

Measuring the Distribution of Education:
Global Trends, Forecasts, and Inequality Metrics

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Abstract

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As perhaps the single most important social determinant of health, the measurement of educational attainment is of paramount importance for health research. There is substantial reason to believe that estimates of the distribution of educational, and measures of educational inequality, could be useful tools for population health research. In this study, we compile a large database detailing the distribution of educational attainment, and provide the first set of comprehensive estimates of the distribution of education by age, sex, geography, and time, that will allow further studies to explore the importance of the distribution of education for health. We provide the first description of the global course of educational inequality and a basic comparison of the implications of the choice of inequality metric. We also provide projections to 2040, by leveraging cohort information and the extrapolation of current trends.

Introduction

As perhaps the single most important social determinant of health, the measurement of educational attainment is of paramount importance for health research. Educational attainment has been linked to a large number of health outcomes, at the individual and ecological level, in myriad contexts [1–10]. The relationship between maternal education and reductions in child mortality is especially robust, and has been studied extensively [11–17]. Population-level health studies routinely use education as a covariate or explanatory variable, in order to estimate demographic and disease trends in the absence of complete data, or to control for confounding by socioeconomic status [18–20]. In addition, education has been prioritized as a global development indicator, especially in the Millennium Development Goal 2 and Sustainable Development Goal 5 targets [21,22]. The accurate measurement of educational attainment is therefore of paramount importance for facilitating reliable and unbiased health research, and monitoring development targets.

Most population-level studies using education focus on the average years of schooling indicator [23–32], as it represents an easy to understand single number summary of attainment, and it is the only indicator comprehensively available over time and geography. Although an abundant number of data sources exist describing education by level, no comprehensive set of estimates of the complete distribution of educational attainment exists for all countries over time.

There is substantial reason to believe that estimates of the distribution of educational, and measures of educational inequality, could be useful tools for population health research. A number of studies have shown that the relationship between education and health exhibits dose response effects[33,34]. It has not been established that average years of schooling is the most predictive aspect of the distribution of education for modeling health outcomes. Furthermore, it has not been reliably established to what degree inequality in education, as opposed to simply the education experienced by each individual, may be related to health. Therefore, a closer examination of the distributional of categorical education within countries, and an assessment of other traits of the distribution of education for their relevance to health, could prove useful in predictive and inferential disease modeling.

In this study, we compile a large database detailing the distribution of educational attainment, and provide the first set of comprehensive estimates of the distribution of education by age, sex, geography, and time, that will allow further studies to explore the importance of the distribution of education for health. We provide the first description of the global course of educational inequality and a basic comparison of the implications of the choice of inequality metric. We also provide projections to 2040, by leveraging cohort information and the extrapolation of current trends.

Methods

Data

We compiled 2,017 census and surveys (tabulations by data family shown in table 1; see appendix for complete list), covering 194 countries and territories, from 1960-2015. Each source included information on educational attainment by country, year, sex, and 5-year age group, as well as data regarding the distribution of attainment within the population of interest. Ideally, each data source provided information on the distribution of education in single years of attainment. However, when larger bins of attainment were provided, a space-time distance crosswalk method was used to probabilistically split the larger bins into single year proportion (method to be published separately). Data are top-coded to 18 years, as it is a common choice among providers of single-year education data [35], and it is reasonable to assume that the importance of education for health diminishes greatly after the completion of 18 years, which represents 2 to 3 years of graduate education in most educational systems.

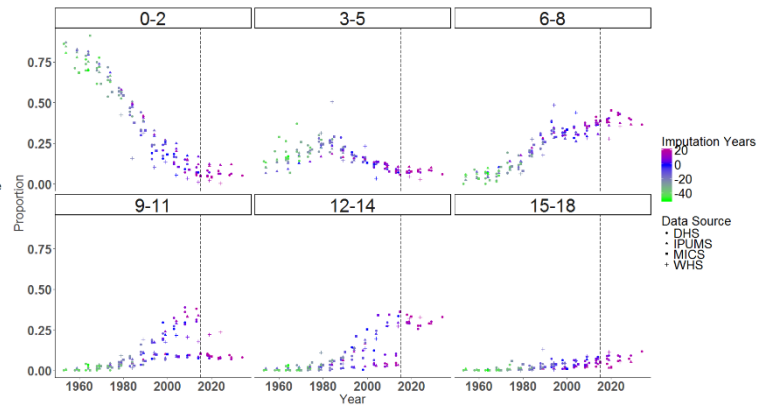
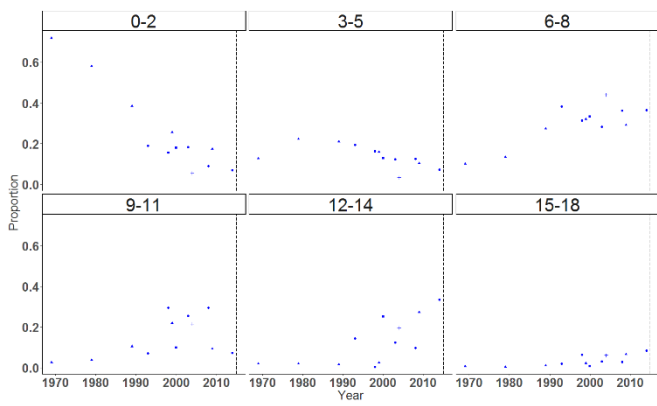
Data Family	Country-Years
ISSP	514
EUROBAROMETER	501
IPUMS	261
DHS	217
Other Census	169
MICS	119
BRFSS	68
WHS	56
WFS	40
MCSS	32
RHS	31
Other Survey	9
Total	2,017

Table 1. Sources by data family

Modeling Approach Summary

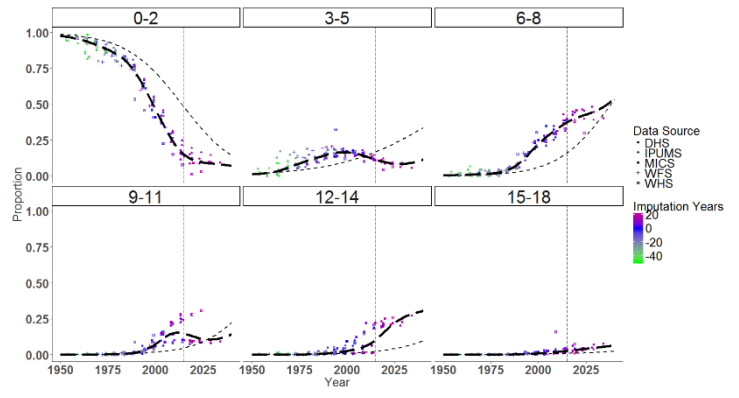
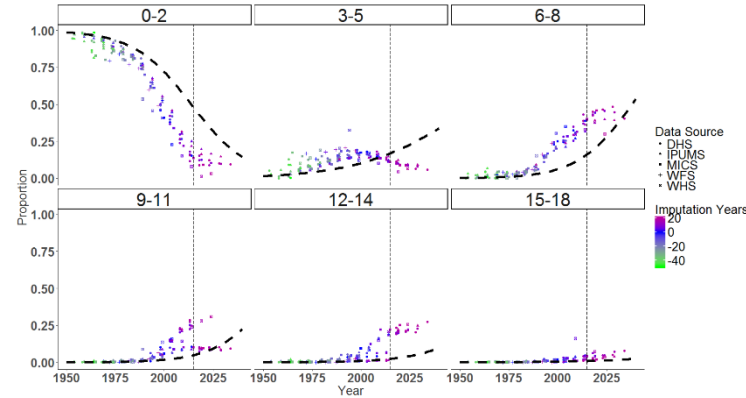
A multi-stage categorical modeling framework was used to model the distribution of educational attainment over space and time. First, the proportion of each distribution within larger bins (0-2 years, 3-5 years, 6-8 years, 9-11 years, 12-14 years and 15-18 years) was modeled, to leverage the greater stability in the data of these larger categories. The predicted proportions of these groups were normalized to ensure they add to 100%. Subsequently, the proportion of the population with each single year of attainment was modelled, and normalized to the larger bins.

Figure 1 shows an example for one set of multi-year bin timeseries in each stage of the modeling process. To model the proportion of educational attainment within each single and multi-year bin, two types of models are used. An age-cohort model was used to project observed cohorts through time, accounting for differences in mortality and migration by education status, as well as education later in life. An age-period model was then used to extrapolate outside of observed birth cohorts, and complete all timeseries. Gaussian process regression was used to synthesize these models with the input data, ensuring a good model fit where data are available, and produce estimate uncertainty.



