills: 92 percent are Type 1, 6 percent are Type 2, and 2 percent are Type 3, while for mathematics the respective figures are 89 percent for Type 1, 7 percent for Type 2; and 4 percent for Type 3. Tables 1 and 2 below show the descriptive statistics of school characteristics of the three types of schools for reading and mathematics respectively.

Table 1: Descriptive Statistics (Reading)

Characteristic	Type 1: Schools without skilled students in reading (N=504; 92% of sample)		Type 2: Schools with no more than 10% students who are skilled in reading (N=31; 6% of sample)		Type 3: Schools where more than 10% of students are skilled in reading (N=14; 2% of sample)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
School characteristics						
Student-teacher ratio	15.67	9.14	16.00	6.76	17.00	2.66
Public school (Yes=1)	0.50	0.50	0.74	0.44	0.71	0.47
School is in a city (Yes=1)	0.12	0.32	0.13	0.34	0.36	0.50
School is in a large city (Yes=1)	0.05	0.21	0.13	0.34	0.50	0.52
Principal authority						
Fire teacher (Yes = 1)	0.34	0.47	0.19	0.40	0.36	0.50
Increase teacher salary (Yes=1)	0.33	0.47	0.06	0.25	0.21	0.43
Allocate budget (Yes=1)	0.79	0.41	0.61	0.50	0.86	0.36
Formulate student assessment policy (Yes=1)	0.75	0.44	0.81	0.40	0.86	0.36
Principal practice						
At least once a month - use of student performance results to develop the school (Yes=1)	0.27	0.45	0.32	0.48	0.50	0.52
At least once a month - promote teaching practices based on recent educational research (Yes=1)	0.35	0.48	0.39	0.50	0.71	0.47
At least once a week - take initiative to discuss matters when a teacher has problems (Yes=1)	0.24	0.43	0.26	0.44	0.64	0.50
At least once a week - when a teacher brings up a classroom problem, we solve it (Yes=1)	0.35	0.48	0.39	0.50	0.64	0.50
Teacher characteristics						
Proportion of teachers with professional certification	0.51	0.35	0.76	0.25	0.72	0.26
Proportion of teachers with bachelor's degree or above	0.76	0.26	0.80	0.28	0.75	0.25

Source: PISA 2009-2015.

Table 2: Descriptive Statistics (Mathematics)

Characteristic	Type 1: Schools without skilled students in mathematics (N=487; 89% of sample)		Type 2: Schools with no more than 10% students who are skilled in mathematics (N=38; 7% of sample)		Type 3: Schools where more than 10% of students are skilled in mathematics (N=24; 4% of sample)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
School characteristics						
Student-teacher ratio	15.55	8.53	15.05	4.56	20.44	17.20
Public school (Yes=1)	0.49	0.50	0.76	0.43	0.71	0.46
School is in a city (Yes=1)	0.11	0.32	0.13	0.34	0.29	0.46
School is in a large city (Yes=1)	0.05	0.21	0.16	0.37	0.25	0.44
Principal authority						
Fire teacher (Yes = 1)	0.34	0.47	0.32	0.47	0.25	0.44
Increase teacher salary (Yes=1)	0.32	0.47	0.26	0.45	0.08	0.28
Allocate budget (Yes=1)	0.78	0.41	0.84	0.37	0.79	0.41
Formulate student assessment policy (Yes=1)	0.74	0.44	0.82	0.39	0.88	0.34
Principal practice						
At least once a month - use of student performance results to develop the school (Yes=1)	0.28	0.45	0.24	0.43	0.42	0.50
At least once a month - promote teaching practices based on recent educational research (Yes=1)	0.36	0.48	0.37	0.49	0.50	0.51
At least once a week - take initiative to discuss matters when a teacher has problems (Yes=1)	0.24	0.43	0.34	0.48	0.42	0.50
At least once a week - when a teacher brings up a classroom problem, we solve it (Yes=1)	0.35	0.48	0.34	0.48	0.54	0.51
Teacher characteristics						
Proportion of teachers with professional certification	0.50	0.35	0.69	0.29	0.73	0.26
Proportion of teachers with bachelor's degree or above	0.76	0.26	0.78	0.30	0.77	0.27

Source: PISA 2009-2015.

Across all schools, the average student-teacher ratio is around 1:16. We find no significant difference in student-teacher ratio between high-performing schools in reading (Type 3) and the rest, however, the high-performing schools in mathematics have a larger student-teacher ratio of 20 students per teacher. In addition, around 54 percent and 86 percent of high-performing schools in mathematics and reading respectively are located in either a city or large city, and around 70 percent of them are public schools.

Principals in high-performing schools seem to show more engagement in supervising and supporting teaching activities in their schools. For example, around 42-64 percent of principals in high-performing schools reported that they often discuss with teachers and solve problems related to teaching. Regardless of the school type, a very high proportion of school principals reported that they are involved in budget allocation and policy formulation on student assessment. On the other hand, only around 25-36 percent of principals in high-performing schools reported that they have authority to dismiss teachers.

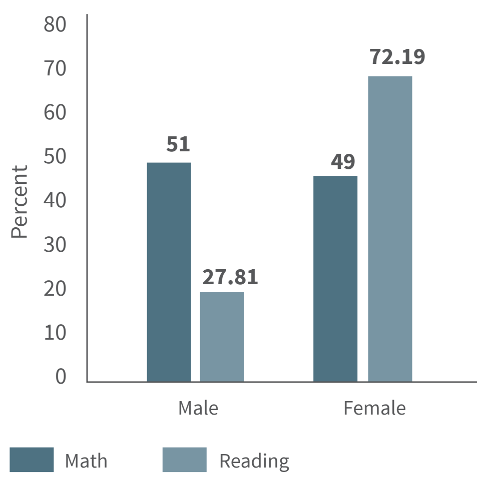
In terms of certified teachers, we find significant differences in the proportion of certified teachers between schools with no high achievers and schools that have high achievers. Only around one-half of teachers in Type 1 schools in either reading or mathematics are certified, while around 70 percent of teachers in Type 2 and 3 schools are certified.

Who are the High-Achieving Students in Indonesia?

Around one-half of students skilled in mathematics are girls (Figure 16), while the proportion of girls skilled in reading is much higher–around 72 percent of top performers are girls. The skilled students also have highly educated parents. Whereas the average adult Indonesian has around eight years of schooling, around 60 percent of the parents of these skilled Indonesian students have a bachelor's degree or higher (Figures 17 and 18).

In addition, more than one-half of these highly skilled individuals live in large cities. Around 56 percent and 65 percent of high-achieving students in mathematics and reading, respectively, live in cities. In cities, around 69 percent and 78 percent of high-performing students in mathematics and reading respectively are enrolled in public schools (Figures 19 and 20), however, in villages and small towns, private schools produced a higher percentage of top performers in reading.

Figure 16: Skilled Students by Sex



Source: PISA 2009-2015.

Figure 17: Skilled Students in Reading by Parental Education Attainment

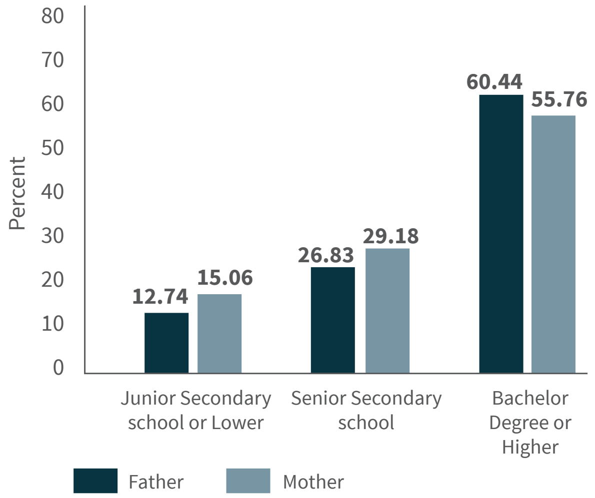
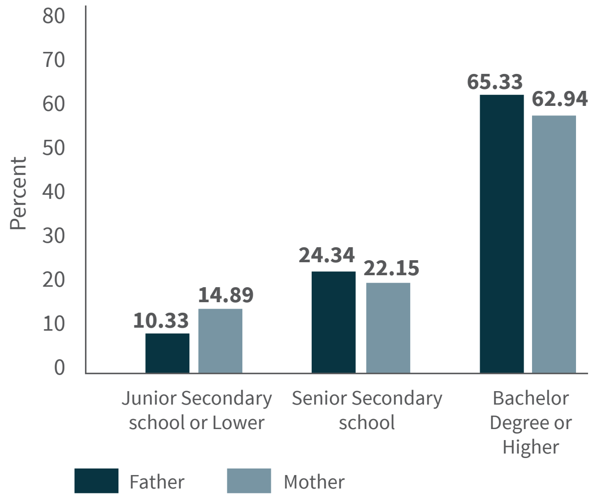


Figure 18: Skilled Students in Mathematics by Parental Education Attainment



Source: PISA 2009-2015.

