Points of convergence and divergence: Long run, between country inequality trends in health, fertility, education, and income

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NOTE TO SESSION REVIEWERS

The following research is derived from a larger, dissertation project, which I am currently condensing into a series of much shorter research papers. I will a polished, abbreviated paper prepared by the paper submission deadline this spring. Below is a portion of the methods chapter that presents some of the core finding that will be in the condense paper.

Abstract

This research introduces a generalized framework for the study of international and global inequality and suggests a theory of inequality transitions. I argue that long-run trends in inequality across a broad range of indicators share many features in common. This research offers 1) a methodological toolkit for the empirical analysis of international and global inequality studies, with particular attention to non-pecuniary measures of human well-being, 2) some of the first estimates of the worldwide *distribution* of fertility inequality in longitudinal design using a number of inequality indexes and regression convergence tests, including supplementary analysis in the health, education, and income domains, and 3) a generalized and *testable* theory of inequality transitions that explains the inequality life-cycle across remarkably different domains. I test my hypotheses using historic and contemporary national-level data for a range of outcome variables, including health, fertility, income, and education.

INEQUALITY ANALYSIS:

Now that I have provided a broad sketch of descriptive trends in education, fertility, and health, I get to the crux of the matter, that is, inequality analysis. In Table 4.8 I report longitudinal estimates of population-weighted means and a measure of inequality in all three domains. In many respects, the results I report are standard fare for an inter-country inequality study, with one exception. I report mean and inequality trends in both metric and complementary forms. For education, for example, I report trends in percent enrollment and its complement, percent not-enrolled. Fertility trends are reported for the total fertility rate and for the complement of the total fertility rate and health trends are reported for life expectancy and its complement.[1] The complementary form of fertility was generated by subtracting all national fertility rate estimates by 12.44. A total fertility rate of 12.44 is the observed population-level fertility rate in the Hutterite population and is widely believed to be a reasonable approximation of 'natural' fertility. Following Cornia and Menchini (2006), I take 100 years to be a rough approximation of maximum attainable population life expectancy and calculate the simple difference between 100 years and all national life expectancy estimates to obtain the life expectancy complement.

To those familiar with previous studies of inter-country inequality in these domains, the results will look familiar. A rising mean primary enrollment coupled with a declining degree of educational inequality is the same overall conclusion drawn by Morrisson and Murtin (2007, Table 4) in their assessment of inter-country educational inequality. Though they study a shorter time period (1870-2000) and a more expansive measure of human capital (years of schooling), they draw the same conclusion as those reported in the first two columns of Table 4.8, namely, a monotonic decline in population-weighted, between-country educational inequality. Though for a shorter time frame, Dorius (2008) documents a similar world trend in fertility inequality and the life expectancy inequality trend I report here is very similar to those reported by Firebaugh and Goesling (2004) and Nuemayer (2004). Furthermore, I get the same overall inequality trend as did Cornia and Menchini (2006) when I similarly construct the complement of life expectancy (100-LEB). The high degree of agreement between my results and those of previous studies using similar or identical outcome variables and estimation methods provides a welcome source of external validity to the analysis I present in this research. That is the good news.

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[1] While the literal meaning of the complement of fertility is somewhat dubious, I have included it in this analysis in order to a) illustrate the mathematics behind complementary variables and inequality trends and b) to remain consistent with the other variables in the analysis.

As I noted in the Methods chapter, the problem is that inequality trends of the same variables are often in direct disagreement when measured in complementary form, as is the case of education and health (see Table 4.8).[2] Figures 4.5 through 4.7 expand on the results from Table 4.8 by graphing inequality trends in all three domains using the Gini coefficient, the Theil index, and the mean log deviation. Though slightly different in the exact shape of their temporal distributions, each of the three measures of inequality agree with one another with regard to the overall trajectory of inequality in each of the three domains. Based on the trends reported in Figures 4.5 through 4.7, I stand by my previous assertion that using measures of inequality with absolutely or logically bounded variables is problematic and that the more telling and valid method for assessing inter-country convergence is to use the standard deviation.

One of the primary purposes of this research was to illustrate the risks of using formal measures of inequality to assess the degree of disproportionality in binary and proportional variables. A closer look at a few values in Table 4.8 illustrates my point. In 1990, the world mean enrollment rate was 93 percent and the Gini coefficient was .061. In 1830, the world *unenrollment* rate was 93 percent and the Gini coefficient was .061. What this illustrates is that the Gini will give consistent values for a 0,1 variable such as enrollments, so long as the values are coded in the same direction. In other words, it matters whether the distribution is entered as (.93, .07) or (.07, .93). Logically, inequality is identical for both distributions, yet for measures such as the Gini, we get different levels of inequality depending on which way the variable is coded. As we will shortly see, the standard deviation is impartial to anonymity in the sense that the variable can be coded 0,1 or 1,0 and the variance will be the same in either case.

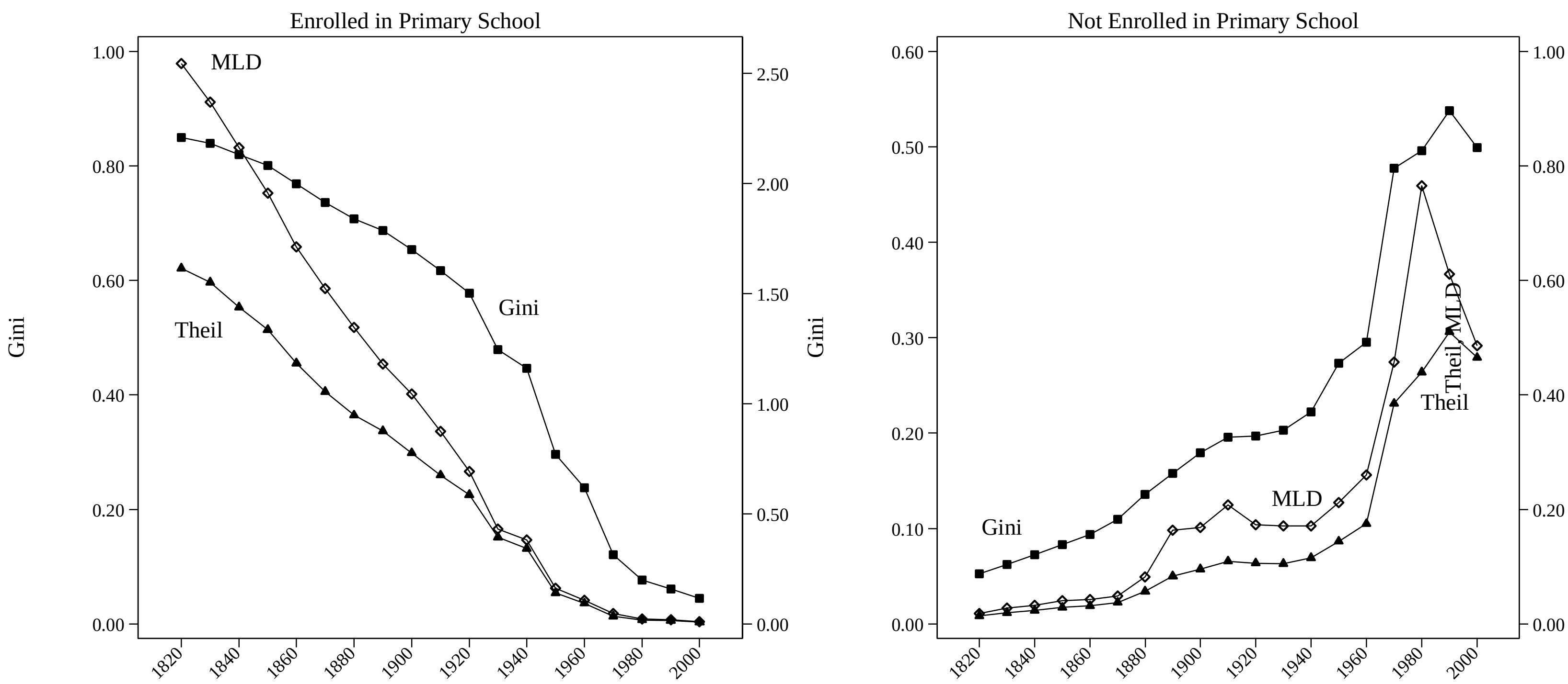
[2] The worldwide decline in fertility rates has been so significant that inequality trends in metric and complementary form yield roughly similar results.