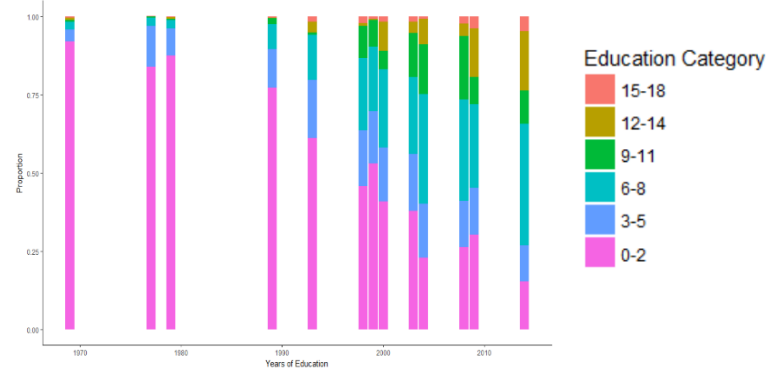
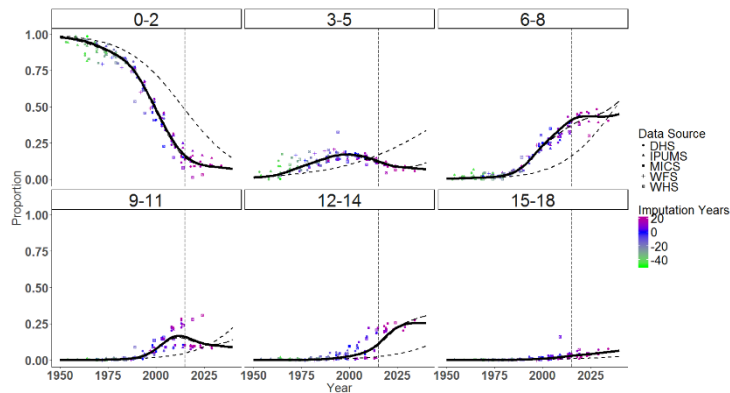
A) Input Data

B) Output from age-cohort model



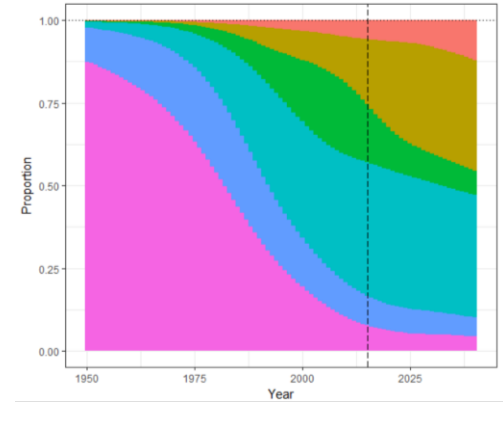
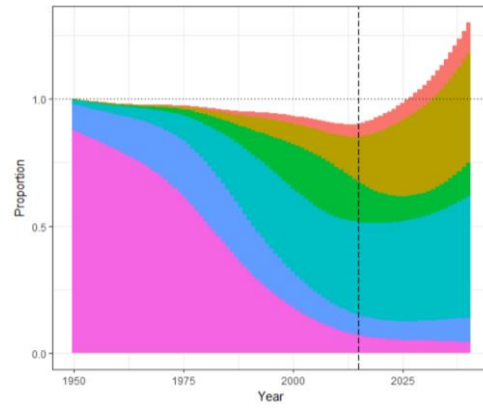
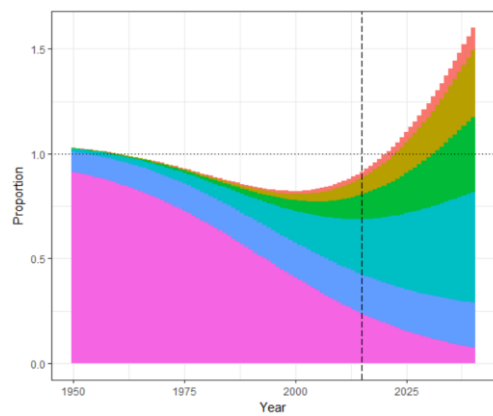
C) Output from age-period model, shown in bold

D) Output from Gaussian process regression, shown in bold



E) Final normalized trend, shown in bold

F) Input data shown in stacked bar plot form



G) Age-Period model output

H) Gaussian process regression output

I) Final estimates

Figure 1. Illustration of the modeling process for a single time series, Nigerian men age 45-49. Input data and steps are shown both as line and scatter timeseries plots, as well as stacked bar plots. A vertical dashed line at 2016 indicates the first year of the forecasts. A dashed horizontal line indicates the 100% line.

Modeling Approach Detailed Description

Age-Cohort Imputation Model

Education is highly stable over time within a given birth cohort after the normal age for completion of education has passed, usually by 20 or 25 years of age. Past analyses have leveraged this stability to project the educational attainment of a cohort through time either by assuming no change [26,27], or modeling the effect of differential migration and mortality by educational status [23,36]. We take a similar approach, projecting cohorts through time after age 25. No cohort imputation is used for age groups 15-19 and 20-24.

We model the observed change in educational attainment for cohorts over time, based on data where the same cohort of individuals was observed in at least two censuses or surveys. We restricted the analyses to instances where cohorts were observed in data from the same data family, to remove noise from systematic differences between data providers. We fit the model using 23,801 pairs of observations of the same cohort at two different periods in time. The dependent variable $Y_{i,ts}$ is the annualized change in the logit-transformed proportion of the population in each single and multi-year bin of educational attainment for each cohort i , observed between points t and s :

$$Y_{i,ts} = \frac{\text{logit}(\text{proportion}_{i,t}) - \text{logit}(\text{proportion}_{i,s})}{t - s}$$

We then modelled $Y_{i,ts}$ using a mixed effect model, with a global intercept β_0 , as well as super-regional random intercepts α_{sr} :

$$Y_{i,ts} = \beta_0 + \alpha_{sr}$$

In order to propagate the uncertainty in the age-cohort process, the standard deviation of the model residual was calculated for each modelled proportion, separately for each super-region grouping used in the Global Burden of Disease 2015 study [37], and used in calculating final uncertainty intervals in the Gaussian process regression step detailed below.

Age-Period Model

Age-period models were fit on all original input data, as well as imputed cohort points, in order to interpolate data for observed cohorts, and extrapolate to all parts of the desired time series, producing single year estimates of attainment from 1950 through 2040. To model the proportion of the population in each multi-year bin, a series of shape-constrained additive models were used, allowing for the estimation of age-period trends, while enforcing the preservation of empirically observed trends in the data throughout extrapolation periods.

Age-period trends in the terminal education bins, 0-2 and 15-18 were observed to be monotonic with respect to time, with the 0-2 year group only decreasing over time, and the 15-18 only increasing. These trends were therefore enforced using monotonic p-splines in extrapolation [38]. Trends in intermediate (non-terminal) bins were observed to be linear over time—constantly decreasing or increasing—or to have a single inflection point. There were no examples of timeseries with several credible inflection points in the observed timeseries of intermediate multi-year bins. As an example, in age groups with

relatively low education, the proportion of the population with 3-5 years of education starts close to zero, as most individuals have almost no education. As the average educational attainment of the population rises, the proportion in the 3-5 bin increases, until it reaches an equilibrium point, and then decreases, as the population begins to achieve mostly at the 6-8 years level and higher. The resulting trend is a concave curve, with a single inflection point at the equilibrium point where the trend shifts from increasing to decreasing. Separately for each sex, and region grouping used in the GBD 2015 study[37], the proportion of the country-age-year specific population in each multi-year bin, $P_{c,a,t}$, was estimated:

$$\text{logit}(P_{c,a,t}) = \beta_0 + S_1 \text{year} + S_2 \text{age}$$

The secular trend, $S_1 \text{year}$, is a monotonically decreasing p-spline for the 0-2 group, a monotonically increasing p-spline for the 15-18 group, and a concave p-spline for all intermediate groups. The effect on age, $S_2 \text{age}$, is an unconstrained cubic regression spline for all modelled proportions. A global intercept β_0 was used for all proportions.

The proportion of the country-age-year specific population in each single-year bin, $P_{c,a,t,b}$ was more variable with respect to secular trend, and no shape constraints were used in estimation of age-period trends. However, since these proportions were ultimately normalized to the larger multi-year bin proportions, constraints were imposed in a top-down fashion from the earlier models. The proportion in each bin was modeled separately for each region-sex group using a mixed effect model:

$$\text{logit}(P_{c,a,t}) = \beta_0 + \beta_1 \text{year} + S_2 \text{age} + \alpha_{c,a}$$

Where β_0 is a global intercept, $\beta_1 \text{year}$ captures the linear secular trend, $S_2 \text{age}$ is a natural spline on age to capture the non-linear age pattern, with knots at 35, 50, and 65 years of age, and $\alpha_{c,a}$ is a timeseries-specific random intercept.

Gaussian Process Regression

In the final estimation step, we used Gaussian process regression (GPR) to synthesize the results of both the age-period and age-cohort models, and ensure that the estimates fit the data well. GPR has been used extensively in the Global Burden of Disease estimation framework as a data synthesis tool [39,40]. GPR uses a covariance function to smooth the residuals from the age-period model, taking into account the uncertainty in each data point. GPR also synthesizes both data and model uncertainty, in order to produce estimate uncertainty intervals.

GPR assumes that the trend in the underlying data follows a Gaussian process, which is defined using a mean function $m(\cdot)$ and a covariance function $Cov(\cdot)$. Therefore, separately for each single and multi-year bin of education, the country-age-sex-year specific population proportions are defined:

$$\text{logit}(P_{c,s,a,t}) = g_{c,a,s}(t) + \epsilon_{c,a,s,t}$$

Where the error term is normally distributed:

$$\epsilon_{c,a,s,t} = \text{Normal}(0, \sigma_p^2)$$

The error variance, σ_p^2 , is composed of the squared standard error of the observed data point, as well as the prediction errors from the age-cohort imputation process. The mean function of the model is the

age-period model predictions, as detailed above. The covariance function of the model is derived using a matern covariance function, consistent with prior applications of GPR in the Global Burden of Disease estimation process:

$$M(t, t') = \sigma^2 \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{d(t, t')\sqrt{2\nu}}{l} \right)^\nu K_\nu \left(\frac{d(t, t')\sqrt{2\nu}}{l} \right)$$

Where $d(\cdot)$ is a distance function, σ^2 is the marginal variance, ν is a smoothness hyper parameter defining the differentiability of the function, l is a link-scale parameter approximately equivalent to the number of years at which two points are no longer correlated, K_ν is the Bessel function, and $\Gamma(\cdot)$ is the gamma function. Similar to previous applications of GPR, we approximate σ^2 as the super-region and sex specific residual from the mean function, set ν to 2, and l to 40, to reflect the inherent smoothness of educational attainment trends overtime.