Figure 19: Highly Skilled Individuals in Mathematics by School Status and Residence

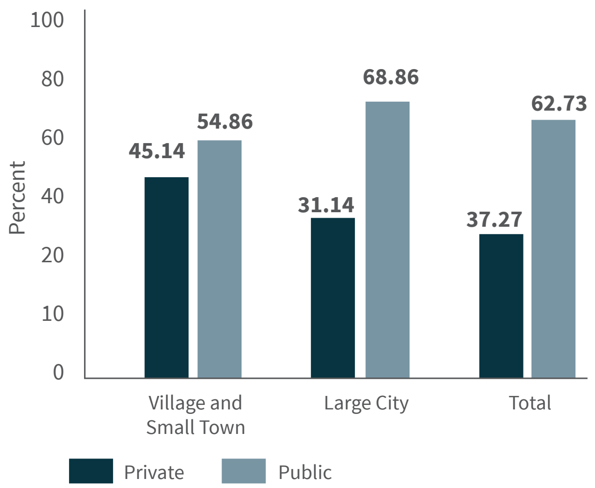
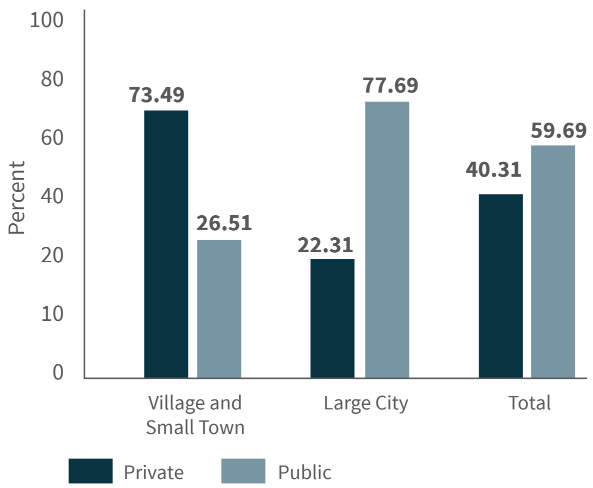


Figure 20: Highly Skilled Individuals in Reading by School Status and Residence



Source: PISA 2009-2015.

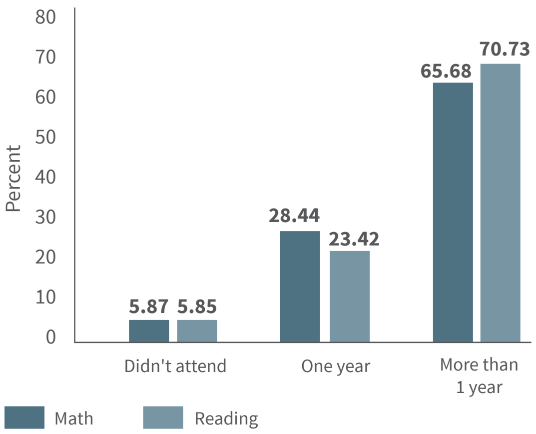
Table 3 shows the descriptive statistics of skilled students. Only one to two percent of students achieved Level 4 or higher in reading and mathematics respectively. We observe significant differences between the characteristics of students on Level 4 or higher and those Level 3 or lower. Some of the starkest differences include pre-school attendance, parental education, and home resources index. The table shows that Indonesia's top student performers have clearly distinct characteristics.

Table 3: Descriptive Statistics

Student Level Summary Statistics	Full Sample (N=15,275)		Mathematics Level 4 or Higher (N=288)		Mathematics Level 3 or Lower (N=14,987)		Reading Level 4 or Higher (N=178)		Reading Level 3 or Lower (N=15,097)	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Learning outcomes										
Achieves mathematics level 4 or higher (Yes=1)	0.02	0.14								
Achieves reading level 4 or higher (Yes=1)	0.01	0.11								
Individual characteristics										
Current school grade	9.46	0.74	9.96	0.46	9.45	0.74	9.96	0.41	9.46	0.74
Female (Yes=1)	0.52	0.50	0.49	0.50	0.52	0.50	0.71	0.45	0.51	0.50
Attended more than one year of pre-school (Yes=1)	0.26	0.44	0.63	0.48	0.26	0.44	0.68	0.47	0.26	0.44
Home and background characteristics										
Has more than 100 books at home (Yes=1)	0.10	0.30	0.29	0.45	0.10	0.30	0.34	0.47	0.10	0.30
Has a quiet place at home to study (Yes=1)	0.58	0.49	0.80	0.40	0.57	0.49	0.80	0.40	0.58	0.49
Mother completed tertiary education (Yes=1)	0.13	0.34	0.60	0.49	0.12	0.33	0.54	0.50	0.12	0.33
Father completed tertiary education (Yes=1)	0.16	0.37	0.61	0.49	0.15	0.36	0.60	0.49	0.16	0.36
Home resources index	0.02	1.47	2.34	2.01	-0.03	1.42	2.35	2.01	-0.01	1.44

Source: PISA 2009-2015.

Figure 21: Percentage of Skilled Students by Kindergarten Attendance



Source: PISA 2009-2015 (authors' analysis).

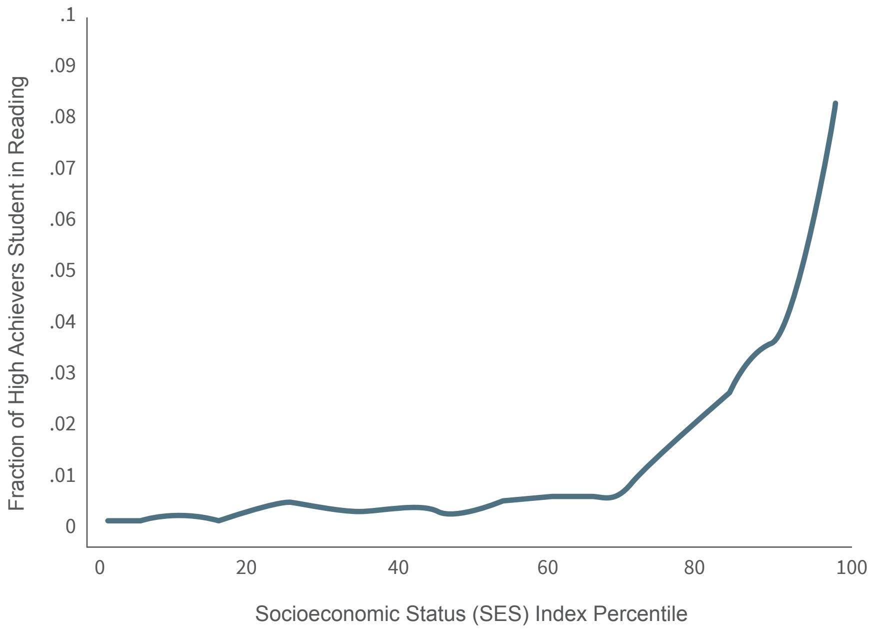
Finally, Figure 21 shows that 94 percent of highly skilled individuals attended at least one year of early childhood education. When we disaggregate by residence, most of the highly skilled individuals in cities (higher than 70 percent) attended more than one year at kindergarten. Meanwhile, only around one-half of top performers in villages and small towns attended early childhood education.

With regards to parental income, we plot the relationship between fraction of skilled students and family socioeconomic status (SES). The family SES index is constructed by PISA based on parents' highest level of education, parents' highest occupation status, and home possessions as a proxy for family wealth (OECD 2016). PISA also adjusted the SES index for trend analysis. We use the adjusted index that is comparable over cycles for our analysis below.

In general, the higher the SES index, the higher the probability of being a skilled student. The findings are similar to those of Aghion et al. (2017) and Bell et al. (2019) who find an exponential increase in rates of innovators with parental income. As with their findings, we also find that an upward-sloping relationship between skilled students' rates and SES is even steeper among families with an SES above the 90th percentile.

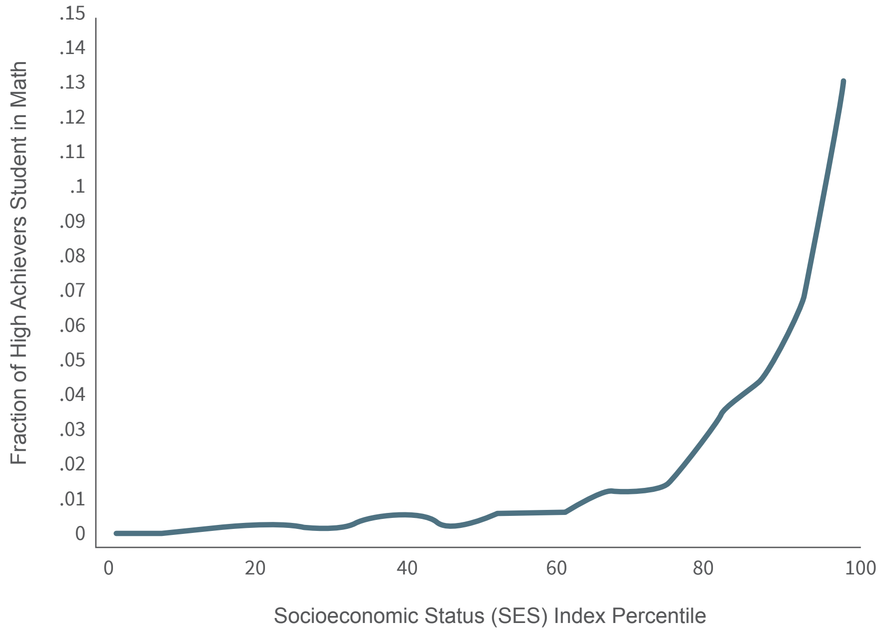
Among families at the top percentile, there are around 8 in 100 students who are skilled in reading (Figure 22), while in mathematics the probability is higher–around 13 in 100 students are skilled (Figure 23). On the other hand, students from lower than the 60th percentile have a negligible chance to be skilled in reading and/or mathematics.