Table 4.8 The Problem of Complements: Between-Country Trends in Health, Education, and Fertility

	Education				Fertility				Health			
	Enrolled		**Not Enrolled**		**TFR**		**(12.44 - TFR)**		**LEB**		**(100 – LEB)**	
Year	*Mean*	*Gini*	*Mean*	*Gini*	*Mean*	*Gini*	*Mean*	*Gini*	*Mean*	*Gini*	*Mean*	*Gini*
1820	5.9	.849	94.1	.053	.	.	.	.	26.5	.074	73.5	.027
1830	7.0	.839	93.0	.062	.	.	.	.	26.9	.083	73.1	.031
1840	8.2	.820	91.8	.073	.	.	.	.	27.4	.092	72.6	.035
1850	9.4	.801	90.6	.083	5.7	.086	6.7	.073	27.8	.101	72.2	.039
1860	10.9	.769	89.1	.094	5.7	.089	6.8	.075	28.3	.111	71.7	.044
1870	13.0	.736	87.0	.110	5.7	.093	6.8	.078	28.9	.121	71.1	.049
1880	16.2	.708	83.8	.136	5.7	.096	6.8	.080	29.4	.129	70.6	.054
1890	18.7	.687	81.3	.158	5.6	.103	6.8	.084	29.9	.137	70.1	.058
1900	21.6	.654	78.4	.180	5.6	.110	6.9	.089	31.4	.152	68.6	.069
1910	24.1	.617	75.9	.196	5.4	.126	7.0	.096	32.8	.166	67.2	.081
1920	25.5	.578	74.5	.197	5.3	.139	7.1	.103	35.7	.166	64.3	.092
1930	29.8	.480	70.2	.203	5.1	.169	7.3	.118	38.5	.168	61.5	.105
1940	33.7	.447	66.3	.222	5.1	.175	7.4	.120	44.4	.142	55.6	.113
1950	48.4	.297	51.6	.273	5.1	.173	7.4	.119	49.5	.132	50.5	.134
1960	57.7	.238	42.3	.295	5.0	.178	7.4	.120	54.6	.119	45.4	.136
1970	82.4	.121	17.6	.477	4.5	.206	7.9	.117	60.1	.103	39.9	.133
1980	90.8	.076	9.2	.496	3.7	.253	8.8	.106	63.3	.089	36.7	.128
1990	93.0	.061	7.0	.538	3.1	.259	9.3	.087	65.5	.084	34.5	.130
2000	94.8	.044	5.2	.499	2.7	.252	9.8	.069	67.9	.084	32.1	.145
2010	.	.	.	.	2.4	.213	10.0	.052	70.0	.076	30.0	.147
2020	.	.	.	.	2.2	.163	10.2	.036	71.9	.066	28.1	.146
2030	.	.	.	.	2.1	.118	10.4	.024	73.6	.058	26.4	.143
2040	.	.	.	.	2.0	.080	10.4	.015	75.1	.051	24.9	.140

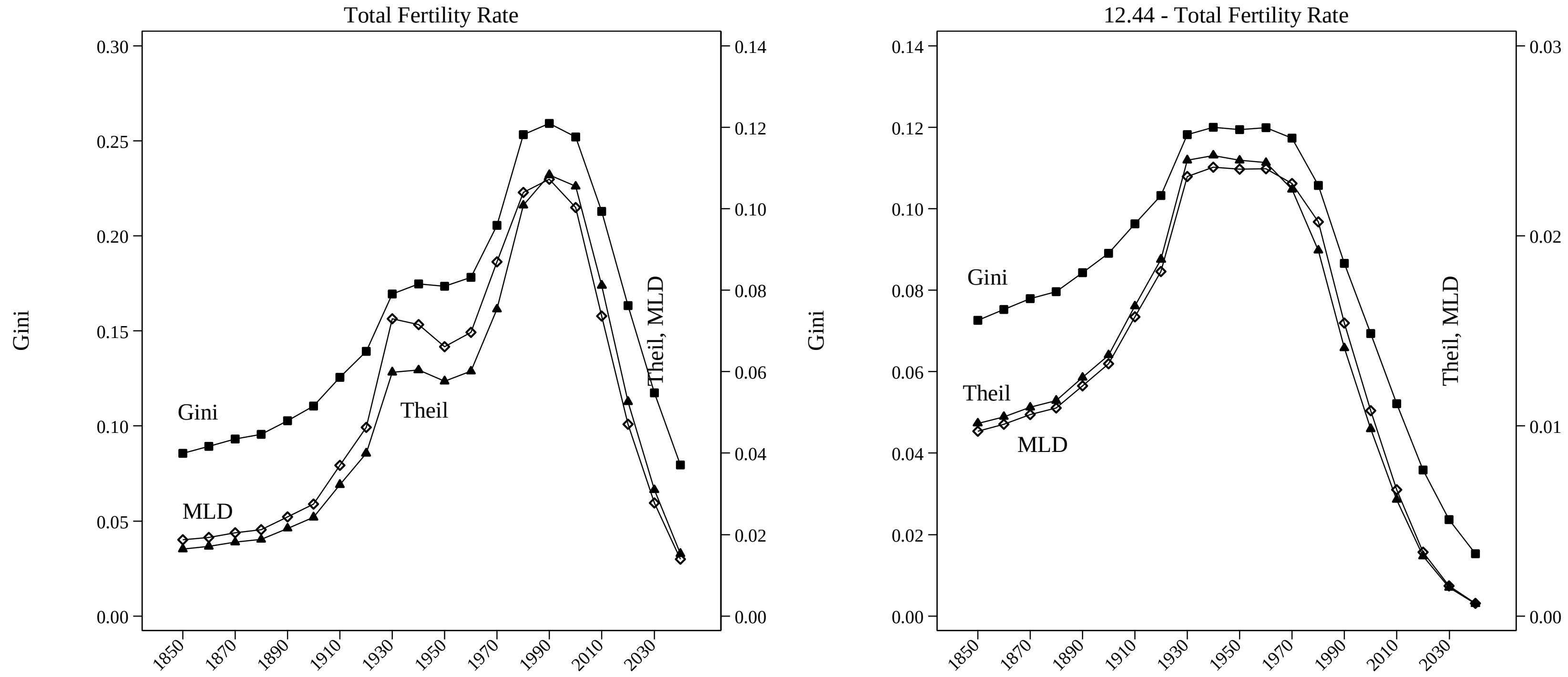
NOTES: Estimates are population-weighted and derived from author's calculations. The complement to the total fertility rate (~TFR), is based on the estimated Hutterite population (12.44).

Figure 4.5 Between-Country Educational Inequality Using Three Measures of Inequality