Normalization Process

The final estimated proportions obtained from the GPR process are then normalized, to ensure that all the multi-year bins add to 100%, and the single year bins add to their respective multi-year bins. In normalizing the multi-year bins, a multi-stage process is used, to attempt to prevent the normalization process from violating the same empirical phenomena enforced in the age-period model. Similarly to the age-period model, the monotonicity of the terminal education groups is enforced, and these groups are given priority in the normalization, as they are the most stable over time and therefore the easiest tends to reliably extrapolate. The intermediate groups are normalized to maintain a single inflection point, unless this is incompatible with the total proportions adding to 100%. We use the following multi-stage normalization algorithm:

- The proportion of the 15-19 age group with 15-18 years of educational attainment is set to zero, as this group is unable to ever achieve 15 years of education due to not having lived a sufficient number of years, even if they began schooling at age 4.
- In order to enforce the single inflection point assumption for intermediate multi-year bins, all inflection points in the timeseries-specific GPR output are detected, as the year in which a change in trend direction is observed. The most 'data centered' inflection point for each timeseries is identified, as the inflection point which has the minimum average absolute distance in years from all data used in the estimation of the timeseries in question.
- Moving forwards and backwards from this inflection point for each timeseries, any additional inflection points resulting from the extrapolation process are removed by forcing flat trends.
- Moving backwards in time, the proportion of individuals with 0-2 years of education is forced to monotonically increase by holding trends flat anywhere they are found to be decreasing. Similarly, moving forwards in time, the proportion of individuals with 15-18 years of education is forced to monotonically increase by holding trends flat where found to be decreasing.
- The terminal multi-year bins are used in their state at this stage of the process, while the intermediate bins are proportionally normalized, to ensure that the total proportion of individuals across all multi-year bins add to 100%.
- The single-year bins are then proportionally normalized to ensure they add to the normalized multi-year bin proportions from the prior step.

Aggregations and Counts of Population by Educational Attainment Level

To obtain counts of the number of individuals with each category of educational attainment, the final normalized proportions were applied to population numbers obtained from the World Population Prospects 2015 files [41]. These populations were also used to produce all regional and global aggregations shown in the text.

Results and Discussion

Global Trends in the Distribution of Educational Attainment

Estimates and figures detailing the distribution of education for the 15+ adult population of 195 countries from 1950 to 2016 can be found in the supplemental materials. Table 2 provides values for 15+ adults by multi-year bins.

Globally, the world has seen a dramatic shift towards an increasingly educated population from 1950 to 2016, and our projections suggest that this trend will continue through 2040. Figure 2 shows the global distribution of the world's population by educational attainment categories over time. The proportion with the lowest category of attainment, 0-2 years, has fallen from 48.86% (95% CI: X.X- Y.Y%) to 12.90% (X.X- Y.Y%) in 2016, and is forecasted to reach 7.28% (X.X- Y.Y%) by 2040. Concurrently, the proportion of individuals attaining education in the tertiary 15+ bin has risen from only 1.50% (X.X- Y.Y%) in 1950 to 16.15% (X.X- Y.Y%) in 2016, and is projected to reach 35.46% (X.X- Y.Y%) by 2040.

Globally the world has seen a closing of genders gaps in absolute terms, although some disparities remain. Figure 3 shows the global distribution of educational attainment by gender. Over time the gender disparity in the lowest attainment group, 0-2 years, has shrunk, although not entirely closed by 2040, with proportions of 5.67% (X.X- Y.Y%) for men and 8.89% (X.X- Y.Y%) for women. In the 15-18 years

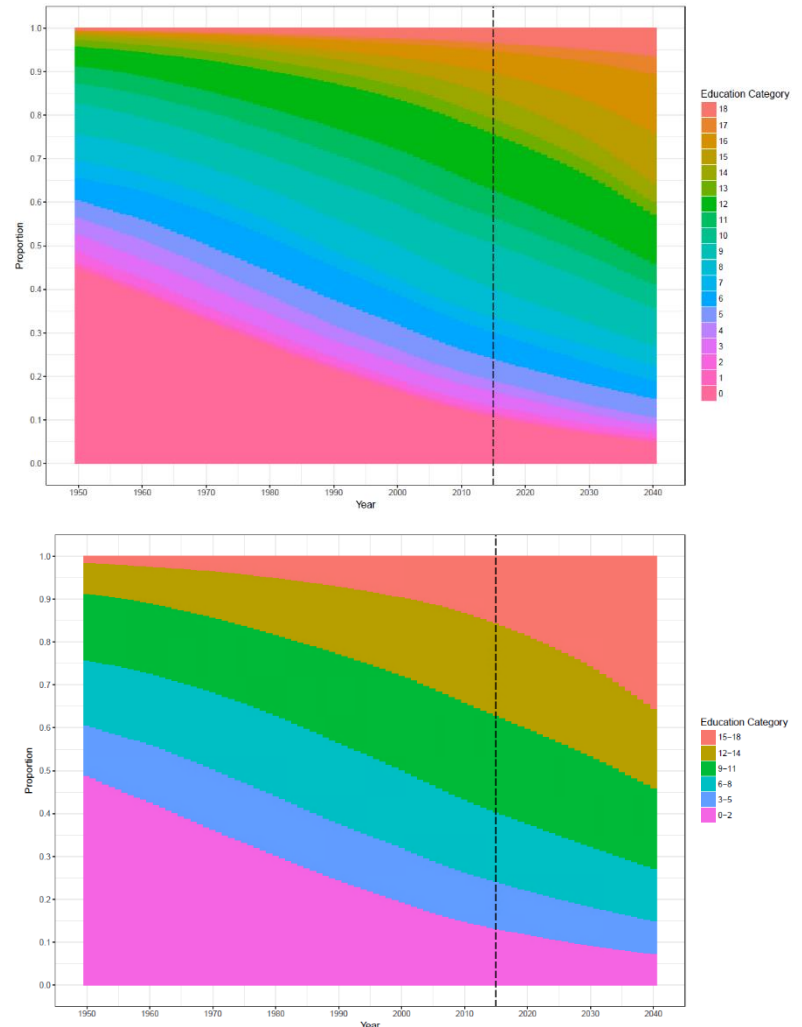


Figure 2. Global distribution of educational attainment shown in both single-year (top) and multi-year (bottom) bins. The vertical dashed line indicates 2016, the last year before forecasts begin.

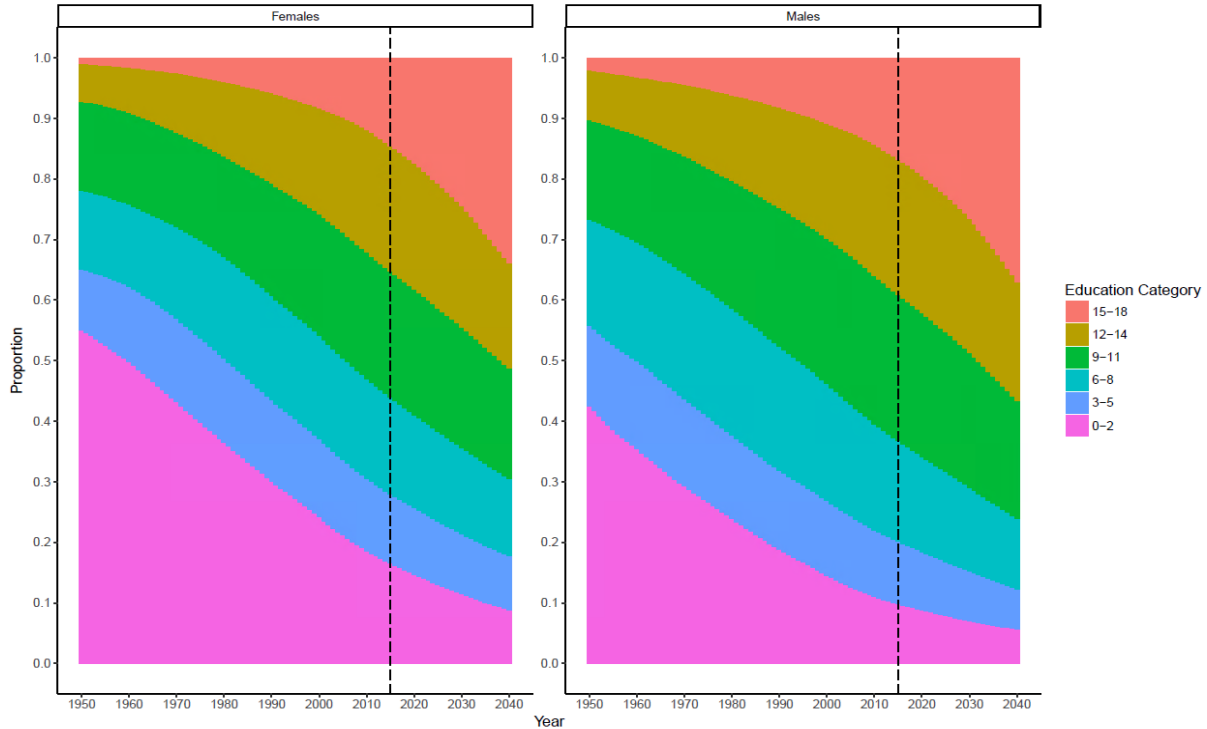


Figure 3. Global distribution of educational attainment shown multi-year bins for males (right) and females (left). The vertical dashed line indicates 2016, the last year before forecasts begin.

of attainment group, women have nearly caught up with men, by 2016 with proportions of 17.25% (X.X- Y.Y%) for men and 15.04% (X.X- Y.Y%) for women. By 2040 the proportion of the global population with tertiary education has grown substantially for both groups, but a small gap remains with 36.98% (X.X- Y.Y%) for men and 33.92% (X.X- Y.Y%) for women.