Figure 22: Relationship Between Family SES and Skilled Students in Reading



Source: PISA 2009-2015 (authors' analysis).

Figure 23: Relationship Between Family SES and Skilled Students in Mathematics



Source: PISA 2009-2015 (authors' analysis).

Regression Results

In this section, we estimate the correlates of schools with skilled students. Specifically, we examine the following aspects: (i) principal authority; (ii) principal practice; (iii) teacher qualification; and (iv) basic school characteristics such as student-teacher ratio and location of school. We then look at the parental background and home conditions of the skilled students. Given the nature of PISA data, the estimates show correlations, not causal relationships.

Characteristics of Schools With Skilled Students

For mathematics, we find no evidence that principal authority or practice are correlated with the proportion of skilled students in a school (Table 4). The point estimates of these variables are also very small. In contrast, teacher qualifications have a mixed correlation with having skilled students. Schools with a higher proportion of teachers with professional certification are more likely to have more skilled students and the correlation is large. A standard deviation (0.35) increase in the proportion of teachers with certification increases the probability of a school to be a Type 3 by about 1.8 percentage points. As mentioned above, only 4 percent of schools in our sample are Type 3 in mathematics.

Table 4: Characteristics of Schools with Skilled Students in Mathematics

Student Level Summary Statistics	Schools without skilled students in mathematics (1)	Schools with no more than 10% students who are skilled in mathematics (2)	Schools where more than 10% of students are skilled in mathematics (3)
Principal authority			
Fire teacher (Yes = 1)	-0.031	0.016	0.015
	(0.035)	(0.018)	(0.016)
Increase teacher salary (Yes=1)	0.069 *	-0.036 *	-0.033 *
	(0.037)	(0.019)	(0.019)
Allocate budget (Yes=1)	0.004	-0.002	-0.002
	(0.034)	(0.018)	(0.016)
Formulate student assessment policy (Yes=1)	-0.043	0.022	0.020
	(0.032)	(0.017)	(0.015)
Principal practice			
At least once a month - use of student performance results to develop the school (Yes=1)	0.002	-0.001	-0.001
	(0.028)	(0.015)	(0.013)
At least once a month - promote teaching practices based on recent educational research (Yes=1)	0.000	0.000	0.000
	(0.026)	(0.014)	(0.012)
At least once a week - take initiative to discuss matters when a teacher has problems (Yes=1)	-0.037	0.020	0.018
	(0.033)	(0.018)	(0.016)
At least once a week - when a teacher brings up a classroom problem, we solve it (Yes=1)	0.022	-0.011	-0.010
	(0.033)	(0.018)	(0.015)
Teacher qualifications			
Proportion of teachers with professional certification	-0.111 ***	0.059 ***	0.053 ***
	(0.043)	(0.023)	(0.022)
Proportion of teachers with bachelor's degree or above	0.120 **	-0.063 **	-0.057 **
	(0.055)	(0.030)	(0.027)
School characteristics			
Student-teacher ratio	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Public school (Yes=1)	-0.068 **	0.036 **	0.032 **
	(0.030)	(0.016)	(0.014)

Characteristic	Schools without skilled students in mathematics (1)	Schools with no more than 10% students who are skilled in mathematics (2)	Schools where more than 10% of students are skilled in mathematics (3)
School location (ref: in a village)			
School is in a city (Yes=1)	-0.087 ***	0.046 ***	0.041 ***
	(0.033)	(0.018)	(0.017)
School is in a large city (Yes=1)	-0.149 ***	0.078 ***	0.070 ***
	(0.039)	(0.022)	(0.021)
Year fixed effects		Yes	
R-squared		0.15	
Number of observations		549	

Notes: *** 1% significance; ** 5% significance; * 10% significance; Multinomial probit regression; Coefficients are average marginal effects; standard errors in parentheses.

Our second proxy for teacher qualifications–the proportion of teachers with a bachelor's degree or above–shows a negative correlation with having high mathematics performers. A standard deviation (0.26) increase in the proportion of teachers with a bachelor's degree–controlling for the share of teachers with certification–is associated with a 1.4 percentage-point lower probability to be a Type 3 school. While this seems counterintuitive, the explanation is that teachers need a bachelor's degree to receive certification. Holding the share of certified teachers constant, a higher share of teachers with a bachelor's degree, therefore, indicates that more of these teachers are not yet certified.

On school characteristics, we find that public schools have a significantly higher likelihood to be Type 2 or Type 3, by about 3.6 and 3.2 percentage points respectively. Finally, schools in a city or a large city have a much higher chance to be a Type 2 or Type 3 school compared to schools in a village.

Higher principal authority, specifically to increase teacher salary or to allocate budget, is negatively associated with the probability of being a Type 2 or Type 3 school in reading (Table 5). Together with the previous results on mathematics, we find no evidence that principal authority or practice has any correlation with the proportion of reading superstars in a school.

Table 5 shows that a higher proportion of certified teachers is positively associated with the probability of being a Type 2 or Type 3 school. A standard deviation increase in this particular teacher qualification increases the probability of a school being in Type 3 by 1.6 percentage points. This is a very large correlation given that only 2 percent of schools in our sample are Type 3 in reading.

In contrast to mathematics superstars, public schools are not more likely to be in Type 2 or 3 than private schools. Regarding location, we find that schools in a large city are significantly more likely to have reading superstars.

Table 5: Characteristics of Schools with Skilled Students in Reading

Characteristic	Schools without students skilled in reading (1)	Schools with no more than 10% students who are skilled in reading (2)	Schools where more than 10% of students are skilled in reading (3)
Principal authority			
Fire teacher (Yes = 1)	-0.030	0.019	0.012
	(0.028)	(0.018)	(0.011)
Increase teacher salary (Yes=1)	0.067 **	-0.041 *	-0.025 **
	(0.032)	(0.021)	(0.012)
Allocate budget (Yes=1)	0.055 **	-0.034 ***	-0.021 ***
	(0.025)	(0.017)	(0.010)
Formulate student assessment policy (Yes=1)	-0.030	0.018	0.011
	(0.027)	(0.017)	(0.010)
Principal practice			
At least once a month - use of student performance results to develop the school (Yes=1)	0.000	0.000	0.000
	(0.022)	(0.013)	(0.008)
At least once a month - promote teaching practices based on recent educational research (Yes=1)	-0.019	0.012	0.007
	(0.020)	(0.013)	(0.008)
At least once a week - take initiative to discuss matters when a teacher has problems (Yes=1)	-0.025	0.015	0.010
	(0.028)	(0.017)	(0.011)
At least once a week - when a teacher brings up a classroom problem, we solve it (Yes=1)	-0.028	0.017	0.011
	(0.027)	(0.017)	(0.010)
Teacher qualifications			
Proportion of teachers with professional certification	-0.120 ***	0.074 ***	0.046 ***
	(0.038)	(0.025)	(0.017)
Proportion of teachers with bachelor's degree or above	0.067	-0.041	-0.026
	(0.049)	(0.030)	(0.020)
School characteristics			
Student-teacher ratio	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.000)
Public school (Yes=1)	-0.045 *	0.028 *	0.017 *
	(0.026)	(0.017)	(0.010)

Characteristic	Schools without students skilled in reading (1)	Schools with no more than 10% students who are skilled in reading (2)	Schools where more than 10% of students are skilled in reading (3)
School location (ref: in a village)			
School is in a city (Yes=1)	-0.055 *	0.034 *	0.021 *
	(0.029)	(0.018)	(0.013)
School is in a large city (Yes=1)	-0.158 ***	0.098 ***	0.060 ***
	(0.033)	(0.022)	(0.018)
Year fixed effects		**Yes**	
R-squared		**0.19**	
Number of observations		**549**	

Notes:*** 1% significance; ** 5% significance; * 10% significance; Multinomial probit regression; Coefficients are average marginal effects; standard errors in parentheses.

Home Conditions and Parental Education Levels of Skilled Students

We now look at the characteristics of skilled students.

Attending more than one year of kindergarten doubles the chance to be a skilled student in mathematics at the age of 15 while having a tertiary-educated mother triples the chance to be a skilled student (Table 6). Having a tertiary-educated father has a lower effect, although it is still positive and large. Of the home conditions, having many books at home and living in well-off households (proxied by the home asset index) is positively correlated with being a skilled student. Given what we know about very high-performing individuals–for example, inventors in Finland (Aghion et al. 2017) and the United States (Bell et al. 2019)–these results show that skilled students come from privileged backgrounds.

Table 6: Characteristics of Skilled Students in Mathematics

Characteristic	Whole Sample		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Individual Characteristics						
Current school grade	0.010***	0.004*	0.007***	0.001	0.013***	0.006*
	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)
Female (Yes=1)	-0.003	-0.008***				
	(0.002)	(0.002)				
Attended more than one year of kindergarten (Yes=1)	0.019***	0.000	0.020***	0.001	0.019***	-0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Parental Education						
Mother has tertiary education (Yes=1)	0.040***	0.016***	0.039***	0.014**	0.041***	0.019**
	(0.006)	(0.005)	(0.008)	(0.007)	(0.008)	(0.008)

Characteristic	Whole Sample		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Father has tertiary education (Yes=1)	0.012***	0.004	0.013**	0.003	0.012*	0.002
	(0.005)	(0.004)	(0.007)	(0.006)	(0.007)	(0.007)
Home Conditions						
Has more than 100 books at home (Yes=1)	0.014***	0.007	0.012*	0.005	0.017**	0.008
	(0.005)	(0.005)	(0.007)	(0.006)	(0.008)	(0.008)
Has a quiet place to study at home (Yes=1)	0.002	0.001	0.001	-0.001	0.003	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Home asset index	0.011***	0.002	0.010***	-0.000	0.013***	0.004**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-0.097***	-0.022	-0.073***	0.003	-0.123***	-0.039
	(0.011)	(0.022)	(0.015)	(0.034)	(0.017)	(0.027)
Year fixed effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
School fixed effects	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**
R-squared	**0.071**	**0.288**	**0.065**	**0.339**	**0.078**	**0.297**
Number of observations	**15,275**	**15,275**	**7,878**	**7,878**	**7,397**	**7,397**
Sample mean of dependent variable	**0.019**		**0.018**		**0.019**	

Notes:*** 1% significance; ** 5% significance; * 10% significance; Multinomial probit regression; Coefficients are average marginal effects; standard errors in parentheses.