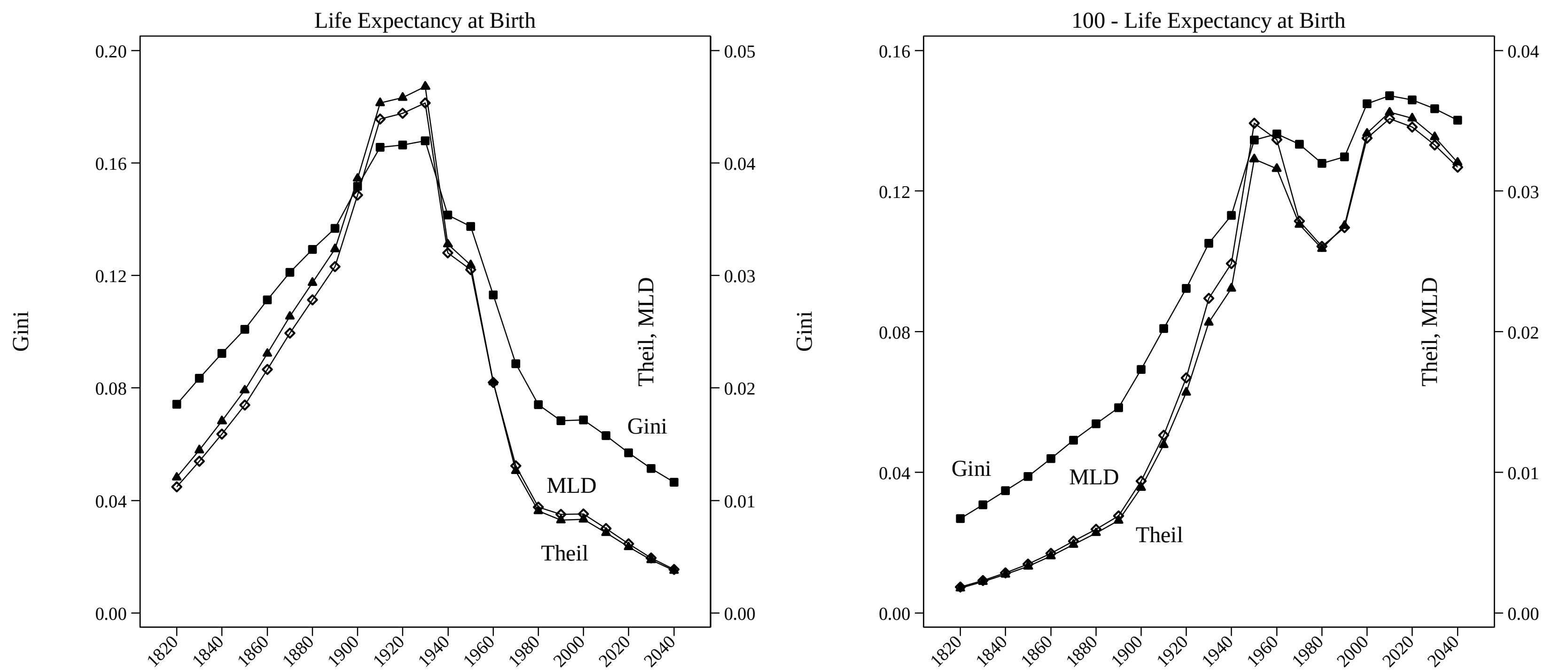
NOTES: All estimates are population-weighted and based on author's calculations.

Figure 4.6 Between-Country Fertility Inequality Using Three Measures of Inequality



NOTES: All estimates are population-weighted and based on author's calculations.

Figure 4.7 Between-Country Health Inequality Using Three Measures of Inequality



NOTES: All estimates are population-weighted and based on author's calculations.

Table 4.9 and Figures 4.8 through 4.10 report inequality trends in all three domains using the standard deviation. The table and the figures report trends for the variables in metric and complementary form. The summary result from the table and graphs, though redundant, is important to note: The inequality trends in all four domains are identical when the standard deviation is used to assess long-run convergence. This is an important methodological contribution of this research. Using the standard deviation, we have weighted a one percent increase in enrollments equally to a one percent decrease in unenrollments. Similarly, a one child decrease in fertility is equivalent to a one child increase in its complement and a one year rise in life expectancy is equivalent to a one year decline in its complement. My central methodological assertion is that convergence analysis performed on logically or absolutely bounded variables that relies on the standard deviation has a higher degree of validity than similar analysis that relies on formal measures of inequality.

The trends in Figures 4.8 through 4.10 also represent important substantive contributions to the global inequality literature. I suggest that the most important substantive conclusion to be drawn from the inequality trends documented in these three figures is that when between-country inequality is measured over the long-run so as to capture the full inequality life-cycle a clear pattern of rising and them falling inter-country inequality emerges. To be sure, inequality curves in the three domains differ in a number of important ways, but the overall shape of the curves follow a similar, inverted U-shape trajectory. One possible explanation for the broadly similarly inequality curves is that some common single, exogenous variable *X* or perhaps common vector of variables Z is responsible for the observed inequality trend.

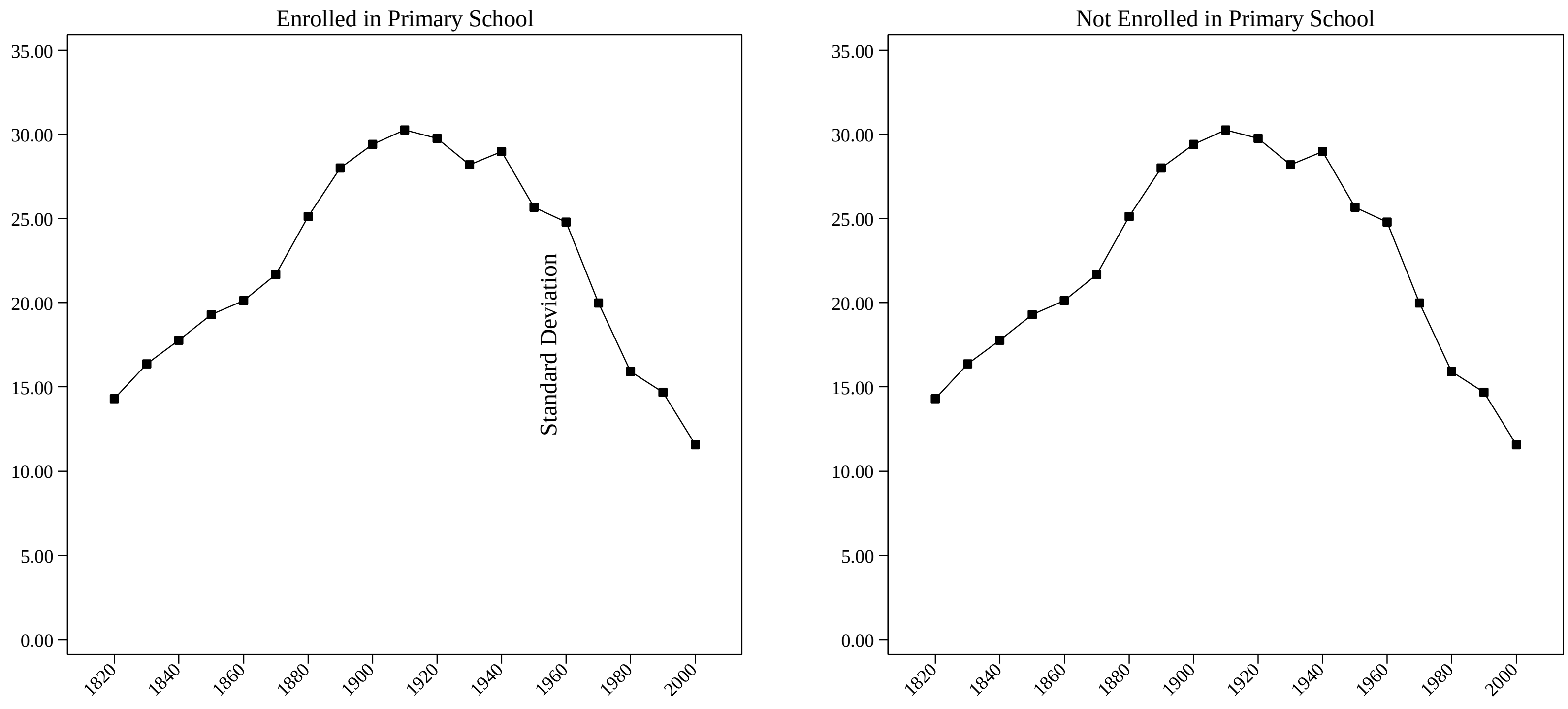
Table 4.9 Solving the Problem of Complements using the *Standard Deviation*: Between-Country Trends in Health, Education, and Fertility

	Education		Fertility		Health	
	Enrolled	**Not Enrolled**	**TFR**	**(12.44 - TFR)**	**LEB**	**(100 – LEB)**
1820	14.4	14.4	.	.	4.36	4.36
1830	16.5	16.5	.	.	4.85	4.85
1840	17.9	17.9	.	.	5.35	5.35
1850	19.4	19.4	0.99	0.99	5.85	5.85
1860	20.2	20.2	1.00	1.00	6.42	6.42
1870	21.7	21.7	1.03	1.03	6.98	6.98
1880	25.2	25.2	1.05	1.05	7.49	7.49
1890	28.0	28.0	1.11	1.11	7.99	7.99
1900	29.5	29.5	1.17	1.17	9.11	9.11
1910	30.3	30.3	1.30	1.30	10.31	10.31
1920	29.8	29.8	1.42	1.42	11.26	11.26
1930	28.2	28.2	1.65	1.65	12.29	12.29
1940	29.0	29.0	1.66	1.66	11.78	11.78
1950	25.7	25.7	1.64	1.64	12.50	12.50
1960	24.9	24.9	1.65	1.65	11.17	11.17
1970	20.0	20.0	1.68	1.68	9.45	9.45
1980	15.9	15.9	1.68	1.68	8.43	8.43
1990	14.6	14.6	1.51	1.51	8.25	8.25
2000	11.5	11.5	1.32	1.32	8.59	8.59
2010	.	.	1.07	1.07	8.21	8.21
2020	.	.	0.79	0.79	7.65	7.65
2030	.	.	0.56	0.56	7.05	7.05
2040	.	.	0.37	0.37	6.44	6.44

NOTES: Estimates are population-weighted standard deviations derived from author's calculations. The complement to the total fertility rate (~TFR), is based on the estimated Hutterite population (12.44).