Figure 4 shows the distribution of education by super-region used in the Global Burden of Disease 2015 study [42]. All regions show evidence of substantial progress, however clear disparities remain throughout the timeseries and projections. The proportion of individuals in North Africa and the Middle East, South Asia, and Sub-Saharan Africa with 0-2 years of education was quite high in 1950, with proportions of greater than 80% in each case. However, by 2016 these proportions have fallen substantially to 16.63% (X.X- Y.Y%), 29.23% (X.X- Y.Y%), and 27.57% (X.X- Y.Y%) respectively. Global gains in the tertiary education 15-18 years bin have been driven largely by progress in the High-income and Central Europe, Eastern Europe, and Central Asia super regions. The proportion in the High-income super region grew from 3.85% (X.X- Y.Y%) in 1950 to 34.82% (X.X- Y.Y%) in 2016, and is forecasted to reach 56.19% percent (95% CI X.X- Y.Y%) by 2040.

Figure 5. shows the distribution of education for the world's most populous countries. Interesting differences can be noted between the world's two most populous countries, China and India. While China has steadily reduced the number of individuals in the lowest educational category, a substantial number of individuals in this category remain in this category in India throughout the projections. Similarly, the number of individuals in China achieving tertiary education has grown rapidly in recent years, and will continue to grow at a rapid pace if current trends continue. By 2040, we expect

Bangladesh, India, Pakistan, and Nigeria will continue to have substantial numbers of individuals in the lowest education category.

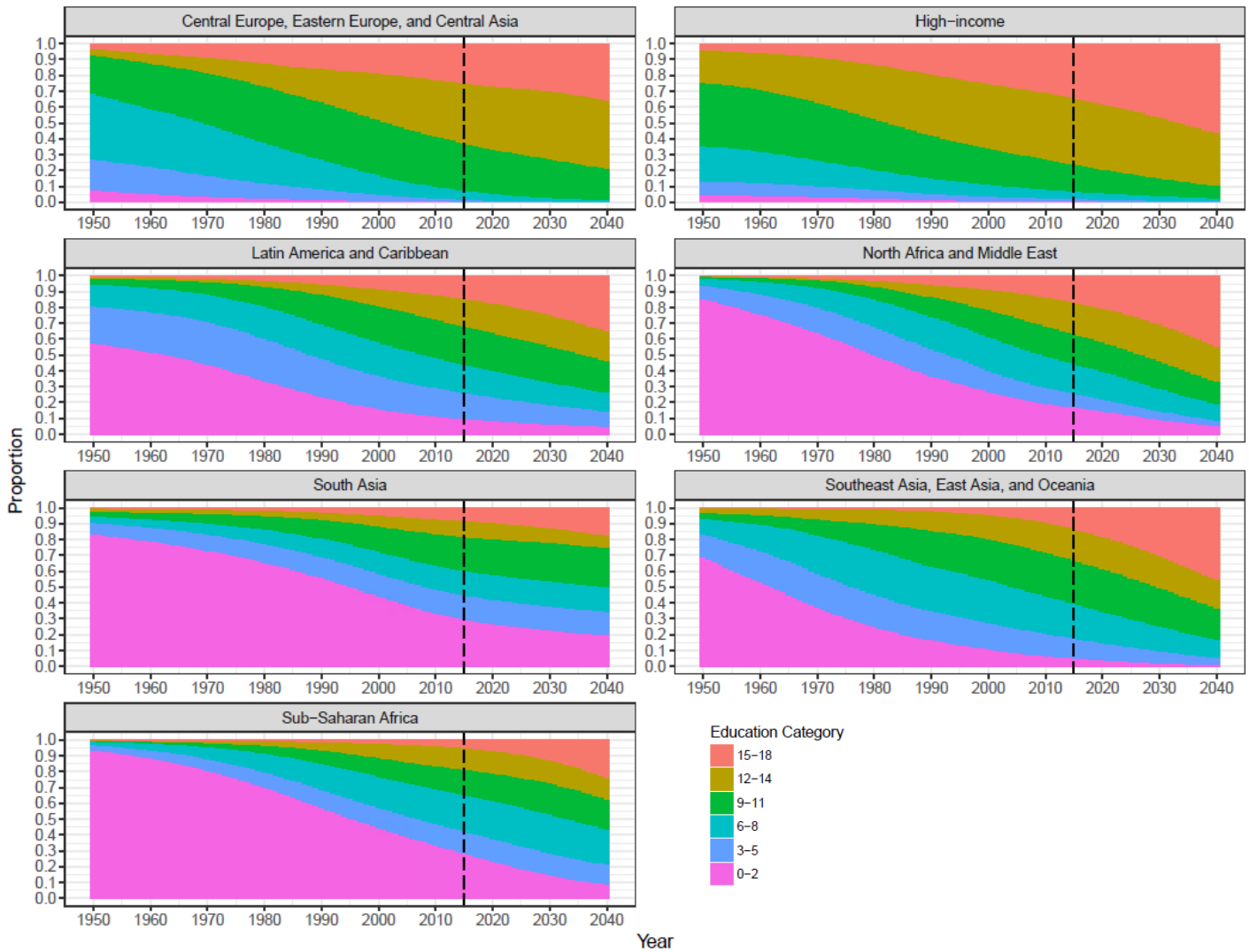


Figure 4. Distribution of educational attainment shown multi-year bins for each super-region used in the GBD 2015 study. The vertical dashed line indicates 2016, the last year before forecasts begin.

Country	0-2		3-5		6-8		9-11		12-14		15-18	
	2016	2040	2016	2040	2016	2040	2016	2040	2016	2040	2016	2040
Afghanistan	82.499	20.376	11.321	9.496	1.564	9.641	2.319	16.378	1.532	25.762	0.764	18.347
Albania	1.278	0.354	4.846	0.778	30.967	10.42	6.386	3.413	44.228	60.213	12.295	24.822
Algeria	5.428	1.999	19.12	6.695	29.777	16.039	25.1	16.85	8.311	16.814	12.263	41.604
Andorra	0.282	0.182	0.392	0.147	2.4	0.585	19.616	8.263	36.272	29.002	41.038	61.821
Angola	16.15	2.279	29.847	17.633	30.462	22.247	14.452	20.135	7.718	12.21	1.371	25.496
Antigua and Barbuda	5.116	2.092	6.515	2.294	16.624	6.026	27.809	21.833	26.946	28.622	16.99	39.132
Argentina	1.919	0.518	4.575	1.49	26.367	15.227	16.49	12.455	29.574	29.012	21.075	41.298
Armenia	0.443	0.122	1.077	0.175	8.717	3.281	37.602	31.335	25.021	29.565	27.139	35.521
Australia	0.2	0.191	0.269	0.121	2.312	0.297	19.349	7.955	34.838	25.84	43.032	65.595
Austria	0.337	0.286	0.116	0.087	0.394	0.147	31.005	14.808	43.948	38.021	24.201	46.65
Azerbaijan	0.844	0.184	1.032	0.164	5.221	2.757	61.746	49.659	17.258	22.907	13.898	24.329
Bahrain	20.208	6.882	4.497	1.819	16.314	10.591	20.941	14.275	27.491	27.445	10.551	38.987
Bangladesh	35.509	25.238	21.833	21.382	15.558	16.98	19.083	22.485	5.74	4.698	2.277	9.217
Barbados	1.362	0.65	5.042	1.404	8.604	2.524	42.474	27.129	20.353	25.137	22.165	43.156
Belarus	0.327	0.108	1.694	0.049	3.01	0.319	21.504	10.065	41.633	47.085	31.834	42.374
Belgium	0.236	0.212	0.132	0.088	1.424	0.276	15.282	4.957	37.045	28.729	45.882	65.738
Belize	7.057	2.551	7.725	3.019	27.558	15.627	23.687	27.728	28.967	41.294	5.006	9.781
Benin	44.712	15.576	15.901	16.616	14.987	17.621	13.575	17.159	6.596	8.531	4.228	24.497
Bhutan	41.099	27.3	14.921	16.35	13.714	14.986	17.143	20.164	5.66	5.051	7.463	16.149
Bolivia	12.292	5.583	15.495	7.02	12.538	6.878	19.629	17.738	22.018	20.84	18.028	41.941
Bosnia and Herzegovina	4.5	0.708	7.312	1.63	16.073	6.117	21.463	10.5	41.425	59.483	9.227	21.563
Botswana	7.305	1.589	6.67	2.959	23.137	14.398	34.389	27.704	23.641	22.081	4.858	31.269
Brazil	11.834	7.388	27.1	18.828	18.675	15.418	18.582	17.18	12.045	14.14	11.764	27.047
Brunei	2.947	0.746	0.6	0.094	0.675	0.126	7.199	1.345	43.972	27.319	44.608	70.37
Bulgaria	0.333	0.263	0.761	0.343	4.134	1.599	16.236	6.169	45.916	51.945	32.621	39.681
Burkina Faso	60.571	19.983	10.482	16.544	13.916	19.778	10.29	19.694	3.167	7.834	1.574	16.167
Burundi	26.039	7.54	35.605	23.012	23.235	28.275	6.769	15.582	5.746	10.931	2.606	14.66
Cambodia	21.685	7.194	24.521	12.198	26.028	21.288	16.502	20.571	7.746	13.293	3.517	25.456
Cameroon	20.824	7.428	15.054	11.436	26.868	20.451	21.755	21.992	9.148	10.289	6.352	28.404
Canada	0.179	0.133	0.366	0.272	1.332	0.354	7.51	2.895	36.712	30.03	53.899	66.317
Cape Verde	24.373	12.109	28.452	20.347	22.677	19.235	16.027	16.634	4.243	6.545	4.228	25.13
Central African Republic	24.402	4.038	31.123	19.099	21.634	20.017	13.892	19.449	6.785	11.856	2.163	25.542
Chad	52.942	16.756	15.463	17.567	12.753	17.938	10.176	17.336	5.411	8.463	3.254	21.94
Chile	1.426	0.323	6.165	2.314	16.372	11.671	12.856	9.627	40.855	34.788	22.326	41.277
China	3.86	0.512	12.091	4.107	20.672	9.199	28.073	18.022	19.96	17.72	15.344	50.44
Colombia	11.451	5.918	20.353	9.455	13.928	9.744	30.837	24.22	12.186	16.602	11.245	34.061
Comoros	30.744	9.506	12.501	12.076	21.252	22.216	17.748	18.628	10.355	12.008	7.4	25.566
Congo	11.514	1.854	13.553	11.389	25.331	17.831	27.198	19.75	14.87	12.502	7.535	36.674
Costa Rica	7.308	3.987	9.381	4.869	33.701	18.582	25.383	21.286	10.011	14.407	14.216	36.868