When we include school fixed effects, virtually all individual-level estimates become much smaller and lose their statistical significance. The only exceptions are females, who now have a 0.8 percentage points lower chance of becoming a skilled student (42 percent from the mean). The results suggest that there may be a within-school barrier to females becoming skilled. Unfortunately, we cannot further investigate this issue due to data limitations. Students with tertiary-educated mothers also continue to have a higher chance of becoming skilled. The point estimate, however, is more than halved.

The results indicate that there is little variation in these variables within schools while, in contrast, student background appears to be correlated with school choice. For example, there are significantly more students with tertiary-educated mothers in Type 3 schools than in Type 1 schools. This finding indicates that schools in Indonesia are segregated–students from privileged backgrounds are enrolled in one set of schools and other students are enrolled in a different set of schools. We find very similar results when we disaggregate the sample by sex (Columns 3-6).

We find that females have a significantly higher chance of becoming skilled in reading (Table 7). The point estimate of 0.9 percentage points is large relative to the proportion of skilled students in reading. We also find that attending more than one year of kindergarten more than doubles the probability of becoming a skilled student at the age of 15. We find similar point estimates for mother's education and book availability at home. Meanwhile, a father's education and home asset ownership also positively affect the probability of being skilled in reading–albeit with a smaller magnitude compared to the mother's education.

Unlike the results in Table 6, the statistical significance and effect size of sex remains robust after we include school fixed effects (Column 2). The positive effect of attending kindergarten remains significant, although the size declines to 0.5 percentage points. All other previously significant variables become very small and statistically insignificant.

Table 7: Characteristics of Skilled Students in Mathematics

Characteristic	Whole Sample		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Individual Characteristics						
Current school grade	0.005***	0.002	0.006***	0.003	0.004***	0.002
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
Female (Yes=1)	0.009***	0.006***				
	(0.002)	(0.002)				
Attended more than one year of kindergarten (Yes=1)	0.015***	0.005**	0.022***	0.008**	0.006**	0.001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Parental Education						
Mother has tertiary education (Yes=1)	0.016***	0.001	0.023***	-0.001	0.009*	-0.000
	(0.005)	(0.005)	(0.008)	(0.008)	(0.005)	(0.005)
Father has tertiary education (Yes=1)	0.009**	-0.000	0.010	-0.005	0.008*	0.004
	(0.004)	(0.004)	(0.007)	(0.007)	(0.005)	(0.005)
Home Conditions						
Has more than 100 books at home (Yes=1)	0.014***	0.008*	0.019***	0.012*	0.008	0.002
	(0.004)	(0.004)	(0.007)	(0.007)	(0.005)	(0.005)
Has a quiet place to study at home (Yes=1)	0.000	0.000	0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Home asset index	0.008***	0.000	0.011***	0.001	0.005***	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	-0.054***	-0.014	-0.056***	-0.011	-0.041***	-0.012
	(0.008)	(0.016)	(0.014)	(0.031)	(0.009)	(0.016)
Year fixed effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
School fixed effects	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**
R-squared	**0.044**	**0.198**	**0.058**	**0.266**	**0.026**	**0.169**
Number of observations	**15,275**	**15,275**	**7,878**	**7,878**	**7,397**	**7,397**
Sample mean of dependent variable	**0.012**		**0.017**		**0.007**	

Notes:*** 1% significance; ** 5% significance; * 10% significance; Multinomial probit regression; Coefficients are average marginal effects; standard errors in parentheses.

We also find evidence of sex heterogeneity in the individual and background characteristics of students skilled in reading. First, 1.7 percent of female students are skilled in reading, more than double the rate among males. Second, attending kindergarten and home asset ownership have a positive and sizeable effect for both males and females, but the latter is much greater. Similarly, having a tertiary-educated mother or book availability at home significantly increases the probability of being skilled in reading–but only for females. Once school fixed effects are included, no individual characteristic remains significant for males. Overall, our model can explain between 5.8 percent to 26.6 percent of variations among females, but only 2.6 percent to 16.9 percent of variations among males. Comparing across Tables 6 and 7, we therefore have the least evidence on the correlates of becoming skilled at reading among males.

Section 5

Conclusions

This study is the first step to measuring the stock of skills in Indonesia.
Using an international benchmark, we find that Indonesia has an extremely small proportion of individuals skilled in literacy and numeracy. Between 2009 and 2015 the PISA results indicate an increasing trend, however, the absolute number remains very low. Only around 79,000 students out of 3.1 million in 2015 can be considered as skilled in mathematics. Of that number, 14,300 individuals have high mathematics skills. The number of individuals skilled in reading is even lower. Only 35,900 individuals could be considered as skilled, and 1,900 of those have high literacy skills.

We find that the probability of being a skilled individual is correlated with maternal education attainment and SES. Even among the top 10th percentile of the family SES index, the positive slope between these two variables is steeper. On the other hand, students from the bottom 60th percentiles have a negligible chance to be skilled. Early childhood education attendance and home asset ownership have sizeable effects on a higher probability of being skilled, particularly for females.

Our regression results indicate that the proportion of high-achieving students is associated with the proportion of certified teachers. Meanwhile, we find no evidence that a principal's authority or practice are correlated with the proportion of these skilled individuals in a school. We also find that skilled students are concentrated in a relatively small number of schools. Students within these schools have similar characteristics–indicating the strong influence of parental choice.

On the question of whether an individual's skill levels at the age of 15 come from talent or nurture, unfortunately, we have no data on the former but our results indicate that nurture is critical in the formation of skills. Nurture could be stronger at home–for example from high-income and highly educated parents–or it could come from school, for example from high-quality teaching. Separately measuring these effects requires the measurement of school value added, which is not available from PISA.

In closing, with such a small stock of skills, Indonesian policy makers face two challenges: (i) an active policy to identify and nurture talent must be in place; and (ii) ensuring an efficient allocation of skills is critical. The literature shows that, to realise the optimal social benefit, the most skilled individuals must be engaged in occupations that would give them the highest private returns and simultaneously the highest social returns. This is a huge endeavour requiring policy reforms in the health, education, social protection, and labour market sectors.

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REFORM ON VILLAGE FUNDS FORMULATION

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Abstract

The Law No. 6 of 2014 about the Village brought fundamental changes in the management, arrangement and implementation of village governance. In village finances, the law governs the source of village income which can implicates the budget allocation for the village, both sourced from the central budget as well as the regional budget. Since the year 2015, the allocation of village funds increased quite significantly, both nominal rupiah and proportion to the total funds transfer to the area. Over the last 5 years, the village fund increased almost 3.5 times to Rp 70 trillion in 2019, with a total allocation of Rp 257.2 trillion for five years. The National Team of Accelerating Poverty Reduction (TNP2K) has supported the Directorate General of Financial Balance (DJPK) of the Ministry of Finance to make adjustments to the allocation of the formula to be more equitable and equitable by considering Increase the nominal value of village funds in the national budget in the future.

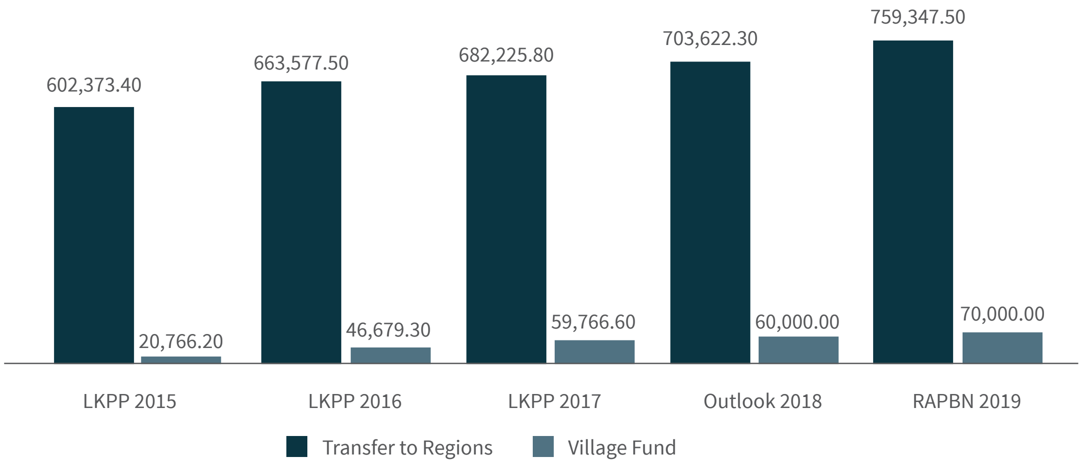
In the year 2015-2017, the proportion of basic allocation was 90% of the total village funds budgeted. After the adjustment process with various considerations and inputs, the basic allocation is gradually decreased to 77% and 72% respectively in the fiscal year 2018 and 2019. Some of the recommendations that need to be follow up include: i) to refine the allocation distribution of fairness by increasing the proportion of formula-based allocation; ii) to encourage accountability of priority utilization of village funds with priority-based planning; III) update index of geographical difficulties and transparency of calculations; and IV) to consider building institutional fund management of villages.