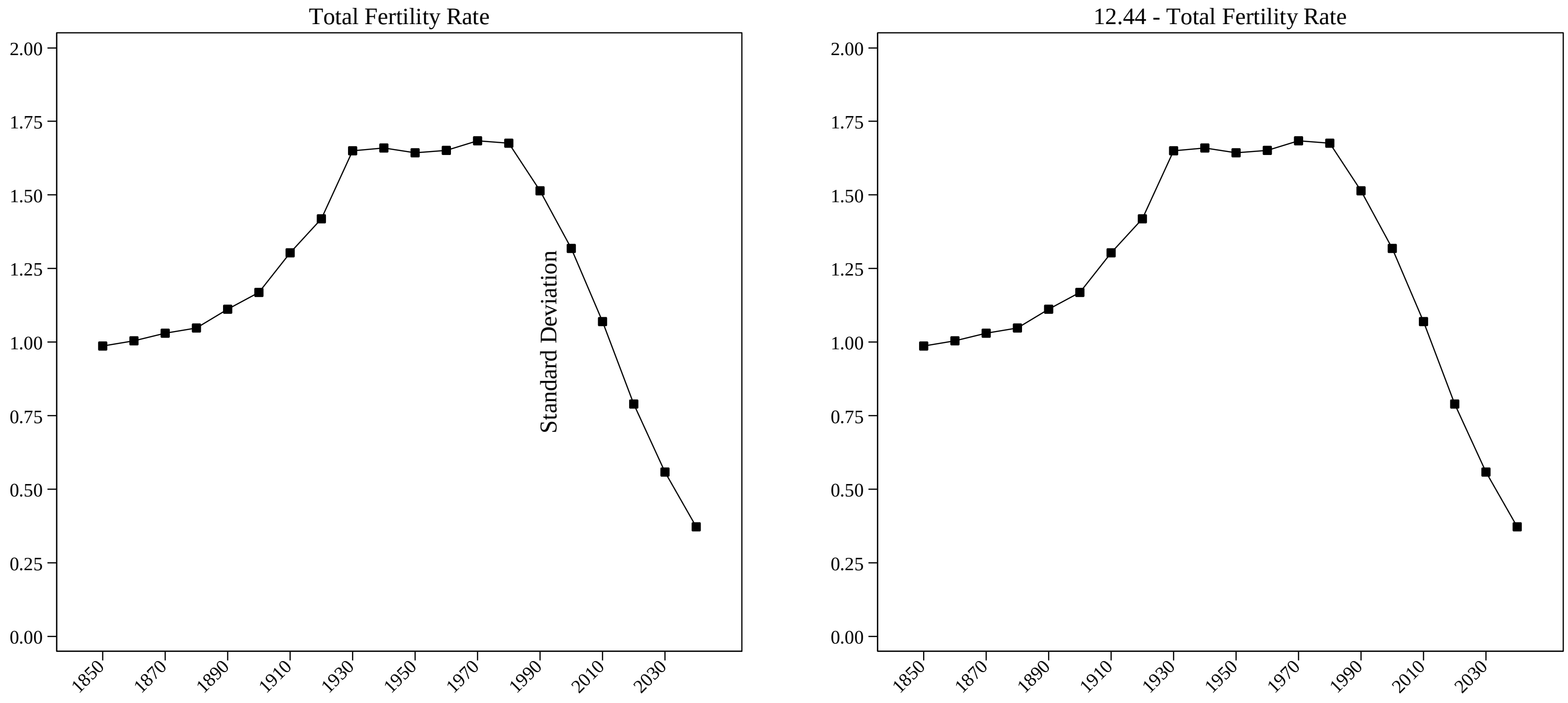
While I do not rule out the possibility of a common exogenous X or vector of Z variables, I am hesitant to agree with this conclusion for two reasons. First, the specific shape of each of the three curves is sufficiently different to call into question the common-cause hypothesis. Education and fertility inequality both had a pronounced 'crown', or peak, that spanned approximately 50 years. Health inequality, on the other hand, had a much narrower crown of only 20 years. When we compare the shape of the crowns in education and fertility, we see a relatively smooth curve in educational inequality with a true peak in 1930, while the fertility crown was virtually flat from 1930 to 1980. A second difference between the three curves can be seen in the timing of key points in the life-cycle of inter-country inequality. Educational inequality was rising at a steady rate in 1820, crowned from 1890 to 1940, and then followed a precipitous decline for the remainder of the 20^{th} century. Fertility inequality did not begin to appreciably rise until about 1900, then crowned from 1930 to 1980, after which it also entered a steep and unabated decline. Finally, health inequality rose steadily from 1820 to 1930, crowned for just two decades from 1930 to 1950 and then began a rapid decline. Unlike the other two inequality curves, however, life expectancy inequality did not monotonically decline for the entire period following peak inequality in 1950. From 1980 to 2000, the trend toward declining inequality stalled and rose slightly around 1990. And third, the overall magnitude of inequality differed considerably across the three domains. With a maximum value of 100 percent enrollment, educational inequality peaked in 1910 with a standard deviation of 30.25, which is 30 percent of the underlying educational measurement scale. Fertility inequality peaked much later (1970) with a standard deviation of 1.68, which is only 14 percent of the Hutterite ceiling of 12.44. Educational inequality peaked in 1950 at 12.50, which is less than 13 percent of the maximum of the life expectancy scale (100 years).

