Economics Bulletin

Volume 46, Issue 2

Measuring gender disparity in educational attainment using the relative mean deviation for 146 countries and economies over the period 1950-2015

Takahiro Akita
International University of Japan

Abstract

This study measures gender disparity in educational attainment using the relative mean deviation from 1950 to 2015, based on the Barro-Lee dataset. The relative mean deviation is proposed as an alternative to the between-gender education Gini derived from the decomposition of the education Gini by gender. Through a dynamic panel data analysis, the study demonstrates that gender disparity, as measured by the relative mean deviation, follows a U-shaped relationship with mean years of education. Gender disparity initially declines as education expands, but after reaching a minimum at an estimated mean years of education of 8.7, it begins to increase.

The author gratefully acknowledges financial support from the Japan Society for the Promotion of Science (Grant-in-Aid for Scientific Research Issue 2K01409). The author would also like to thank the anonymous reviewer for helpful comments.
Citation: Takahiro Akita, (2026) "Measuring gender disparity in educational attainment using the relative mean deviation for 146 countries and economies over the period 1950-2015", *Economics Bulletin*, Volume 46, Issue 2, pages 664-674
Contact: Takahiro Akita - akita@iuj.ac.jp.
Submitted: December 28, 2025. **Published:** June 30, 2026.

1. Introduction

The absolute gender gap in mean years of education and the male-to-female (M/F) ratio — or alternatively the female-to-male (F/M) ratio — of mean years of education have been used to measure gender disparity (or the gender gap) in educational attainment (e.g., van der Vleuten. 2016; Baten et al., 2021). However, these measures have limitations: the former does not satisfy the principle of mean independence, while the latter does not satisfy the principle of anonymity. To overcome these limitations, Akita (2025) suggested the between-gender education Gini, derived from the decomposition of the education Gini coefficient by gender, as a measure of gender disparity in educational attainment.

This study proposes the relative mean deviation as an alternative to the between-gender education Gini for measuring gender disparity in educational attainment. Like the between-gender education Gini, the relative mean deviation satisfies the principles of anonymity, mean independence, and population-size independence (Anand, 1983). The study uses the relative mean deviation to measure gender disparity in educational attainment for 146 countries and economies worldwide at five-year intervals from 1950 to 2015, based on the Barro and Lee dataset on educational attainment. It also examines the relationship between the relative mean deviation and mean years of education through a dynamic panel data analysis (Barro and Lee, 2013).

2. Measuring gender disparity in educational attainment using the relative mean deviation

Consider a country with seven levels of education: (0) no formal education, (1) incomplete primary, (2) complete primary, (3) lower secondary, (4) upper secondary, (5) incomplete tertiary, and (6) complete tertiary education. Let e_h and q_h be the cumulative years of education for *h*th level of education and the proportion of individuals who have completed *h*th level of education as their highest level, respectively. Then, mean years of education for the country is given by $\mu = \sum_{h=0}^{6} q_h e_h$, where $\sum_{h=0}^{6} q_h = 1$.

To define the relative mean deviation as a measure of gender disparity, we let p_{1h} be the proportion of females with *h*th level of education and p_{2h} the proportion of males with *h*th level of education, where $\sum_{h=0}^{6} p_{1h} = 1$ and $\sum_{h=0}^{6} p_{2h} = 1$. Then, $\mu_1 = \sum_{h=0}^{6} p_{1h} e_h$ and $\mu_2 = \sum_{h=0}^{6} p_{2h} e_h$ are the mean years of education for females and males, respectively. Using μ, μ_1, and μ_2, the relative mean deviation can be defined by

$$RD = \frac{1}{2\mu} \sum_{i=1}^{2} |\mu_i - \mu| \tag{1}$$

If we let s_1 and s_2 be the population shares of females and males, respectively, then we have $q_h = s_1 p_{1h} + s_2 p_{2h}$ where $\sum_{i=1}^{2} s_i = 1$. Consequently, we obtain

$$\mu = s_1 \mu_1 + s_2 \mu_2 \tag{2}$$

Substituting Equation (2) into Equation (1), we can modify Equation (1) as follows.

$$RD = \frac{1}{2\mu} |\mu_1 - \mu_2| \tag{3}$$

As a measure of inequality, this index satisfies several desirable properties, including the principles of anonymity, mean independence, and population-size independence.