Background

Law No. 6/2014 on Villages brought fundamental changes in the management, regulation, and implementation of village governance. The law gives governance authority to villages to accelerate equitable village development. Villages as the lowest level of government administration need to be empowered to become strong, progressive, and independent. Village empowerment in the spirit of openness and freedom can be the basis for supporting national governance and development towards a fair, thriving, and prosperous society.

The Village Law regulates several aspects of village governance, such as village finances and assets. For village finances in particular, the Law regulates village sources of revenue that could have implications on special budget allocations for the village, both from the national budget (APBN) or the regional budget (APBD). Central transfer funds, or the Village Fund, is a source of revenue from the APBN that is transferred through the district/ city regional budget (APBD) and used to fund government administration, development, and community empowerment and development.

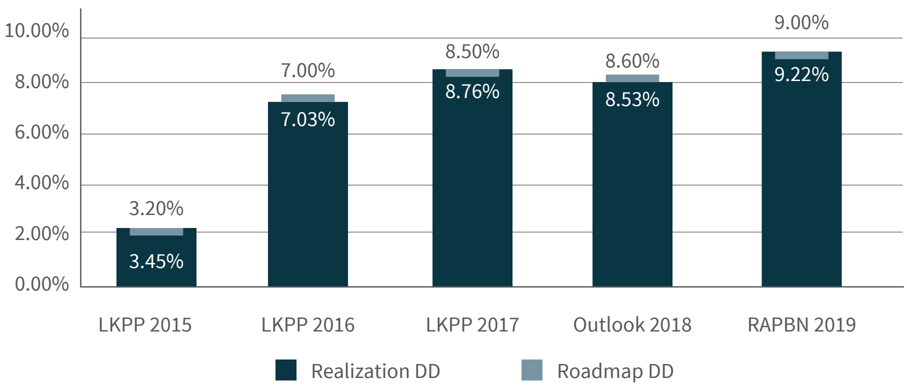
Figure 1: Village Funds Relative to Transfers to Regions in National Budget (APBN) (Trillions of Rupiah) (2015-2019)



Source: DJPK, Kementerian Keuangan, 2019.

Since 2015, the allocation of village funds has increased significantly, both in nominal rupiah terms and as a proportion of total fund transfers to regions. The Village Fund total in 2015 was Rp 20.76 trillion, increasing by almost 3.5 times to Rp 70 trillion in 2019. In five years (2015-2019) a total of Rp 257.2 trillion has been allocated from the APBN to the Village Fund.

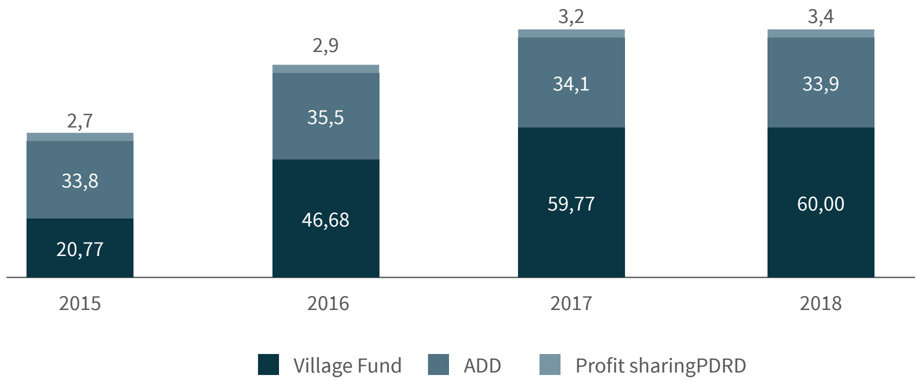
Figure 2: Realisation of, and Outlook for, Village Fund Allocation (2015-2019)



Source: DJPK, Kementerian Keuangan, 2019.

The Village Law stipulates that village funds should be the equivalent of 10 percent of the regional transfer fund. This target has been implemented gradually according to budget availability since the Law became effective. Referring to the established road map, the ratio of village funds to the total transfer to regions has increased gradually–from 3.2 percent in 2015 to 9 percent in 2019, nearing the set target.

Figure 3: Village Finances by Sources of Revenue (2015-2018)



Source: DJPK, Kementerian Keuangan, 2019.

There are three main sources of revenue for villages: (i) a budget allocation from the APBN called the Village Fund (Dana Desa – DD); (ii) a Village Fund Allocation *(Alokasi Dana Desa* – ADD) which is part of the Fiscal Balance Fund received from the District/City Regional Government of at least 10 percent.

from the share of regional tax and retribution from the district /city; and (iii) part of the Central and Regional Fiscal Balance Fund–funds received by districts/cities that constitute at least 10 percent of Regional Taxes and Retributions *(Pajak Daerah dan Retribusi Daerah* – PDRD).

Village Funds from the APBN is the largest contribution to village finances at an average of Rp 800 million/village in 2018, an increase from Rp 280 million/village in 2015. Villages received a total of Rp 33.8 trillion from ADD in 2015, increasing slightly to Rp 33.9 trillion in 2018. In 2018, total PDRD receipts was Rp 3.4 trillion–an increase from Rp 2.7 trillion in 2015.

The proportion of Village Funds from the APBN to total village finances has almost doubled from 36 percent in 2015 to 61 percent in 2018.

In 2019-2021, regional transfers and Village Funds are projected to continue increasing from 5.3 percent of GDP in 2019 to 5.7 percent of GDP in 2021. This increase is in line with strengthening the transfers to the regions and the Village Fund (*Dana Desa*) to support inclusive development.

Transfers to regions have a significant effect on the total allocation of Village Funds and are projected to increase proportionally every year. This increase is, however, yet to be accompanied by a more equitable allocation, where the proportion of fixed allocation that follows the principle of equity is still relatively large. To be more proportional, the basic allocation (*Alokasi Dasar* – AD) proportion of Village Funds should ideally be similar to the basic allocation as applied in the General Allocation Fund (Dana Alokasi Umum – DAU), which is indeed intended to improve the equity of fiscal capacity between regions.

Another problem is that the current organisational structure for delivery of the Village Fund has not been very effective in promoting development of rural areas due to inefficient bureaucracy and coordination at the central level, which has had implications on implementation at the village level. Authority for the Village Fund is currently shared between three ministries: (i) financial authority under the Ministry of Finance (MoF); (ii) administrative aspects under the Ministry of Home Affairs (MoHA); and (iii) utilization aspects under the Ministry of Villages, Disadvantaged Regions and Transmigration. A study by Corruption Eradication Commission (KPK) has shown a potential overlap of authorities between MoHA and the Ministry of Villages. In the study, the KPK recommended the formation of a steering committee for the implementation of Village Law led by a coordinating ministry.

A Geographic Difficulty Indicator (*Indikator Kesulitan Geografis* – IKG) is an effective instrument to evaluate village development and determine priorities for use of the Village Fund. Activity planning that is focused on indicators of disadvantaged villages, in terms of both quantity or quality, will help planning, budgeting and development to be more focused. In addition, such a focus would also make it easier to synchronize central and regional programs with village priorities, as well as assisting the process of program monitoring and evaluation.

This cycle is a continuous system where planning, implementation and evaluation is based on IKG-constituent indicators—one of the references in planning activities. For more detailed activities, an estimation of the size and percentage of the allocation for village development priorities and activities can refer to the various constituent components. In that way, the village administration will more easily determine allocations and priorities for village development.

The Challenge of Updating Composite Indicators

The main challenge in indicator-based planning for the utilization of Village Funds is that most indicators used in the models for calculating and determining allocations are not aligned with national development goals. For example, population constitutes 10 percent of the formula allocation (*Alokasi Formula* – AF). The consequence of this indicator is that the greater the population, the greater the Village Fund allocation. The implication of this indicator is that there is no incentive for village heads to contribute to the success of the Population Growth Rate Reduction Program. The village area contributes 15 percent to the AF–the problem with this indicator is that there is currently no official data on the size of the area that could be used as a reference.

These two indicators show that, proportionally, villages with relatively higher populations and larger areas will receive a larger AF than villages with relatively lower populations and smaller areas. Even if the village area and population are separated into distinct variables, it would be less relevant because area is a constant variable that will not change over the years, unless there is a village division.

A study by the World Bank shows a disparity in distribution of Village Funds between regions. Villages with a relatively large population, as an aggregate, receive relatively large allocations, but average per capita allocations tend to be lower compared to villages with relatively small populations. The reason is the large proportion of the AD compared to the AF, so the difference in population size between regions is not significant enough to determine the amount of allocation received by the village.

The number of poor people contributes 50 percent to the AF. The greater the Village Poverty Rate, the greater the Village Fund allocation. The implication of this indicator is that there is no incentive for villages to reduce the rate of poverty which is contrary to Article 78 of the Village Law. Until now, there has been no official data released by relevant ministries/institutions to provide poverty indicators at the village level.