Figure 4.8 Between-Country Educational Inequality Using the Standard Deviation



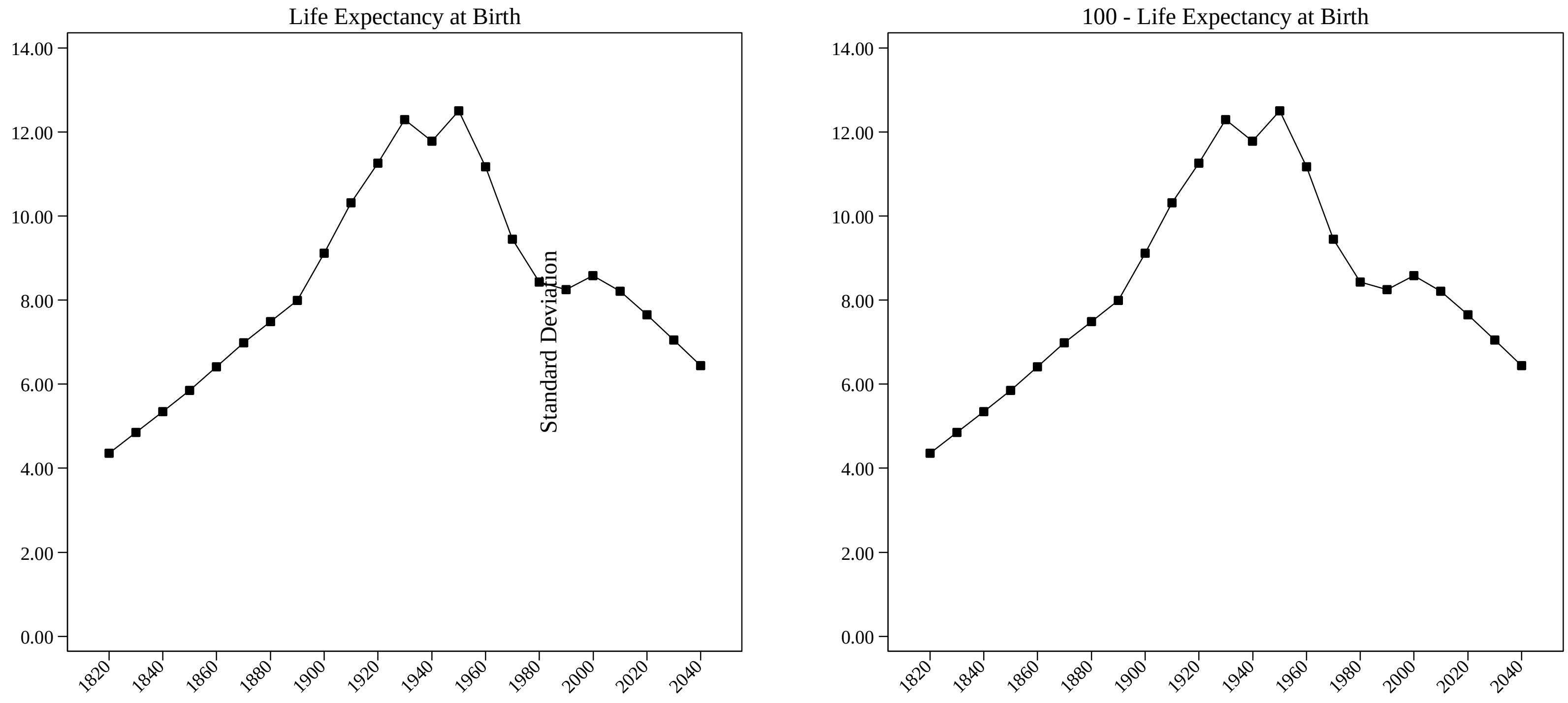
NOTES: All estimates are population-weighted and based on author's calculations.

Figure 4.9 Between-Country Fertility Inequality Using the Standard Deviation



NOTES: All estimates are population-weighted and based on author's calculations.

Figure 4.10 Between-Country Health Inequality Using the Standard Deviation

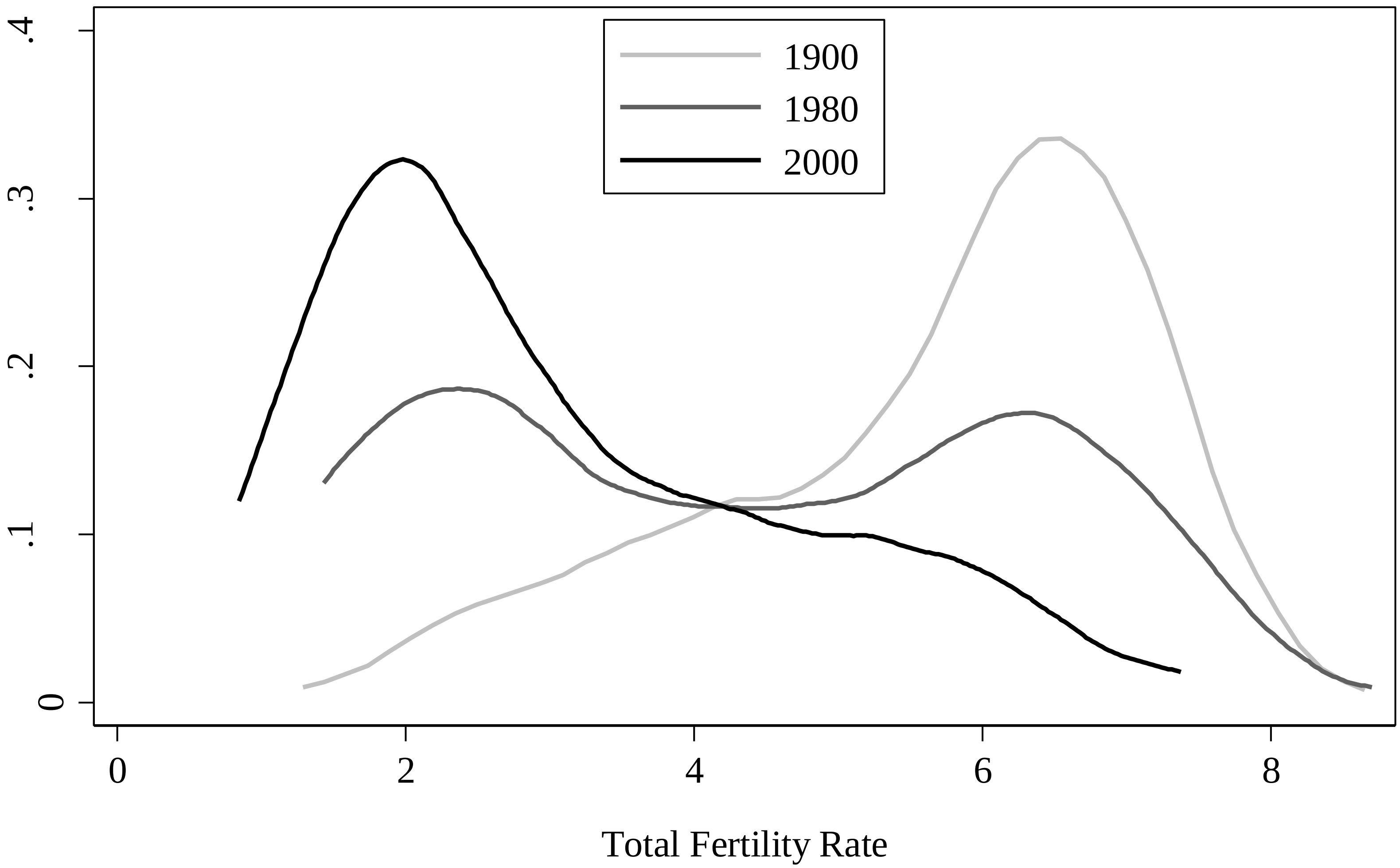


NOTES: All estimates are population-weighted and based on author's calculations.

A more plausible explanation—one that accounts for the overall similarity of the three inequality curves, yet also allows for the afore mentioned points of divergence across the three curves—is that inequality trends in each of the three domains is being effected by a similar underlying process but by different causal mechanisms. The underlying process I am referring to is diffusion, the process by which innovation spreads across borders as an ever larger share of the world's people adopt the innovation. I will spend more time discussion this idea in the next chapter, but before doing so, let us look at the education, health, and fertility distributions in a slightly different way.