On the other hand, Thomas et al. (2001) introduced the education Gini coefficient as an extension of the Gini coefficient used to measure income inequality. Since then, many researchers have employed the Gini coefficient to measure educational inequality.[1] Using μ, e_h, and q_h, the education Gini coefficient is defined by

$$G = \frac{1}{2\mu}\sum_{h=0}^{6}\sum_{k=0}^{6} q_h q_k |e_k - e_h| \quad (4)$$

It satisfies the principles of anonymity, mean independence and population size independence, and the Pigou-Dalton transfer principle (Anand, 1983). It ranges between zero (perfect equality) and one (perfect inequality).

Based on grouped data on educational attainment, Akita (2025) developed a method to decompose the education Gini coefficient by gender, as follows.

$$G = G_{WG} + G_{BG} + G_R, \quad (5)$$

where G_{WG}, G_{BG}, and G_R are the within-gender, between-gender and residual education Gini components, respectively. Akita (2025) suggested that the between-gender education Gini, defined as follows, can be used as a measure of gender disparity in educational attainment.

$$G_{BG} = \frac{1}{2\mu}\sum_{i=1}^{2}\sum_{j=1}^{2} s_i s_j |\mu_i - \mu_j|, \quad (6)$$

With some manipulation, Equation (6) can be rewritten as

$$G_{BG} = \frac{s_1 s_2}{\mu}|\mu_1 - \mu_2| \quad (7)$$

From Equations (3) and (7), we obtain the following relationship between the relative mean deviation and the between-gender education Gini.

$$RD = \frac{1}{2s_1 s_2} G_{BG} \quad (8)$$

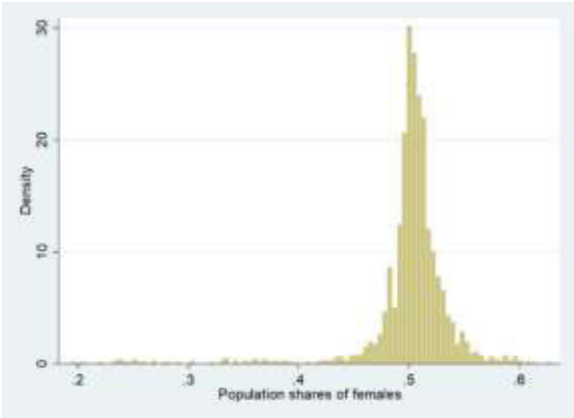
Therefore, if s_1 and s_2 are stable across countries and economies, RD can serve as an alternative measure to the between-gender education Gini derived from the decomposition of the education Gini coefficient by gender.

3. Measuring gender disparity in educational attainment for 146 countries and economies over the period 1950-2015

Based on the Barro and Lee dataset on educational attainment for individuals aged 25–64 in 146 countries and economies at five-year intervals over the period 1950–2015, we calculate the population share of females or males (Barro and Lee, 2013). Figure 1 displays the frequency distribution of the population share of females across 146 countries and economies. With the exception of some Middle Eastern countries in certain years — such as Bahrain, Kuwait, Qatar, Saudi Arabia, and the United Arab Emirates — the population share of females (s_1) ranges between 0.4 and 0.6, implying that $s_1 s_2 = s_1(1 - s_1)$ varies from 0.24 to 0.25. Therefore, according to Equation (8), the relative mean deviation should be highly positively correlated with the between-gender education Gini.

[1] See, for example, Lim and Tang (2008), Fordvari and van Leeuwen (2011), Meschi and Scervini (2014), Coady and Dizioli (2018), Lee and Lee (2018), and Castello-Climent and Domenech (2021).

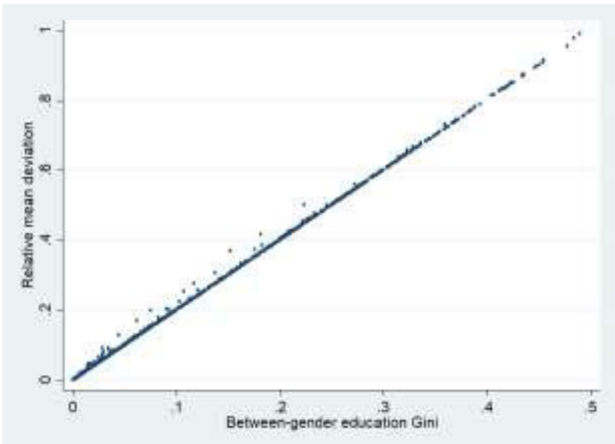
Figure 1. Population shares of females across 146 countries and economies, 1950-2015



(Source) Barro and Lee dataset on educational attainment for individuals aged 25-64 for 146 countries and economies over the period 1950-2015 (Barro and Lee, 2013).