The Construction Cost Index (*Indeks Kemahalan Konstruksi* – IKK) contributes 25 percent to the AF and is applied at district/city level. This indicator is a reference point for purchasing power between regions. Nevertheless, this indicator is very difficult to use as a basis for development at the village level.

The IKG contributes 25 percent and is applied at the village level. The greater the index, the greater the funds allocation. The IKG component can be used as a basis for village development but is less relevant than indicators at the district/city level. The main challenge for this indicator is that it is only available every three years following the Village Potential Survey (*Podes*) and, therefore, the IKG does not always describe the most current conditions in each village. In addition, the calculation of Village Funds for the past three years has faced problems of lack of information availability, especially for newly established villages, thus requiring special treatment for these areas.

The Purpose of Adjusting the Village Fund Formula

Study findings and evaluation of 2015-2017 allocations by several research institutions show the need to adjust the composition of both the AD and AF of the Village Funds to support the achievement of national development goals. Analysis shows that AD positively correlates only with poor population size. This confirms that the AD weight of 90 percent is not consistent with the principle of “equitable” allocation. In addition, the principle of “even distribution” in the AD does not clearly reflect the level of poverty, inequality and difficulty of each village in carrying out development.

Analysis of AF composition shows that it correlates negatively with village area. This is also supported by the finding that allocations before 2018 used a less ideal percentage composition for indicators of population, poverty rate, area, and IKK to calculate Village Funds at the district level, and/or the IKG on Village Funds calculations at the village level. In addition, the use of indicators that are not like-for-like–between the IKK at the district/city level and the IKG at the village level–is another problem.

Based on the two findings mentioned above, the Village Fund formula needs to be adjusted to make it more just without overriding the principle of equity. The formula adjustment needs to fulfil several prerequisites, namely:

(1) The total allocation of Village Funds per village should not be smaller than the previous year's allocation;
(2) The average ratio of the smallest and largest Village Fund recipient is the lowest;
(3) The proportion of the AF should be gradually increased while still considering the availability of government budget. Increasing the AF demonstrates a fairer allocation to reduce inequity in the Village Fund distribution.

Transformation of Village Fund Allocation Policy

Since the 2018 Fiscal Year, the government has implemented a series of Village Fund allocation policies to enhance an fairer allocation of Village Funds. First, the allocation of Village Funds for each village is now calculated by considering indicators of population, poverty rate, village area, and the IKG. Second, the Village Fund allocation formula was improved by adjusting the proportion of the AD and AF and applying affirmation to disadvantaged villages and highly disadvantaged villages with large poor populations. Third, there is a greater focus on alleviating poverty and inequality through the AF by giving a greater weight to the poverty rate and village area indicators. Fourth, the quality of distribution based on implementation performance has been improved, namely performance of absorption and achievement of program and activity outputs at the village level. Fifth, distribution through National Treasury Service Offices (Kantor Pelayanan Perbendaharaan Negara – KPPN) in regions to bring services closer, improve efficiency and facilitate coordination with local governments, and improve the effectiveness of monitoring and evaluation. Sixth, improve Village Fund utilization priorities for development and community empowerment directed at efforts to improve the quality of life of village communities to reduce poverty, inequality in the provision of basic infrastructure, and expand employment opportunities.

The formula adjustment was done by considering three main aspects that are the basic objectives of Village Fund allocation: (i) adjusting the weight of indicators with an emphasis on poor population size to accelerate poverty reduction; (ii) changing the proportion of the AD for equity and the AF composition for a fairer distribution; and (iii) adding affirmative policy consideration in calculating Village Funds for disadvantaged and highly disadvantaged regions, taking into account inequality between regions.

Table 1: Comparison of Component Proportion to Total National Allocation

Description	2015	2016	2017	2018
Number of Villages	74,093	74,754	74,954	74,958
Allocation Composite				
Basic Allocation	90%	90%	90%	77%
Formula Allocation	10%	10%	10%	20%
Population	25%	25%	25%	10%
Poor Population	35%	35%	35%	50%

Area Size	2015	2016	2017	2018
IKG/IKK	10%	10%	10%	15%
Affirmative Allocation	30%	30%	30%	25%
Total Allocation (Millions)	0	0	0	3%
Minimum				
Maximum	254.00	569.44	726.71	624.69
Basic Allocation (Millions)	1,121.00	2,221.00	2,280.00	8,854.47
Formula Allocation (Millions)	150.00	565.40	720.44	616.35
Minimum				
Maximum	104.00	4.04	6.27	8.34
Affirmation Allocation	971.00	1,656.00	2,099.00	8,238.13
Minimum				
Maximum	-	-	-	157.54
Number of Villages	-	-	-	315.09
Total Budget (Trillions)	-	-	-	9,943
Total Anggaran (Triliun)	20.77	46.68	59.77	60,00

Source: DJPK, Kementerian Keuangan, 2019.

Since 2017, The National Team for the Acceleration of Poverty Reduction (TNP2K) has provided technical support to the Directorate General of Fiscal Balance (DJPK) in the Ministry of Finance to adjust the Village Fund formula for the 2018 and 2019 fiscal years, including: (i) analysis of changes to Village Fund formulation by considering the principle of equity and improving the principle of fairness; (ii) harmonisation of indicators used as the basis for calculating the Village Fund and its allocations per village for the 2018 and 2019 fiscal years; (iii) providing a tool for optimising the weighting ratio of the AF; and (iv) initial simulation of Village Fund calculations for the 2018 and 2019 fiscal years.

The current Village Fund allocation is the best so far because: first, it considers aspects of equity and fairness; second, the ratio between the smallest and largest Village Fund receipts is the lowest, which is 1 to 4; third, it has a low standard deviation; fourth, it uses a calculation method that is consistent with previous years.

Overview of Village Fund Allocation

Adjustments to 2019 Village Fund formula are sought to fulfill the Village Law that mandates equitable and fair allocation. The principle of equity is applied to the AD, which is a fixed allocation for each village. The principle of fairness is applied to the AF which is a flexible budget distribution. The flexible allocation is strongly dependent on four indicators, namely: population size, poor population size, village area, and the geographic difficulty. Since the 2018 fiscal year, the Village Fund formulation has added an affirmative allocation component for disadvantaged and highly disadvantaged regions. Affirmative allocation is part of the fairness allocation but with a regional priority approach.

Basic Allocation (AD)

The AD is an allocation that is distributed equally to all villages to avoid disparities in the Village Fund amount that each village will receive. **The AD percentage that is currently used is based on the fair and equitable allocation principle of the Village Law. The 90:10 composition implemented from 2015-2017 has been improved with a 77:20:3 ratio since the 2018 fiscal year.** This proportion is the optimum simulation result according to the available budget.

Formula Allocation (AF)

The AF generally considers the level of inequality and poverty of the village, progress of development in the village, and population density of the area. The AF is calculated based on the village population, village poverty rate, village area, and the IKK for district/city level allocation and the IKG for village level allocation. **The AF has been increased from 10 percent to 20 percent of total Village Funds budgeted in 2018. In addition, since the 2018 fiscal year, the AF has given a greater weight to the size of the poor population (50 percent) and area (15 percent).** The IKG/IKK weight is decrease to 25 percent and, for the 2018 fiscal year, the population weight has, therefore, been reduced significantly from 25 percent to 10 percent.

Affirmative Allocation (AA)

An important innovation in the allocation of Village Funds in 2018 is the introduction of an Affirmative Allocation (AA), specifically for disadvantaged and highly disadvantaged regions using the principle of fairness and regional priority approach. **Nationally, the Village Fund allocation for Disadvantaged Regions (*Daerah Tertinggal* – DT) and Highly Disadvantaged Regions (*Daerah Sangat Tertinggal* – DST) has increased from Rp 36.7 trillion to Rp 37.3 trillion. The average Village Fund in DT and DST with a high number of poor increased from Rp 750 million to Rp 1.15 billion.**

In disadvantaged regions, border areas and remote islands, the Village Fund per capita in DT increased to Rp 587,000 and in DST Rp 1.182 million. This figure is greater than the Village Fund per capita in other regions which is Rp 269,500. The average Village Fund per capita in Papua is around Rp 1.517 million, Maluku (Rp 686,400), Sulawesi (Rp 555,600) and Kalimantan (Rp 522,600) which is higher than average Village Fund per capita on Java, Bali and Sumatra. Regional priority is not a new approach to development in Indonesia. The same approach had been used for Inpres Desa Tertinggal (IDT) program.[1]

[1] IDT (*Inpres Desa Tertinggal*): A funding program for disadvantaged villages that was established under Presidential Instruction No. 5/1993.