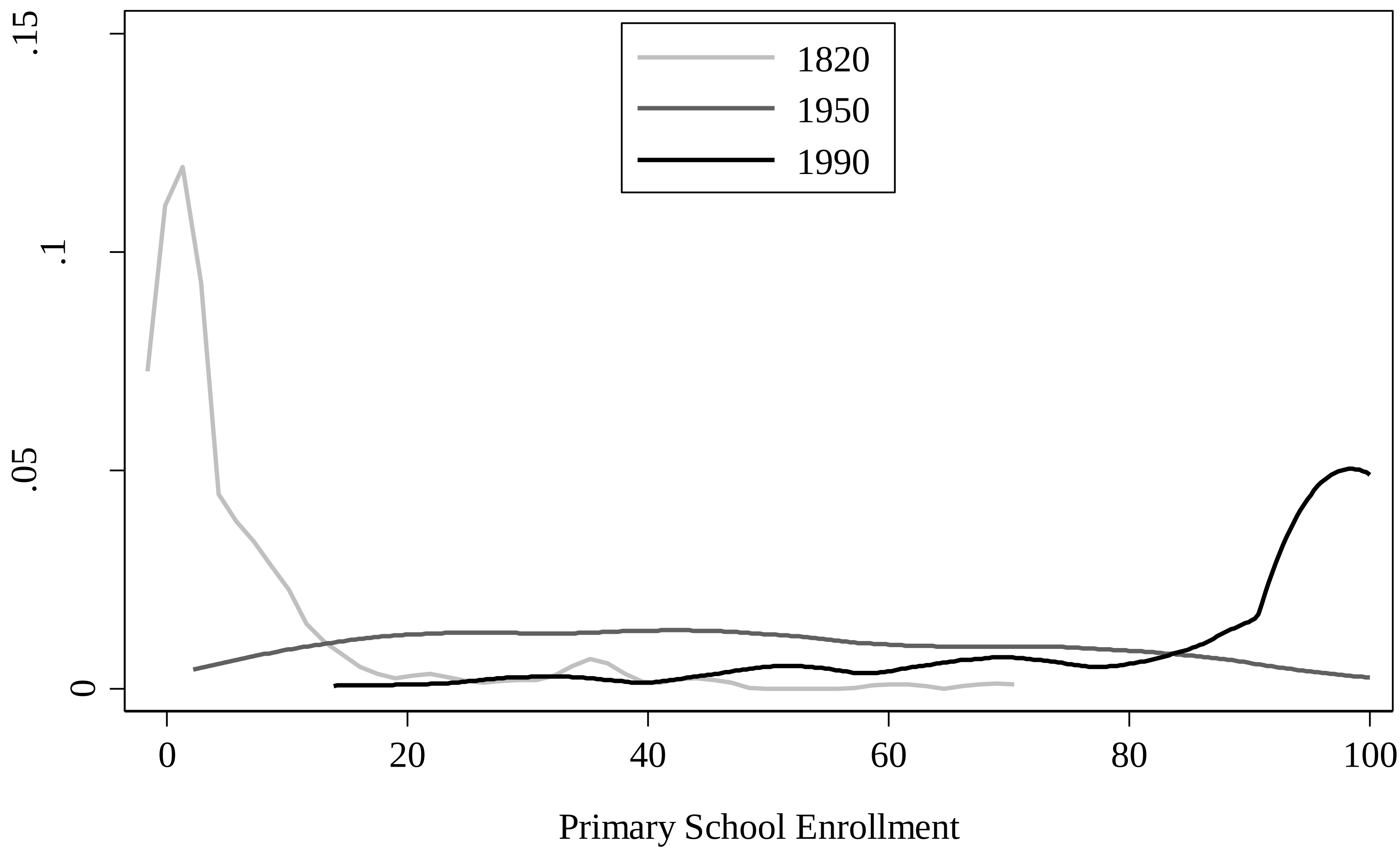
Figures 4.11 through 4.13 graph three unweighted kernel density plots for each of the three distributions. By unweighted analysis, I mean that these estimates are not adjusted for the size of country's populations. In each domain, the three density distributions represent three distinct stages in the diffusion process that correspond to periods of low, medium and high enrollments, fertility, and health. I will explain further by concentrating on the figure dealing with the world distribution of fertility (Figure 4.11), but the same general interpretation is applicable to the other two domains. In Figure 4.11 we have three density distributions that correspond to the years 1900, 1980, and 2000. These dates were selected for illustrative purposes because they correspond to periods when the mean fertility for the world was high (1900), low (2000), and somewhere in between (1980). Because fertility rates have been falling the temporal trend in the graph is from right to left (high TFR to low TFR). The 1900 fertility distribution, left-skewed and largely concentrated around fertility rates ranging from 6 to 8, reflects a world where most women were still engaged in pre-modern fertility practices characterized by high fertility rates. A moderate share of women, largely from Western nations, had already begun the transition to low fertility and this is why the distribution is left, or leader-skewed. By 1980, the world fertility distribution was wide and slightly bi-modal, with a cluster of nations hovering near replacement level fertility and another cluster stuck at pre-modern fertility rates. By 2000, the distribution had shifted markedly to the left as the majority of the world's nations and women were now within about one birth of replacement level fertility. Because a number of countries still lagged behind the world average with high fertility in 2000, the distribution is right-skewed. The sectoral shift from high to lower fertility illustrated in Figure 4.11 is the proximate determinant of the inverted U-shape of the life cycle of inter-country fertility inequality. Though the height and width of the distributions vary across all three domains, the same sector shift is clearly apparent. As the education and health distributions shifted from left to right (low to high) there was a period where the width of the distributions became very wide. This transitional 'middle' period, where the distribution widened and flattened corresponds to the period of high inter-country inequality. The left-skewed and right-skewed distributions representing the early and late stages in the diffusion process correspond to periods of relatively lower inter-country inequality.

Figure 4.11 Unweighted Kernel Density Fertility Estimates: 1850-2000



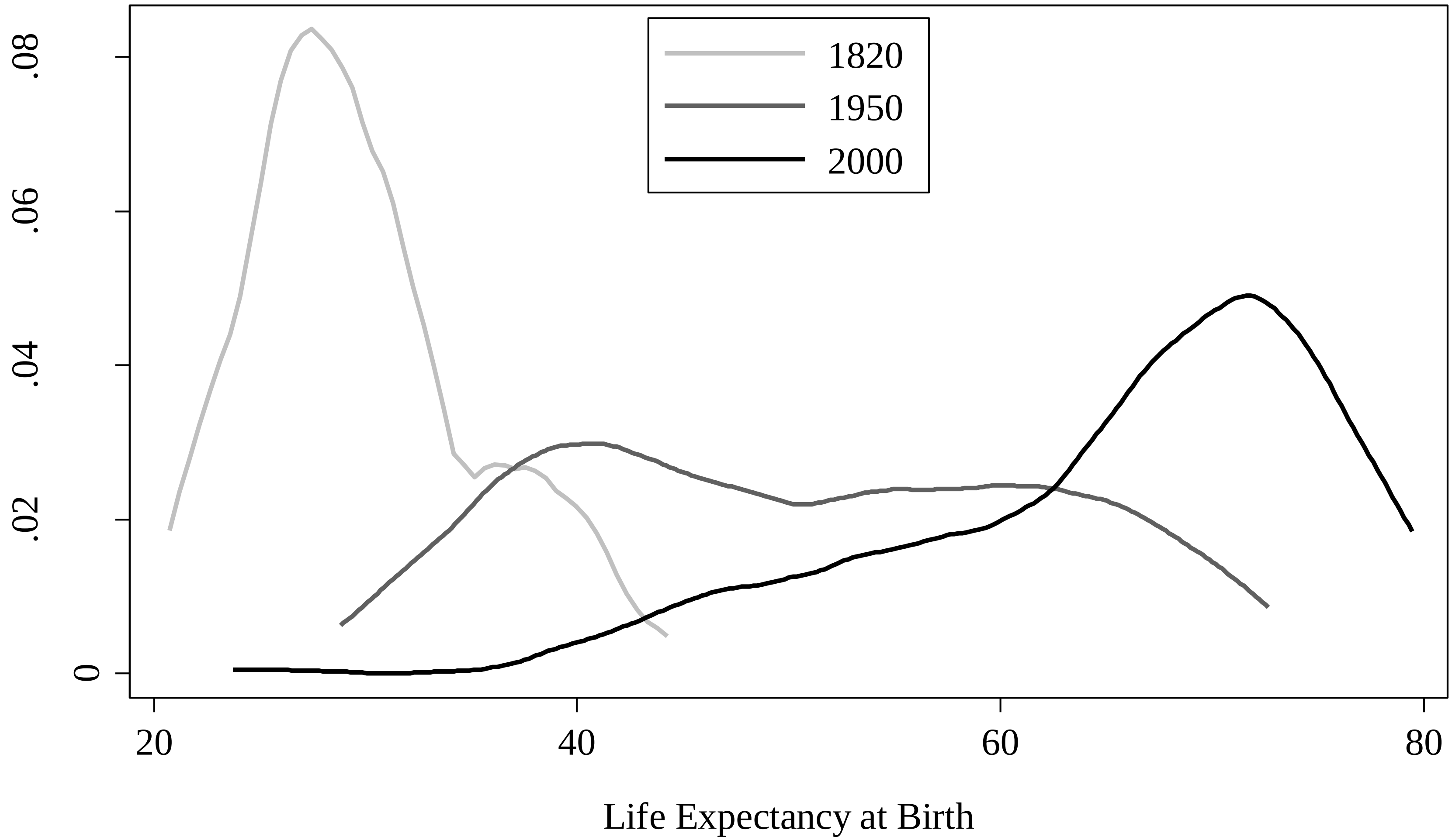
NOTES: Estimates based on author's calculations.