Cote d'Ivoire	38.491	12.171	15.746	15.962	16.835	18.199	15.207	17.625	8.106	8.953	5.616	27.09
Croatia	0.252	0.192	0.854	0.114	3.989	0.442	12.422	4.894	57.311	59.152	25.172	35.207
Cuba	3.246	0.951	1.357	0.651	9.958	3.649	26.37	20.006	47.618	45.602	11.451	29.141
Cyprus	0.285	0.202	1.355	0.12	10.141	1.907	7.851	4.623	43.114	32.872	37.254	60.276
Czech Republic	0.183	0.167	0.107	0.076	0.397	0.166	10.244	4.073	66.147	62.251	22.922	33.267
Democratic Republic of the Congo	12.28	2.027	20.748	11.681	26.968	19.961	21.849	20.368	13.313	13.277	4.841	32.686
Denmark	0.323	0.268	0.104	0.076	0.264	0.114	7.425	3.017	15.296	12.416	76.588	84.11
Djibouti	33.441	12.319	6.232	9.645	24.92	26.301	25.351	22.965	5.389	9.045	4.666	19.725
Dominica	4.193	1.581	12.759	4.052	13.633	5.239	18.158	16.519	28.93	28.06	22.328	44.549
Dominican Republic	12.327	5.316	11.918	3.91	17.357	6.645	19.507	17.841	24.927	30.83	13.965	35.458
Ecuador	7.078	4.081	7.601	4.058	24.987	11.443	17.704	16.904	24.73	22.166	17.9	41.348
Egypt	21.515	7.052	7.533	2.678	9.183	5.615	21.168	16.266	22.668	21.714	17.932	46.674
El Salvador	19.139	8.437	12.406	5.848	17.534	11.235	21.844	18.794	17.484	19.461	11.594	36.225
Equatorial Guinea	12.167	2.279	20.856	13.227	24.562	17.958	25.557	19.812	10.756	11.214	6.102	35.51
Eritrea	31.036	9.743	16.753	14.714	21.767	24.256	17.955	20.574	8.378	11.526	4.112	19.187
Estonia	0.193	0.142	0.107	0.056	0.425	0.094	11.903	5.646	44.926	44.404	42.447	49.659
Ethiopia	48.231	15.895	16.521	16.15	18.457	24.2	8.936	16.521	5.415	10.758	2.441	16.477
Federated States of Micronesia	4.611	0.743	3.012	0.378	10.491	3.023	26.286	15.068	34.751	22.948	20.85	57.841
Fiji	1.267	0.333	3.458	0.635	18.756	4.929	33.445	19.231	25.44	21.545	17.635	53.326
Finland	0.302	0.255	0.281	0.217	1.803	0.224	16.257	5.045	25.736	22.199	55.622	72.06
France	3.26	1.515	6.25	1.809	4.906	1.326	13.752	5.968	33.261	28.23	38.571	61.153
Gabon	11.538	1.979	14.601	9.429	26.101	17.095	25.695	18.765	12.4	11.291	9.666	41.44
Georgia	0.505	0.163	1.253	0.213	3.783	1.719	48.768	39.708	10.306	16.9	35.385	41.296
Germany	0.249	0.214	0.112	0.091	0.363	0.159	40.034	18.454	29.029	28.929	30.213	52.152
Ghana	21.831	8.319	10.306	13.609	20.409	20.603	29.163	16.563	9.502	9.005	8.788	31.901
Greece	0.338	0.217	2.316	0.172	17.459	4.394	9.888	5.196	34.796	30.662	35.202	59.359
Grenada	4.632	1.914	9.495	3.483	27.391	10.856	23.566	21.425	26.326	32.898	8.591	29.424
Guam	0.333	0.119	0.562	0.103	0.665	0.22	13.054	11.275	51.257	25.805	34.128	62.478
Guatemala	23.686	8.888	13.757	6.535	24.283	15.141	19.148	20.245	12.83	19.229	6.297	29.962
Guinea	53.432	18.654	12.082	15.19	12.483	16.266	10.759	16.04	6.158	8.518	5.086	25.331
Guinea-Bissau	42.559	14.147	19.666	18.514	17.812	20.895	15.034	20.823	2.711	6.801	2.218	18.821
Guyana	3.255	1.505	9.158	3.591	21.131	8.045	52.587	39.383	10.949	27.418	2.92	20.058
Haiti	26.797	9.189	15.117	5.79	15.967	6.825	23.208	22.632	13.059	27.027	5.852	28.538
Honduras	17.466	7.301	14.35	6.605	30.729	17.65	13.797	16.48	14.327	18.781	9.331	33.183
Hungary	0.204	0.168	0.273	0.092	3.913	0.678	22.936	10.107	50.198	56.4	22.476	32.555
Iceland	0.159	0.137	0.13	0.082	0.689	0.112	13.186	5.348	14.652	13.848	71.184	80.472
India	26.59	18.444	14.646	13.342	15.768	15.195	22.237	25.391	11.13	8.598	9.629	19.03
Indonesia	9.538	2.606	7.618	3.357	26.595	15.311	21.633	20.395	24.536	20.865	10.079	37.466

Iran	6.055	2.736	6.257	2.334	15.039	7.827	19.28	11.594	28.57	23.27	24.798	52.239
Iraq	14.569	3.331	13.017	4.144	27.994	14.759	15.137	13.709	18.559	22.954	10.724	41.104
Ireland	0.261	0.219	0.14	0.092	2.558	0.612	21.279	8.472	40.587	32.596	35.175	58.008
Israel	0.244	0.155	0.367	0.094	3.361	0.695	8.128	4.446	52.106	37.61	35.793	57
Italy	0.5	0.364	5.571	0.286	10.635	3.158	15.871	8.431	37.464	34.493	29.959	53.268
Jamaica	0.918	0.451	2.392	0.787	15.326	5.37	56.207	41.269	19.737	30.241	5.42	21.882
Japan	0.111	0.096	0.105	0.058	0.786	0.055	13.916	2.4	54.761	38.243	30.321	59.148
Jordan	4.419	1.318	3.209	1.172	10.013	5.81	30.635	16.672	31.46	25.635	20.263	49.393
Kazakhstan	0.646	0.133	1.497	0.233	11.927	4.568	63.234	51.761	15.131	22.601	7.565	20.705
Kenya	10.003	3.559	10.338	8.331	38.552	32.484	15.345	13.988	20.383	20.532	5.379	21.106
Kiribati	26.329	6.076	6.282	1.7	13.7	5.266	44.725	38.281	6.354	21.162	2.61	27.514
Kuwait	6.133	2.579	3.629	1.46	16.232	8.877	19.553	11.501	28.402	20.841	26.051	54.742
Kyrgyzstan	0.424	0.092	0.654	0.119	3.743	1.315	41.889	34.419	31.304	31.989	21.986	32.066
Laos	16.472	4.118	26.837	9.897	19.206	16.01	15.346	18.579	13.878	15.928	8.261	35.467
Latvia	0.168	0.124	0.258	0.077	2.171	0.199	18.403	9.072	45.103	47.117	33.897	43.41
Lebanon	2.455	1.148	4.104	1.281	16.84	9.95	20.801	12.546	31.84	25.353	23.961	49.722
Lesotho	9.995	1.765	12.85	3.839	30.12	14.641	23.937	25.638	12.513	14.522	10.584	39.595
Liberia	35.677	12.182	15.243	16.134	18.865	20.102	14.148	19.092	13.075	12.797	2.991	19.693
Libya	5.726	1.998	4.028	1.83	23.369	11.756	17.791	11.814	32.335	24.148	16.751	48.455
Lithuania	0.228	0.144	0.549	0.071	2.373	0.078	12.575	5.325	42.871	43.602	41.405	50.779
Luxembourg	0.255	0.217	0.297	0.141	2.31	1.312	18.97	8.073	29.1	23.172	49.068	67.085
Macedonia	3.591	0.99	8.635	1.728	26.082	8.746	12.983	7.259	45.903	72.282	2.807	8.995
Madagascar	26.66	7.809	35.696	26.21	21.025	30.819	10.937	16.523	3.678	7.319	2.004	11.319
Malawi	17.674	5.672	23.378	17.948	30.484	27.025	16.194	22.241	10.692	14.98	1.577	12.133
Malaysia	6.394	1.876	6.812	3.29	19.157	11.87	39.663	26.071	12.863	13.665	15.111	43.228
Maldives	17.819	6.165	5.716	4.057	28.812	22.096	33.861	25.661	8.309	11.971	5.483	30.05
Mali	62.592	20.921	10.961	16.492	11.697	16.407	8.42	17.001	3.517	8.275	2.813	20.905
Malta	0.257	0.193	0.309	0.109	2.58	0.648	49.269	26.477	24.268	25.075	23.318	47.497
Marshall Islands	2.149	0.4	3.911	0.477	17.44	3.304	29.469	18.649	31.91	25.515	15.122	51.656
Mauritania	32.959	11.091	17.285	16.417	18.941	18.498	16.201	18.381	9.047	9.426	5.567	26.188
Mauritius	7.299	2.434	8.363	4.468	19.737	14.311	20.183	17.069	32.158	21.946	12.26	39.772
Mexico	4.179	1.753	4.824	2.302	15.781	8.863	26.211	20.202	25.384	20.934	23.62	45.946
Moldova	0.669	0.154	3.533	0.639	10.839	2.293	37.44	18.397	35.978	51.162	11.541	27.355
Mongolia	3.467	0.815	5.666	2.144	16.986	9.1	40.006	39.497	15.815	18.86	18.059	29.584
Montenegro	0.567	0.353	1.505	0.102	1.437	0.161	6.659	2.349	55.599	53.341	34.233	43.695
Morocco	23.349	8.644	12.27	4.444	12.941	8.602	17.538	12.347	21.486	23.581	12.416	42.383
Mozambique	34.428	9.587	28.844	21.086	22.228	27.731	9.728	19.538	3.599	9.901	1.173	12.158
Myanmar	13.344	3.554	25.006	9.615	18.511	15.072	20.34	19.526	12.929	14.072	9.869	38.161
Namibia	10.208	2.011	9.258	3.263	21.156	11.313	31.14	26.496	19.337	19.508	8.901	37.409
Nepal	44.482	28.906	15.858	19.757	16.134	18.439	20.68	26.145	2.348	2.623	0.499	4.131
Netherlands	0.224	0.193	0.132	0.082	1.654	0.256	16.524	5.753	28.677	22.316	52.789	71.4
New Zealand	0.343	0.244	0.739	0.331	0.93	0.207	20.574	8.306	36.689	26.086	40.725	64.825
Nicaragua	16.6	7.784	14.385	6.545	24.331	14.567	24.466	21.391	9.151	14.686	11.067	35.027