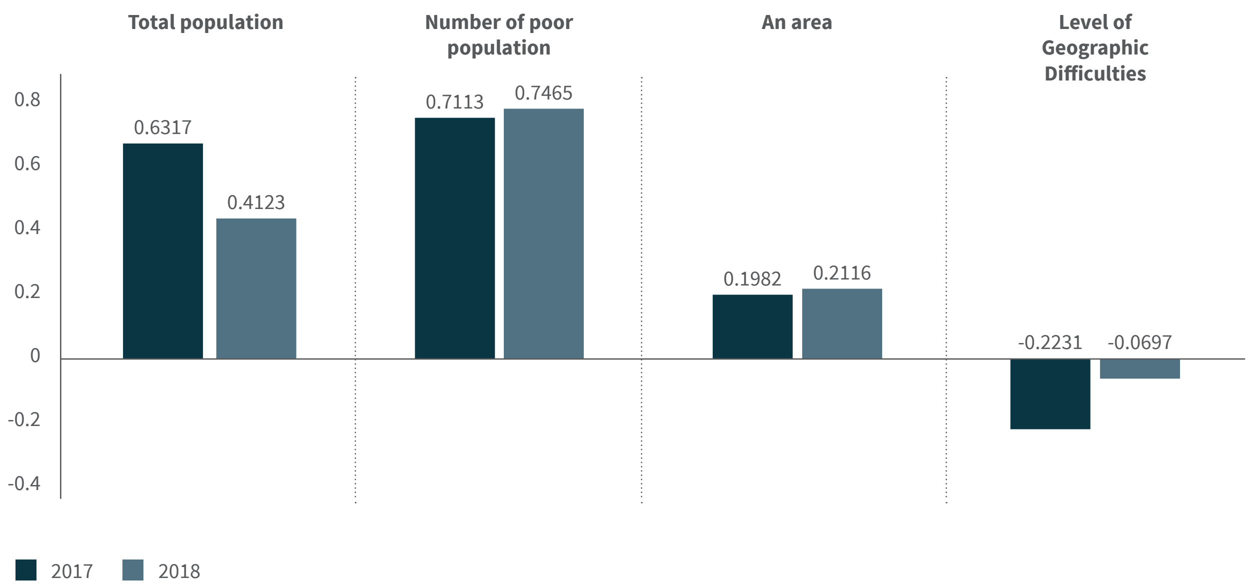
Evaluation of Allocation Before and After Reformulation

Correlation of Village Fund and Forming Indicators

From fiscal years 2015 to 2017, the composition of each indicator in the calculation of the AF was: total population (25 percent), total poor population (35 percent), area (10 percent) and geographic difficulty (30 percent). Under this distribution, regions that score high in these four indicators will receive a higher allocation than regions that have a lower score on these indicators. However, in general, the weight of these four indicators is not sufficient given that the equity-based AD still has quite a high weighting which is 90 percent of the total budget allocated each year. In other words, the principle of fairness represented by the AF with a weighting of only 10 percent is not sufficient to address regional needs.

Given this, in the 2018 fiscal year two important actions were taken to improve the allocation based on regional needs according to the principle of fairness: first, by adjusting the AF weighting to 20 percent from the previous 10 percent; and second, adjusting the weighting of the four AF indicators by reducing the weighting of population size and the IKK/IKG and raising the weighting of area and poor population size.

Figure 4: Correlation of Distribution of Village Funds to Population Size, Poor Population Size, Area, and IKK Indicators

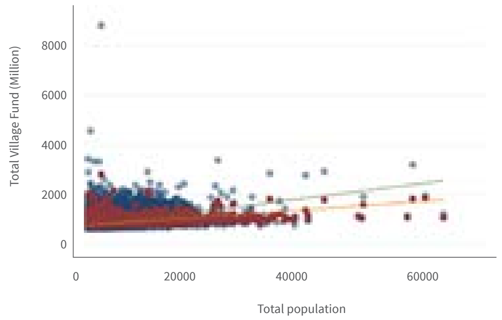


Source: Analysis result, 2018

A simple evaluation of indicators used in the 2018 Village Fund AF indicates that the correlation between the poor population size and village area has increased compared to the correlation in 2017. In addition, the correlation to geographic difficulty improved although it still tended to be negative. Regions with a high level of geographic difficulty have not yet obtained proportional Village Funds. Ideally, there should be a positive correlation between the distribution of Village Funds and AF constituent components.

There are two major component groups in the AF, namely independent components such as the ratios of village population, poverty rate, and village area, and one component that is a composite of various indicators that indicate the village IKG.

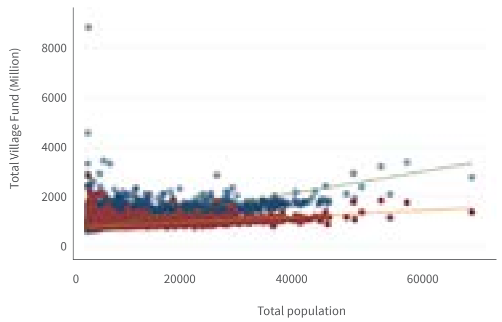
Distribution of Village Funds and Composite Indicators



Source: Analysis result, 2018

Village Population

Population size determines the amount of the AF for each village with a weighting of 25 percent in the period 2015-2017 and 10 percent in 2018. The population size proportionally affects the AF amount and total allocation received by a village, although the effect is greater on the AF than the total allocation.

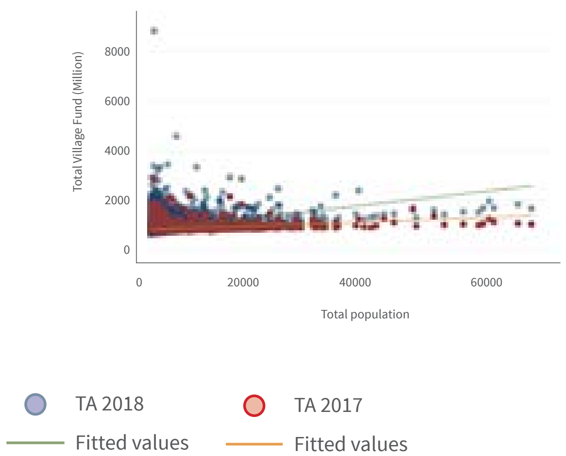


Source: Analysis result, 2018

Village Poverty Rate

The village poverty rate determines the AF amount for each village–with a weighting of 50 percent in 2018 and 35 percent in 2015-2017.

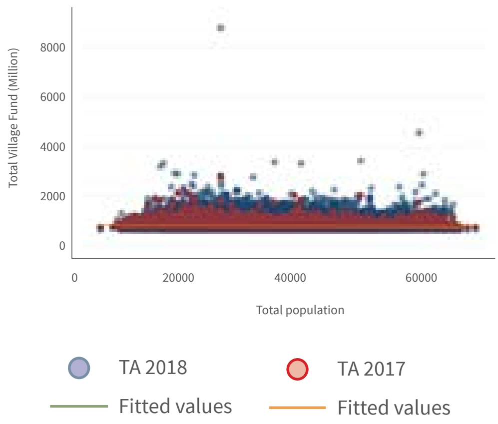
From the figure opposite, the Village Fund AF is more proportional against the village poverty rate–where villages with a higher poverty rate will receive a bigger allocation from the Village Fund.



Source: Analysis result, 2018

Village Area

The village area determines the AF amount for each village with a weighting of 10 percent in 2015-2017 and 15 percent in 2018. An increase in the weighting of 5 percent for the area factor has an implication of an increase in the allocation to villages in general, but specifically to villages with a greater area.



Source: Analysis result, 2018

Geographic Difficulty Index

The last indicator used as a weighting to determine the AF is the IKG. In determining the AF amount for each village, an IKG weighting of 30 percent was applied in 2015-2017 and reduced to 25 percent in 2018. As a result of this adjustment, villages with a high level of geographic difficulty receive lower allocations than previously.

Distribution in Java and Off-Java

The present Village Funds allocation is not yet proportionally distributed to regions with relatively high concentrations of poor villagers. Evaluation results show that Java, Bali and Nusa Tenggara are regions with high concentrations of poor people and tend to receive disproportionately small Village Fund allocations. There needs to be a Village Fund allocation that is more proportional to the population of poor to achieve the target of reducing poverty and inequality.

Changes in the formulation of the Village Funds in 2018 have accommodated this disproportionately allocation problem by allocating more fund to the regions with high poverty rate. Therefore, villages with high poverty rate will receive bigger allocation from Village Fund.

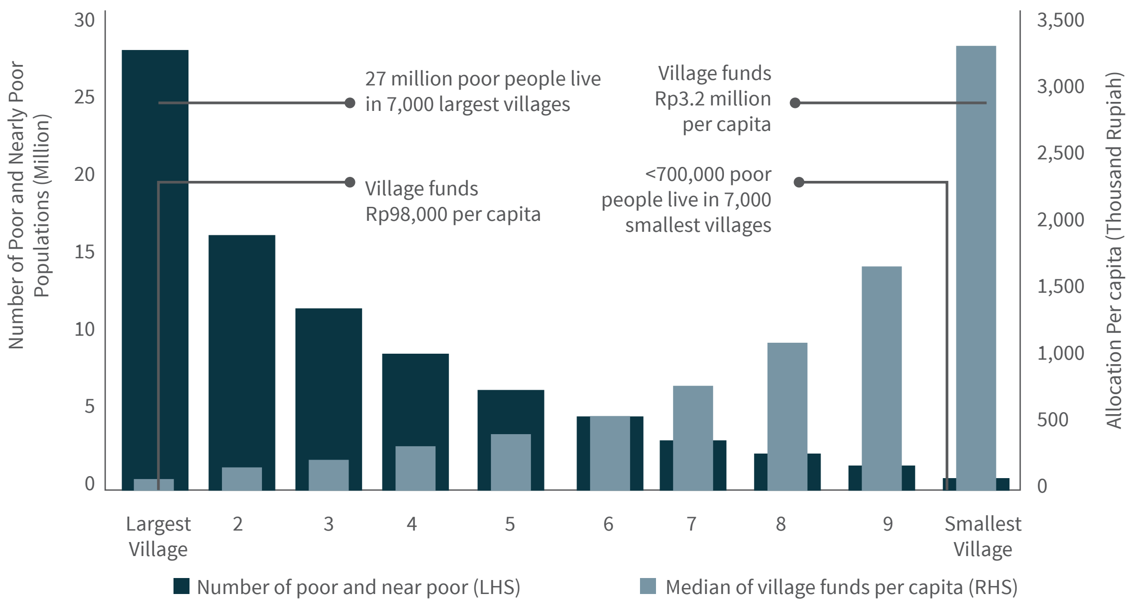
Figure 5: Comparison of Number of Poor Populations with Village Fund Allocation Based on Existing Formula (AD:AF=90:10)