Figure 4.12 Unweighted Kernel Density Schooling Estimates: 1820-1990



NOTES: Estimates based on author's calculations.

Figure 4.13 Unweighted Kernel Density Health Estimates: 1820-2000



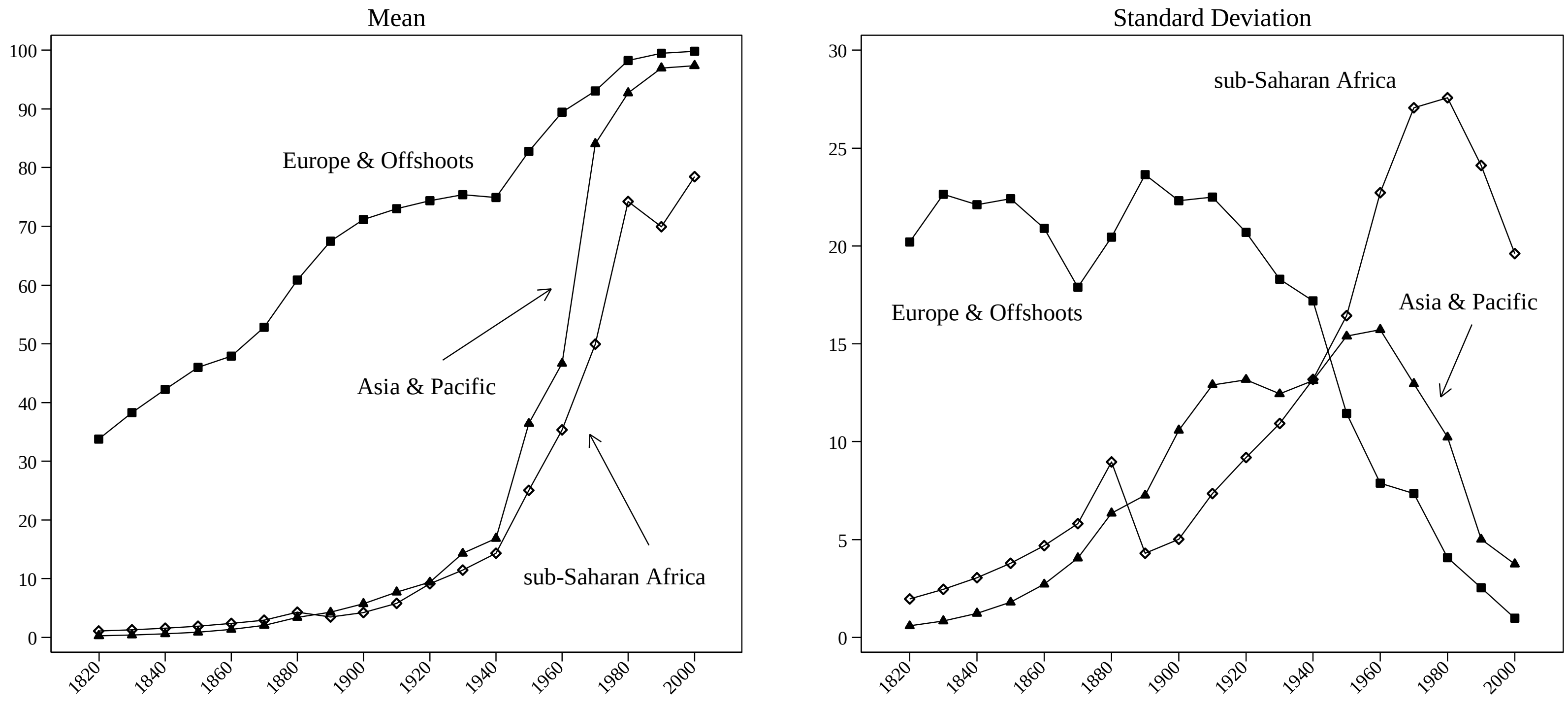
NOTES: 1820 estimates are derived from Bourguignon & Morrisson (2002). Estimates for 1950 and 2000 are derived from author's calculations of United Nations Demographic Yearbook data.

There is just one last issue to which I will draw reader's attention. In Figures 4.14 and 4.15 I reported selected regional mean enrollment and fertility trends (Tables 4.10 through 4.12 contain estimates for all regions in each of the three domains). To this point, my purpose has primarily been to illustrate the broad, world trends in educational inequality, fertility inequality, and health inequality. I will now briefly turn attention to regional inequality trends. By regional inequality, I mean the level of intra-regional inequality in population-weighted national estimates of schooling, fertility, and health.

In Figure 4.14, the population-weighted world trends in the mean and standard deviation of primary school enrollments is graphed for three regions: Europe and offshoots, Asia and Pacific island nations, and sub-Saharan Africa. I chose these regions because they represent three relatively distinct phases in the worldwide diffusion of primary schooling. Europe and offshoot nations were the first to widely implement mass education systems, followed much later by Asia, with the nations of sub-Saharan Africa being last to join the education revolution. The key point that I wish to make with the figures is that intra-regional inequality trends follow the same overall pattern that we have hitherto observed for the world as a whole. Namely, within a given world region, educational inequality was low when primary school enrollments were low, was high toward the middle of the diffusion cycle, and then low again when the regional average enrollment rate in primary schooling was approaching universal status. What is also notable about the inequality trends are the large differences in the magnitude of regional inequality. The diffusion curve of mass education in Asia was much steeper than in Africa or Europe, meaning that primary schooling enrollment began to rise throughout much of Asia at roughly the same time. Not so in Africa, where schooling spread more slowly, such that inter-country inequality peaked at a much higher value in Africa than in Asia. What is also notably about the regional inequality trends is that the rate of diffusion and, consequently, the spread of the inequality curve differs dramatically across world regions. While diffusion theory explains the overall shape of the curves for the mean and variance, it does not explain the causal mechanisms that lead some nations to adopt innovation early, and some much later. Nor can it explain why some diffusion curves are steep and others much more gradual. Educational theory and empirical analysis shed light on the mechanisms that explain the onset and expansion of mass education systems across the world's nations and people—diffusion theory only explains the overall pattern of adoption.