Niger	64.327	19.145	12.482	18.936	10.907	20.108	8.64	18.999	2.155	7.115	1.489	15.696
Nigeria	26.971	9.113	3.749	5.449	20.005	16.429	14.009	18.822	27.148	20.751	8.118	29.437
North Korea	0.534	0.032	12.555	1.563	44.653	12.194	16.19	12.296	15.281	21.234	10.788	52.681
Norway	0.209	0.169	0.252	0.187	0.252	0.121	12.383	4.355	32.874	24.886	54.03	70.281
Oman	14.214	5.897	6.258	2.91	18.686	10.916	19.263	12.52	26.661	24.101	14.917	43.655
Pakistan	41.003	23.693	14.437	17.281	13.1	15.483	18.877	22.87	8.109	6.762	4.473	13.911
Palestine	7.921	2.015	3.054	1.044	13.71	7.311	30.033	16.953	28.588	24.825	16.694	47.853
Panama	7.407	3.91	6.285	3.053	22.928	12.099	19.832	17.159	24.201	21.085	19.347	42.694
Papua New Guinea	24.111	3.995	6.142	1.003	15.857	4.193	18.051	16.456	21.988	24.932	13.851	49.42
Paraguay	8.131	5.006	20.543	14.247	26.707	19.192	14.768	16.223	17.05	16.243	12.801	29.089
Peru	8.601	4.51	11.613	5.512	11.727	7.005	37.736	27.585	16.385	20.397	13.937	34.991
Philippines	1.512	0.665	7.031	3.496	22.49	15.614	42.276	37.445	20.749	17.135	5.942	25.644
Poland	0.281	0.232	0.3	0.104	2.559	0.389	14.774	5.482	47.808	49.194	34.279	44.599
Portugal	0.985	0.37	11.379	3.298	23.898	11.418	19.941	13.608	21.759	25.251	22.039	46.054
Puerto Rico	1.844	0.641	2.705	0.706	4.288	1.463	8.185	6.054	49.357	37.388	33.622	53.748
Qatar	15.271	5.339	4.63	1.627	15.224	7.814	18.076	10.895	19.81	18.63	26.989	55.695
Romania	1.727	0.458	2.138	0.338	5.317	0.69	21.225	8.605	55.28	61.404	14.313	28.507
Russia	0.139	0.09	0.954	0.094	6.021	0.665	26.753	13.724	40.119	47.968	26.014	37.459
Rwanda	25.009	8.281	30.218	21.02	29.858	31.166	8.015	15.853	5.312	10.743	1.589	12.936
Saint Lucia	2.801	1.114	6.78	2.554	26	10.936	15.793	16.018	40.258	42.188	8.368	27.19
Saint Vincent and the Grenadines	6.592	2.761	14.601	5.131	21.35	7.714	28.051	22.922	21.155	30.307	8.251	31.165
Samoa	2.331	0.513	3.476	0.68	12.104	3.311	46.046	25.825	24.016	21.972	12.029	47.699
Sao Tome and Principe	10.772	4.451	35.22	24.377	32.752	26.104	17.123	20.237	1.883	5.57	2.25	19.26
Saudi Arabia	15.758	6.036	1.494	0.67	16.25	6.503	18.537	11.214	24.621	21.592	23.341	53.984
Senegal	49.951	17.572	15.731	21.132	12.814	10.753	11.745	19.465	6.054	9.859	3.705	21.22
Serbia	1.661	0.545	2.908	0.36	3.781	0.839	12.748	4.389	55.096	62.267	23.806	31.6
Seychelles	6.175	1.76	3.746	2.092	27.349	17.354	35.129	26.532	14.696	15.366	12.906	36.896
Sierra Leone	48.947	18.059	9.326	14.27	17.858	19.856	16.355	20.004	4.909	9.403	2.605	18.409
Singapore	3.286	0.576	0.879	0.397	10.491	3.42	21.112	5.295	24.221	23.066	40.011	67.247
Slovakia	0.255	0.2	0.121	0.086	0.376	0.142	9.25	3.385	66.421	62.881	23.576	33.307
Slovenia	0.26	0.209	0.437	0.134	3.274	0.752	15.961	6.452	46.213	48.417	33.855	44.035
Solomon Islands	12.653	2.315	12	1.976	26.283	6.94	32.717	25.049	7.342	19.327	9.005	44.393
Somalia	46.904	12.53	10.503	13.194	18.887	25.96	10.569	17.639	9.032	12.576	4.105	18.1
South Africa	1.834	0.491	4.225	1.642	12.558	7.004	29.942	24.901	39.9	27.011	11.541	38.951
South Korea	1.576	0.123	0.54	0.097	7.609	1.428	5.961	2.574	45.908	32.357	38.406	63.422
South Sudan	58.562	16.941	12.173	13.298	14.787	25.845	8.985	19.589	3.212	9.317	2.281	15.011
Spain	1.238	0.302	3.798	0.539	11.251	3.606	26.067	14.343	24.81	25.349	32.836	55.861
Sri Lanka	7.253	2.369	10.214	5.075	16.128	11.486	35.774	27.193	21.599	18.607	9.031	35.27
Sudan	33.241	8.538	10.112	3.877	21.796	13.686	18.865	16.494	7.966	18.988	8.02	38.417

Suriname	6.533	2.656	12.385	4.283	22.505	7.94	32.633	27.002	20.095	31.881	5.848	26.238
Swaziland	12.096	1.896	9.443	2.985	23.039	12.781	26.181	24.061	20.182	19.401	9.059	38.875
Sweden	0.368	0.291	0.284	0.189	1.805	0.172	15.514	5.799	40.334	35.573	41.695	57.977
Switzerland	1.554	0.715	0.096	0.068	0.103	0.075	0.411	0.958	70.536	45.401	27.3	52.782
Syria	12.158	3.535	6.192	2.446	30.249	14.795	19.637	13.717	21.838	23.206	9.927	42.302
Taiwan	0.865	0.081	0.953	0.122	12.296	3.542	12.928	8.195	39.673	21.336	33.284	66.724
Tajikistan	1.822	0.33	1.673	0.376	9.072	3.073	57.45	47.927	16.766	23.818	13.218	24.476
Tanzania	17.448	5.278	12.681	9.624	53.475	40.905	10.802	20.545	4.092	10.571	1.502	13.078
Thailand	4.473	1.713	25.468	11.159	19.401	13.293	15.698	13.433	11.226	9.619	23.733	50.782
The Bahamas	3.264	1.402	2.392	0.913	7.628	3.113	48.891	32.047	26.655	32.14	11.171	30.385
The Gambia	41.555	13.846	8.217	12.365	16.356	18.546	18.157	20.59	12.02	13.298	3.695	21.354
Timor-Leste	26.641	5.295	10.913	4.133	19.264	14.828	17.194	19.165	15.925	16.205	10.063	40.374
Togo	29.239	10.474	19.025	16.621	23.055	20.287	18.792	19.23	6.457	9.079	3.433	24.308
Tonga	3.439	0.623	3.476	0.614	15.354	3.789	42.078	26.034	28.858	28.488	6.796	40.452
Trinidad and Tobago	3.624	1.568	15.832	5.854	34.618	19.242	20.155	22.294	10.608	14.872	15.163	36.171
Tunisia	17.793	6.133	8.513	3.611	21.015	11.688	15.441	11.441	21.583	23.235	15.655	43.893
Turkey	1.116	0.544	7.605	2.725	27.427	12.747	19.067	12.192	21.771	25.157	23.013	46.634
Turkmenistan	1.048	0.216	1.08	0.187	6.686	2.377	68.198	50.318	11.019	20.1	11.97	26.803
Uganda	16.996	5.429	24.205	16.74	31.166	26.873	16.668	19.577	4.706	8.48	6.259	22.901
Ukraine	0.247	0.112	0.967	0.083	3.744	0.278	24.382	11.556	32.235	41.209	38.425	46.763
United Arab Emirates	4.107	1.905	2.807	1.1	9.333	4.153	17.782	10.654	33.329	22.877	32.642	59.311
United Kingdom	0.124	0.121	0.102	0.072	0.161	0.107	43.691	18.656	28.418	28.454	27.505	52.59
United States	0.329	0.209	0.511	0.386	1.798	1.054	8.786	5.474	51.864	38.484	36.711	54.393
Uruguay	1.212	0.298	5.983	1.743	30.655	18.037	25.382	18.314	18.105	22.653	18.664	38.956
Uzbekistan	0.494	0.1	0.853	0.103	4.075	1.534	67.779	50.445	13.338	21.261	13.462	26.557
Vanuatu	10.782	2.071	9.182	1.78	35.297	10.077	21.276	20.428	14.485	22.853	8.977	42.791
Venezuela	2.923	1.205	3.864	2.036	18.913	10.425	40.916	28.77	19.517	20.81	13.867	36.754
Vietnam	7.474	2.713	17.984	9.339	21.51	19.834	32.57	29.406	16.187	14.939	4.276	23.769
Virgin Islands, U.S.	1.274	0.584	2.196	0.759	3.18	1.38	9.739	8.189	51.618	39.907	31.993	49.181
Yemen	29.363	7.91	11.989	4.472	25.742	14.463	15.367	13.083	7.912	17.909	9.627	42.163
Zambia	12.26	4.286	15.609	14.336	32.576	23.589	21.855	23.226	14.712	18.886	2.988	15.677
Zimbabwe	4.643	0.89	6.169	2.508	26.84	16.505	52.057	38.436	3.191	7.507	7.1	34.155

Table 2. Distribution of adult 15+ population by educational attainment in 2016 and 2040, for 191 countries and territories.