Source: Analysis result, 2018

Inequality of Village Fund Distribution

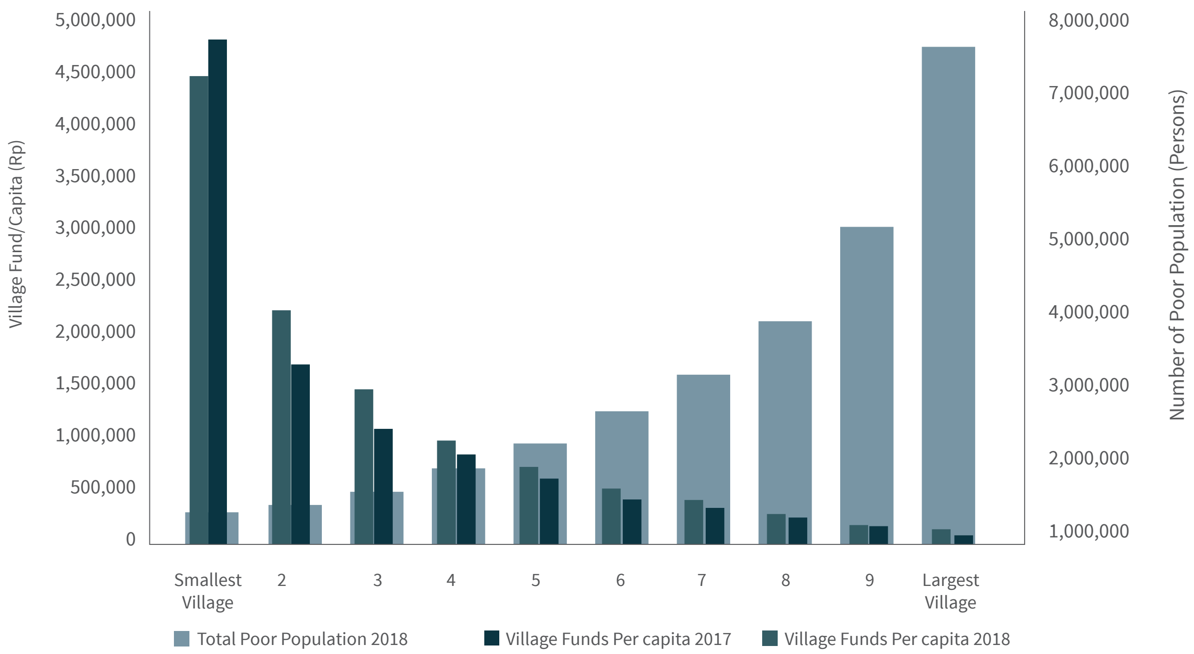
The World Bank considers that the current distribution of Village Funds tends to worsen income distribution, which tends to be greater for villages with relatively small numbers of poor people. Their study showed that the average Village Funds received in areas with a large population of poor is only around Rp 98,000/capita. Meanwhile, in areas with relatively small numbers of poor, the average Village Fund received was Rp 3.2 million/capita. This certainly does not support efforts to improve income equity.

Figure 6: Distribution of Village Funds According to Poor Population (2017)



Source: Inequality and the quality of Village Funds expenditure, World Bank, 2017.

Figure 7: Distribution of Village Funds According to Poor Population (2017 & 2018)



Source: Analysis Results, 2018

Policy Recommendations

Efforts need to be made to improve management effectiveness and the quality of Village Fund use. These efforts should be directed at activities that provide leverage and high added value and have a direct impact on: (i) improving the quality of basic public services in villages; (ii) improving the productive economy; (iii) poverty alleviation; (iv) improving the welfare of village communities; and (v) capacity-building for subdistrict officials, village government officials and village communities through training and mentoring by the government, provincial government and district/city government. In addition, Village Fund distribution that is proportionate to regional conditions and needs is a prerequisite for successful allocations to support development.

Improve Distribution of Fair Allocations

Increase the Proportion of Formula-Based Allocations

There is still room for optimization by reallocating funds from the AD to the AF in stages. This needs to be done to provide better opportunities for disadvantaged villages. **This optimization must consider growth of the total Village Fund allocation in the APBN, inequality in Village Fund allocations between villages, and ensure that no village receives a lower Village Fund allocation than in the previous year.**

Encourage Accountability of Village Fund Utilization Priorities

The utilization of Village Funds needs to be prioritized to finance village activities to improve geographic difficulty indicators. Determining priorities for the use of Village Funds should relate to indicators in every dimension of the IKG.

The Minister of Villages, Development of Disadvantaged Regions and Transmigration should pay attention to the composite index in setting priorities for the use of the Village Fund for development and community empowerment. Furthermore, MoF and MoHA need to issue regulations to support the determination of development priorities every year. Finally, district/city governments should support monitoring and evaluation of the use of funds through a decree or regulation by the district head/mayor.

Priority-Based Planning

Under the existing regulations, village development activities are prioritized to meet village development needs in accordance with the results of village consultations in line with national development priorities. As stipulated in prevailing regulations, the Village Funds can at least be used to fulfill primary needs, basic services, the environment, and community empowerment activities. Using geographic difficulty indicators as a basis for activity planning in the village is one alternative that could be applied, however, this step requires details of the Village Fund budget with indicators that form the basis of development needs. It is hoped that the use of the Village Fund in regions can improve indicators that determine geographic difficulty.

Updating Geographic Difficulty Index and Transparency of Calculations

As stated earlier, the contradiction between indicators that determine the size of the Village Fund and national development goals shows that there is a need to implement an incentive allocation model. Applying an incentive model to the Village Fund is expected to encourage villages to improve the quality and quantity of basic services in their area which will eventually improve indicators of geographic difficulty, without having to worry that Village Funds will decrease due to improved geographical difficulty.

Regular Updates of Village Indicators

It is necessary to have periodic reporting on village characteristics so they become part of the Village Fund disbursement requirements. This is necessary to update the information used as the basis for calculations and to complete information for new villages. The village characteristics report should include at least indicators of IKG, population, number of program recipients, and area size. Based on the village characteristics report, stakeholders should at least obtain two main things: (i) inputs to updates of Village Fund calculation indicators; and (ii) monitoring and evaluation indicators of Village Fund use which is estimated based on a proxy for changes in regional conditions. Problems of data availability, especially data on village expansions as faced for four years in implementation of Village Fund allocations, can be minimized, with each village submitting a report for each Village Fund disbursement period.

Simplification of Geographic Difficulty Index (IKG) Calculations

The method of calculating the IKG needs to be updated by simplifying and adapting it for users at village level. To date, the IKG has been prepared by using statistical methods that are difficult to replicate at program implementer level in the regions. The approach used is Principal Component Analysis (PCA), which basically aims to simplify a series of variables or indicators observed by reducing their dimensions.

PCA has several weaknesses, namely, that it is complicated to use and the results are difficult to interpret, so that if there are regional administrative separations, it could not be easily replicated by local governments. Another disadvantage is the difficulty in connecting improved indicators to the village development process, including monitoring and evaluating of the condition of indicators that have been improved.

One alternative that can be done is to apply an equal weighting approach. This approach uses the value of 1=poor (geographically difficult) and 0=not poor (not geographically difficult) for all index-forming indicators. The total score would indicate the geographic difficulty of a district/city or village. As an illustration, the currently used IKG is formed from 28 factor components (indicators) that consist of the following dimensions: (i) availability of basic services; (ii) condition of infrastructure; and (iii) accessibility/transportation. This leads to 29 IKG value combinations, from the richest with an IKG=0 (all variables are not difficult geographically) to the poorest with an IKG=28 (all variables are difficult geographically).

The resulting IKG value can, therefore, be linked to the planning and budgeting process, the implementation of poverty alleviation programs based on an IKG priority scale, and assist the program monitoring and evaluation process. The process and progress of monitoring and evaluation of village development by using equal weight on IKG can be done every year by observing intervention progress on factor components which are forming indicators.

Improvements in target indicators are undertaken until the indicators improve from a value of 1 (geographically difficult) to a value of 0 (geographically not difficult) in line with priorities set by the Minister of Villages, Development of Disadvantaged Regions and Transmigration (which is included in priorities for use of the Village Fund) or head of district/mayor (which is not included in usage priorities for the Village Fund).

Review of Use of Village Area Indicators as Determinants of Allocations

One alternative solution to reduce inequality in the distribution of Village Funds between regions is to use a density approach. There are three indicators of AF calculation with the potential to be combined into two indicators, namely area, population, and poor population. It is proposed to combine these indicators into population density and poor population density. Both indicators are relevant in describing the needs of the region, where villages with a relatively high population density and density of the poor population will receive proportionately higher AF funds than other villages on average. In addition, merging these three variables would not be in conflict with the Village Law as they still consider village area, population, and poor population as explicitly stated in the regulation.

Building Village Fund Management Institutions

Given the size of Village Fund allocations, the government needs to establish a special institution related to the Village Law to support village development in accordance with the Law. This institution should consist of cross-ministerial elements and be tasked with accelerating rural development at the implementation level, where each ministry focuses on the regulation of rural development.

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