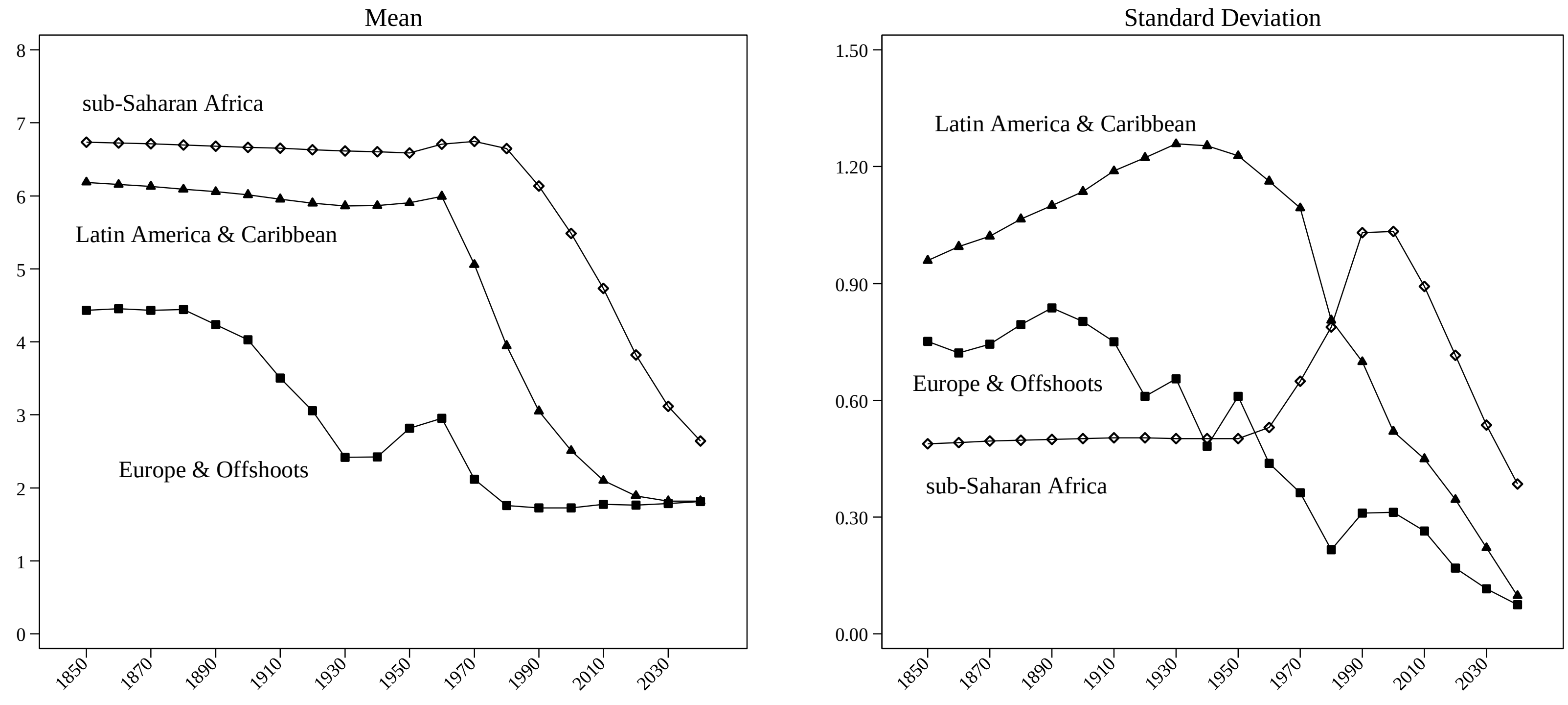
In Figure 4.15 I graph regional trends in the mean and standard deviation of the total fertility rate. The same general conclusions drawn from the trends in primary schooling enrollments hold for fertility. Namely, there is a high degree of regional variation in the onset, duration, and magnitude of intra-regional fertility inequality. The fertility inequality curve in Latin America and the Caribbean was protracted and extreme compared to the African fertility inequality curve. Region fertility inequality rose at a much steeper rate in sub-Saharan Africa, and fell much more rapidly in Latin American than in Europe. In all three regions the mean followed the S-shaped curve that is the hallmark of diffusion, and in all three regions, inequality first rose, and then fell. As is the case with rising world health inequality due to the spread of the HIV/AIDS virus in sub-Saharan Africa, so also, the post-war baby-boom that occurred in Europe and offshoot nations (and to a lesser extent in Eastern Europe) led to a brief rise in regional fertility inequality in Europe. This point is important because it illustrates that long-run inequality trends for bounded variables are not deterministic processes. Period effects and national and regional variation in conditions effecting outcome variables can lead to stalls and reversals in inequality trends.

Figure 4.14 Intercountry Trends in Primary School Enrollment



NOTES: All estimates are population-weighted and based on author's calculations. Countries with enrollements over 100 percent were recoded to 100.

Figure 4.15 Intercountry Trends in Fertility



NOTES: All estimates are population-weighted and based on author's calculations.

Table 4.10 Region Educational Inequality Trends Using the Standard Deviation: 1820-2000

Year	Europe & Offshoots	East Europe & Russia	Latin America & Caribbean	Middle East & North Africa	Asia & Pacific	sub-Saharan Africa
1820	20.20	3.82	2.69	0.16	0.58	1.97
1830	22.64	4.61	3.21	0.24	0.84	2.45
1840	22.11	5.57	3.82	0.36	1.22	3.04
1850	22.42	6.71	4.56	0.54	1.79	3.78
1860	20.89	8.08	5.50	0.80	2.71	4.69
1870	17.90	9.73	6.61	1.18	4.05	5.81
1880	20.45	11.12	8.00	1.75	6.35	8.96
1890	23.64	12.48	8.65	3.03	7.26	4.29
1900	22.31	12.12	10.15	3.49	10.58	5.01
1910	22.49	13.69	11.48	4.49	12.90	7.36
1920	20.70	13.94	13.89	4.49	13.17	9.19
1930	18.30	13.40	12.67	6.29	12.44	10.93
1940	17.29	17.74	12.46	7.75	13.12	13.18
1950	11.50	15.40	9.76	11.01	15.39	16.44
1960	8.97	13.79	14.35	15.56	15.73	22.72
1970	12.31	13.59	14.77	25.74	13.53	27.22
1980	6.91	6.51	16.74	23.89	15.13	33.05
1990	4.70	7.16	20.06	24.80	16.53	25.66
2000	3.91	3.54	19.58	20.19	11.22	23.57

NOTES: Estimates are population-weighted and derived from author's calculations.

Table 4.11 Region Fertility Inequality Trends Using the Standard Deviation: 1820-2040

Year	Europe & Offshoots	East Europe & Russia	Latin America & Caribbean	Middle East & North Africa	Asia & Pacific	sub-Saharan Africa
1850	0.75	1.81	0.96	0.67	0.37	0.49
1860	0.72	1.81	0.99	0.69	0.38	0.49
1870	0.74	1.81	1.02	0.70	0.39	0.50
1880	0.79	1.81	1.07	0.71	0.40	0.50
1890	0.84	1.80	1.10	0.72	0.40	0.50
1900	0.80	1.80	1.14	0.73	0.40	0.50
1910	0.75	1.55	1.19	0.74	0.40	0.50
1920	0.61	1.33	1.22	0.75	0.42	0.50
1930	0.65	1.13	1.26	0.75	0.50	0.50
1940	0.48	0.64	1.25	0.75	0.64	0.50
1950	0.61	0.30	1.23	0.76	0.86	0.50
1960	0.44	0.26	1.16	0.80	1.02	0.53
1970	0.36	0.19	1.09	1.12	0.89	0.65
1980	0.22	0.14	0.81	1.35	1.13	0.79
1990	0.31	0.16	0.70	1.32	0.96	1.03
2000	0.31	0.11	0.52	1.31	0.69	1.03
2010	0.26	0.08	0.45	1.02	0.42	0.89
2020	0.17	0.09	0.34	0.78	0.23	0.72
2030	0.12	0.09	0.22	0.57	0.13	0.54
2040	0.07	0.09	0.10	0.38	0.09	0.38

NOTES: Estimates are population-weighted and derived from author’s calculations.

Table 4.12 Region Health Inequality Trends Using the Standard Deviation: 1820-2040

Year	Europe & Offshoots	East Europe & Russia	Latin America & Caribbean	Middle East & North Africa	Asia & Pacific	sub-Saharan Africa
1820	4.27	1.84	0.28	0.00	2.52	1.41
1830	4.25	2.10	0.34	0.16	2.76	1.60
1840	4.22	2.37	0.39	0.33	3.00	1.80
1850	4.20	2.64	0.45	0.49	3.24	1.99
1860	4.15	2.90	0.51	0.65	3.59	2.18
1870	4.11	3.16	0.57	0.81	3.95	2.37
1880	4.07	3.42	0.64	0.97	4.29	2.55
1890	4.06	3.67	0.71	1.13	4.63	2.73
1900	3.17	3.98	2.04	1.43	4.87	2.82
1910	2.43	4.28	3.42	1.73	5.12	2.89
1920	2.54	3.92	4.13	2.11	4.97	2.65
1930	3.06	3.58	4.83	2.56	4.79	2.39
1940	2.46	1.47	4.87	2.85	4.79	3.34
1950	2.53	2.12	6.09	6.12	6.38	4.18
1960	1.42	1.72	5.38	6.50	6.58	4.62
1970	1.06	0.94	4.67	6.35	7.73	5.14
1980	1.07	1.61	4.29	5.66	6.66	5.83
1990	1.63	2.25	3.36	5.39	6.01	7.01
2000	1.22	4.07	2.98	6.21	5.68	4.31
2010	1.21	3.61	2.78	6.10	5.00	4.56
2020	1.20	3.16	2.38	5.87	4.38	4.48
2030	1.20	2.94	2.05	5.53	3.89	4.14
2040	1.21	2.79	1.78	5.13	3.53	3.67

NOTES: Estimates are population-weighted and derived from author's calculations. Life expectancy estimates prior to 1950 are drawn from Bourguignon and Morrisson (2002). Because of the high level of aggregation in the Bourguignon and Morrisson data, the regional groupings do not perfectly correspond with the regional groupings used by the United Nations.