Measuring Inequality in Education

Implications of Absolute and Relative Inequality Metrics

Educational attainment is a social indicator with somewhat different properties from other indicators typically measured with inequality metrics, such as wealth or income. Unlike income, where huge variations in average levels exists between countries, educational attainment is relatively bounded by the human lifespan, with almost all individuals attaining less than 19 years of education. Furthermore, the presence of individuals with zero education, who in some developing contexts represent the majority of the distribution, complicate which metrics can be applied to education. Studies examining inequality in education are limited, with the most comprehensive publication by Vinod et al. in 2001 examining data from 85 country-years [43]. The authors use the Gini coefficient as their metric of inequality in education, and look at the standard deviation of education to describe a Kuznets curve effect, where inequality first grows over time as average education increases, and then begins to shrink as higher levels of education are attained.

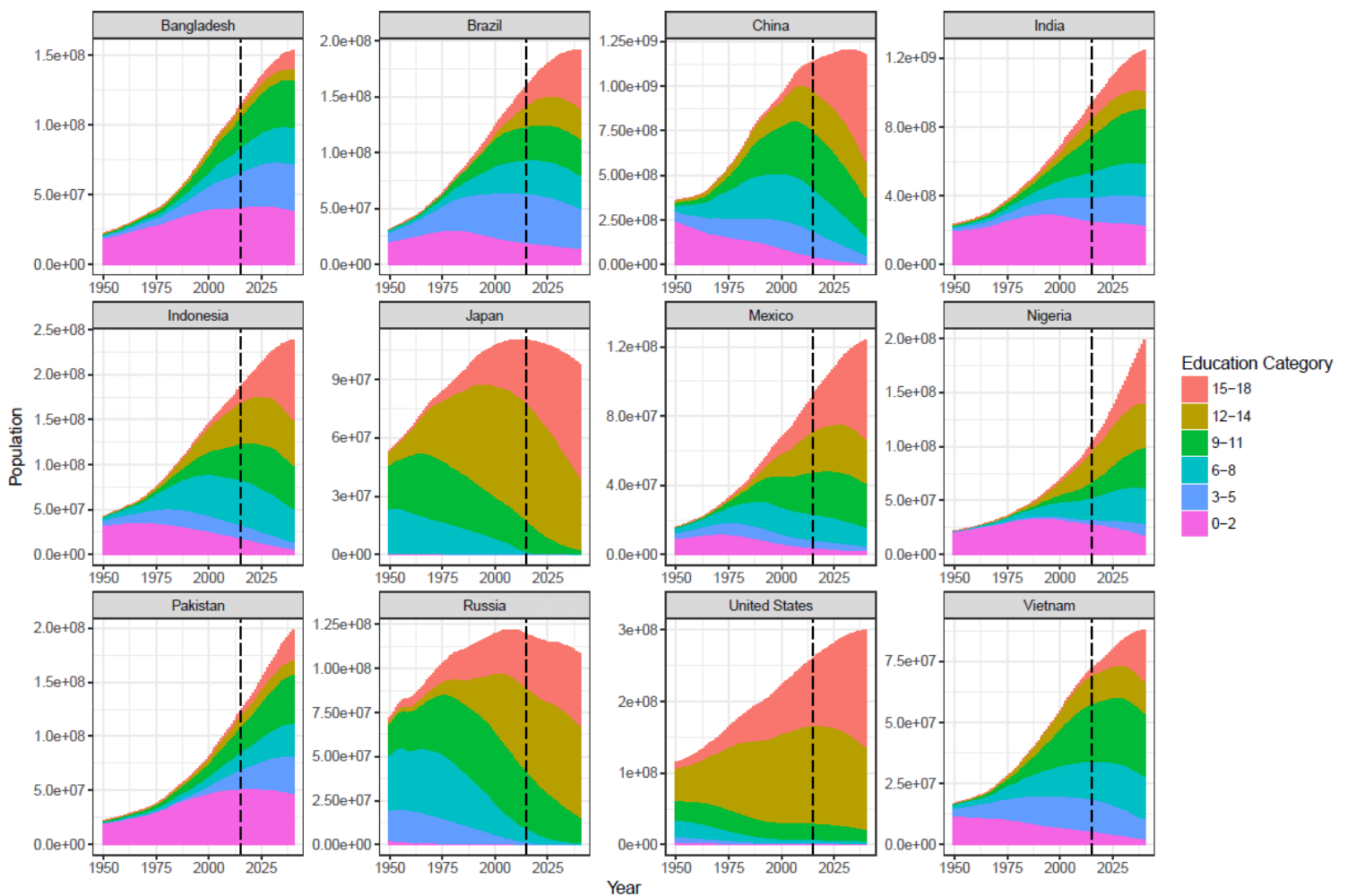


Figure 5. Population of 12 countries with largest number of 15+ individuals in the year 2016, according to WPP 2015 estimates. Shown by multi-year bin of educational. The vertical dashed line indicates 2016, the last year before forecasts begin.

Figure 6 details the relationship between average years of schooling and the Gini coefficient, and the absolute individual difference (AID), an absolute metric equal to the average absolute difference between every possible pair of individuals in a population. The Gini coefficient of education is highly collinear with average years of schooling, with a global correlation coefficient of -0.933, which is a result of the Gini coefficient's formulation as a *relative* inequality metric. As the Gini coefficient can be calculated as the absolute individual difference divided by two times the average years of schooling, average attainment can be thought of as "in the denominator" of the Gini coefficient. In the context of a highly bounded indicator like education, this effect induces very high correlation. Highly uneducated populations have misleadingly high Gini coefficients as only a few individuals have more than zero years of schooling. As populations become more educated, their Gini coefficient heads steadily towards zero, with minimal variation between populations.

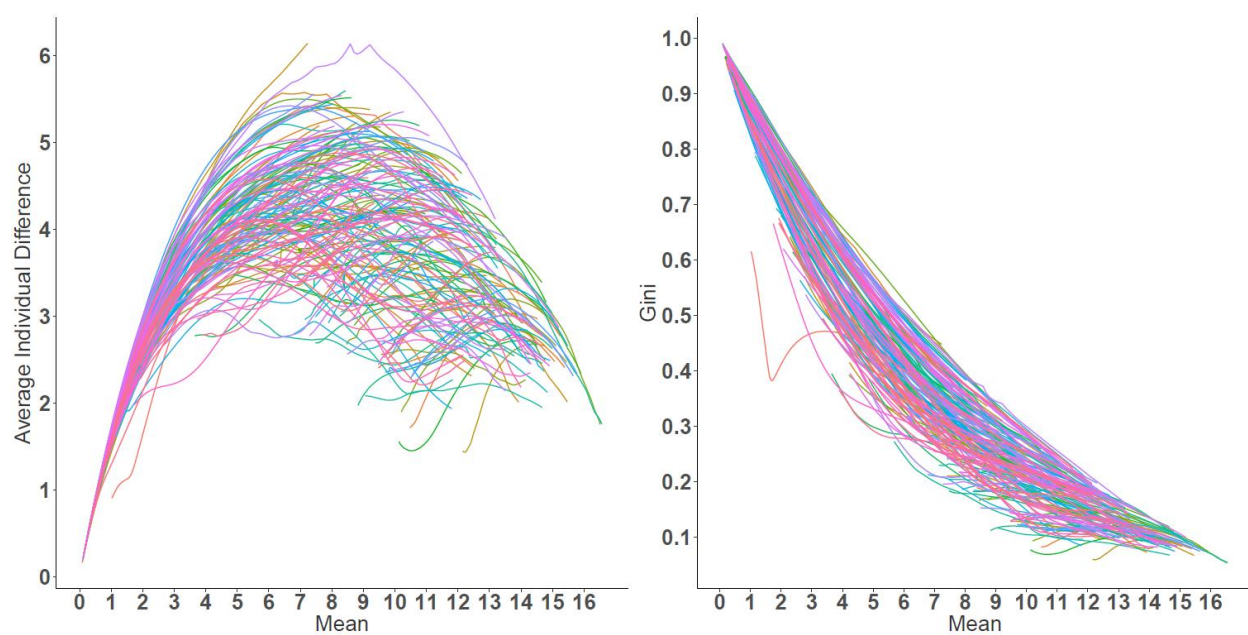


Figure 6. Relationship between average attainment and the average individual difference (left) and Gini coefficient (right) of educational attainment

The AID has a much more intuitive relationship with average attainment for representing inequality in education. Overall the relationship is much less correlated, with a global correlation coefficient of 0.397. We confirm the Kuznets curve pattern observed by Vinod et al. in their 2001 analysis; this trend is very clear in figure 6. All populations have near zero inequality when the total amount of education is very low, but as average education increases in a population, a variety of levels of inequality are observed for the same mean attainment, suggesting different populations have differing levels of equality in distributing the social good of education. Although the discussion of which metric inherently best captures inequality is epistemological in nature[44], our results suggest that relative metrics like the Gini coefficient that include average attainment in the denominator are unlikely to provide additional predictive power in estimating health trends after accounting for average attainment. We argue that absolute metrics such as the average individual difference are more appropriate for examining inequality in education globally.

Global Trends in Educational Inequality

Figure 7 shows the AID of educational attainment over time for each region used in the Global Burden of Disease 2015 study, as well as the global average. Importantly, these are the population-weighted averages of all the country-year-age-sex specific AID values in the region in question, and they do not represent AID values calculated using all individuals in the region. They should be considered to be the average level of country-age-sex specific inequality experiences by an individual in the given region. Figure 7 also shows the same regional average AID values against the average attainment values for each region. The global trend in AID reveals a similar Kuznets curve process, with the inflection point towards greater equality occurring in the 2020's.

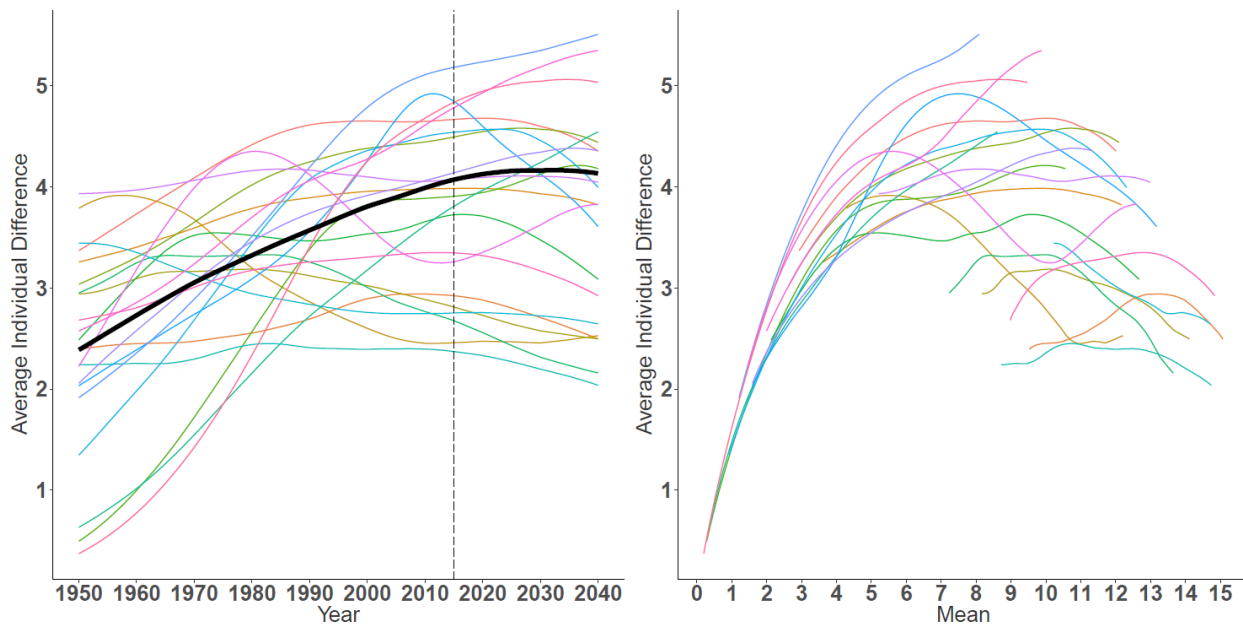


Figure 6. Average individual difference shown over time (left) for each region in color, with the global trend in black. The relationship between the average individual difference and mean attainment is also shown (right) for each region.

Examining the regional trends, it is clear that a large degree of the variation in AID between regions in 2016 can be explained by the average level of attainment, with each region experiencing a slightly different moment of its Kuznets curve. However, it is also clear that substantial region variation exists in the degree of inequality experienced for a given amount of average attainment. So while we do find that the world is becoming more equal, simply as a product of increasing average education, the importance of these differences in the height of the Kuznets curve experienced in each country should be further explored.

Conclusions and Future Directions

Summary

Here we provide the first set of comprehensive estimates of the full distribution of educational attainment from 1950 to 2016 for 195 countries and territories, with projections through 2040. Building on previous attempts to model categorical education, we provide estimates of the proportion of the population of each location by single years of educational attainment, single temporal year, five-year age groups, and gender. We also provide the first set of projections through 2040 of categorical education that leverage country specific information where available to make the best possible of individual nation's attainment trajectories. Using these estimates, we have also provided the first description of inequality in education over time, using the absolute individual difference metric. We identify important differences in the implications of using absolute or relative inequality metrics, and we determine that absolute inequality metrics may be more appropriate for measuring inequality in education. We also show that using absolute inequality metrics, substantial differences are observed in the level of inequality between countries with the same level of average attainment. The health implications of these differences remain to be explored.

Comparison to Other Estimates

The main notable previous works that have modelled the distribution of educational attainment include the set of estimates published by Samir KC et al. in 2010 [36], and those of Barro and Lee in 2013[25]. Here we compare our methods to both previous approaches. As each analysis only offers distributional information in ISCED categories, and not number of years, it is not possible to directly compare our timeseries to the previous estimates. Furthermore, as the other analyses have major differences in methodology and purpose from our own, it is not clear that such a comparison would be fruitful.

Both analyses differ in their approach from our own in several important ways. Samir et al. used a demographic model, inputting only data from a single census or survey for each country in the year 2000, for 120 countries. They extrapolate forwards in time for observed cohorts by using a set of assumptions about differential mortality by educational attainment status after age 65. The authors do not attempt to most accurately predict the future course of attainment in unobserved cohorts, such as new cohorts of young individuals entering their model after the year 2000, using any kind of country-specific information. Instead, they have various 'scenarios' of growth that impose a mixture of global trends estimates from statistical models and expert knowledge.

Barro and Lee use 621 census and survey datasets, available over the period of 1960-2010, heaping to the closest 5th year. They also use cohort information to extrapolate, assuming no differential mortality by educational level until age 65. Where multiple imputed datapoints are available for the same year, they take a weighted average of the two points to produce a single estimate. Barro and Lee do leverage country specific information about completion ratios to estimate education for new unobserved cohorts. However, the authors do not project past the year 2010.

Both the demographic model approach undertaken by Samir KC et al. and the timeseries approach undertaken in this study and by Barro and Lee have distinct advantages. The timeseries approach allows for the use of all available data, instead of limiting the analysis to data sources available in years proximate to a single year. Given the substantial degree to which different sources of ostensibly reliable

data may disagree in details of the distribution of education, having a model that can use all available sources of information and rectify differences by assessing data uncertainty is desirable. The demographic model approach does have the advantage of producing implicitly coherent proportions; while we rely on normalization to ensure proportions add to 100%. The model allows for the direct inclusion of mortality and migration assumptions into the model. We instead model age-cohort changes with a single correction factor. It is not clear which approach is more predictive of true age-cohort patterns, but their approach is closer to representing the underlying mechanisms, and may be more versatile in assessing the importance of factors like differential mortality and migration for educational inequality.

Both previous analyses produce results only for every five years, which do not reflect the uncertainty in either their modeling processes or data. The authors also only estimate educational attainment by broad categories, which are not years of attainment, rather ISCED categories such as “Primary Attainment,” which differ from country to country in the number of years of duration. Both analyses therefore require heaping data into large bins, which limits the usability of their results. For example, they are required to make crude assumptions to calculate distributional features such as the average years of schooling, while our single-year estimates allow for the direct calculation of any distributional feature. Our approach differs in that it can input data from any available year, and therefore uses all available data in estimating trends, and produces estimates for every single year from 1950 to 2040. We also use country-specific information to forecast outside of observed cohorts, attempting to extrapolate based on the continuation of previously observed trends. Our approach also reflects the uncertainty in both data and the modeling process, and combines conflicting data sources while taking into account the data uncertainty of each source.

Limitations

Our analysis is, like any exercise in prediction, limited by data availability. Although we have at least one input data source for 194 of the 195 countries modeled in the analysis (all except Andorra), data quality and the number of available data points differs by country. Therefore, we leverage regional information to make predictions about temporal trends in many countries. Although in this way we may be missing important country-specific trends in data-sparse countries that do not follow regional patterns, no better alternative exists that leveraging all existing data and smoothing over region. Furthermore, the uncertainty intervals in data-sparse locations are larger, and likely include possible unexpected deviations. One possible exception is that our current analysis does not attempt to incorporate timeseries disjunctions or ‘shocks’ that may entail large scale differential mortality by educational status. To our knowledge no database detailing differential mortality by educational status in genocides or other mass mortality events exists, however this remains an important area for further study.

Our projections assume that trends in recent decades continue into the future. We have not attempted to leverage any expert knowledge nor have we modelled the capacity of the education system directly. We are merely projecting what we would expect is existing trends in the demographic composition by educational status continue to progress at a similar rate. It is possible that this will be unrealistic in some cases. For example, we would expect that if current trends continue, the number of individuals attaining tertiary education in China will increase dramatically in the next 25 years. However, it is possible that the tertiary education system will not be able to continue to increase capacity at the current rate, and growth will slow.

Our analysis is also simply a measurement of the quantity of education, and we cannot comment on the distribution of the quality of education. Our estimates may therefore not fully represent the fully inequality in educational attainment.

Future Directions

This analysis is in many ways the first description of educational inequality globally, and more work is required to understand important differences in the equality of educational trajectories between and within countries. Although we believe that understanding and ameliorating educational inequality is a valuable goal in its own right, it is also our hope that these estimates will allow for a better understanding of the effects of educational inequality on health. Ideally, our estimates of the distribution of education can be used to model the role of education as a risk factor in a more granular fashion, and explore how social inequality is related to inequality in health.

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