Figure 2 exhibits the relationship between the relative mean deviation and the between-gender education Gini across 146 countries and economies over the period 1950-2015. As expected, the two variables are highly positively correlated, with a correlation coefficient of 0.999. This result indicates that the relative mean deviation, as defined in Equation (3), can be used to measure gender disparity in educational attainment.

Figure 2. Relationship between the relative mean deviation and the between-gender education Gini across 146 countries and economies, 1950-2015



(Source) Same as Figure 1.

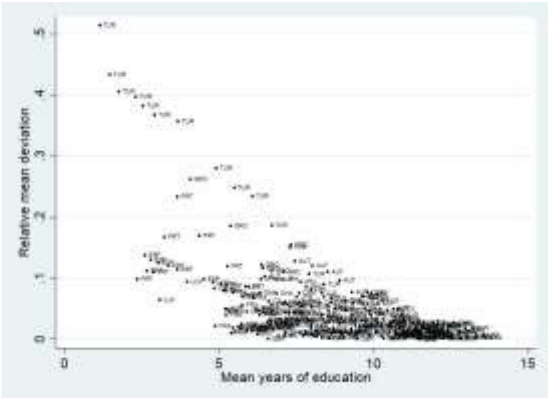
4. Relationship between the relative mean deviation and mean years of education across 146 countries and economies, 1950-2015

Following Barro and Lee (2013), 146 countries and economies are classified into seven regional groups: Advanced Economies (AE), East Asia and the Pacific (EAP), Europe and

Central Asia (ECA), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA), South Asia (SA), and Sub-Saharan Africa (SSA). Please see Table A1 in the appendix for the classification of countries and economies and their World Bank country codes.

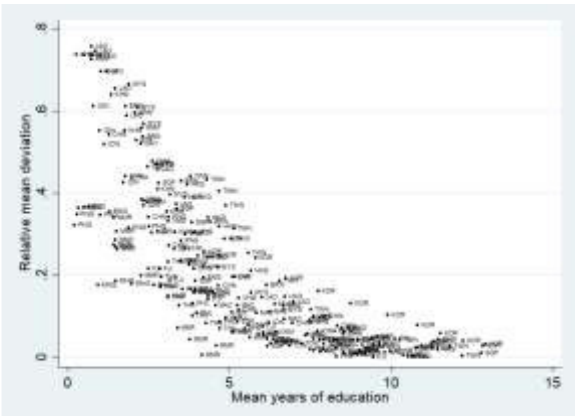
Figures 3a-3g present the relationship between the relative mean deviation and mean years of education for these seven regional groups. In all regional groups, the relative mean deviation seems to be negatively related to mean years of education, suggesting that the expansion of education tends to reduce gender disparity in educational attainment. However, each group exhibits a distinct pattern. In AE, excluding Greece, Portugal, and Turkey, the relative mean deviation was relatively small, clustering around 0–0.1, with mean years of education ranging between 5 and 14 (Figure 3a). EAP includes a wide range of countries and economies, from lower-middle-income to high-income. In EAP, a U-shaped pattern is observed: the relative mean deviation declines until mean years of education reach 10, after which it begins to rise (Figure 3b).

Figure 3a. Relationship between relative mean deviation and mean years of education for Advanced Economies (AE)



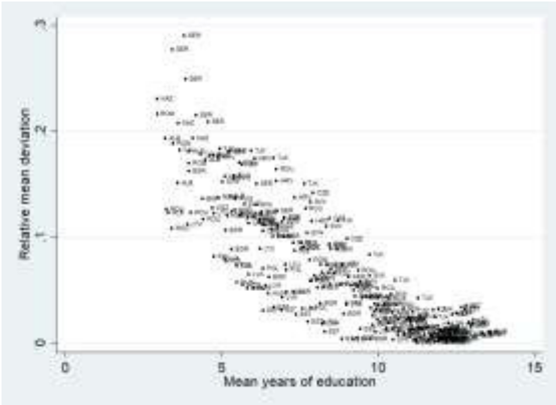
(Note) Each country is identified by its World Bank country code.
(Source) Same as Figure 1.

Figure 3b. Relationship between relative mean deviation and mean years of education for East Asia and the Pacific (EAP)



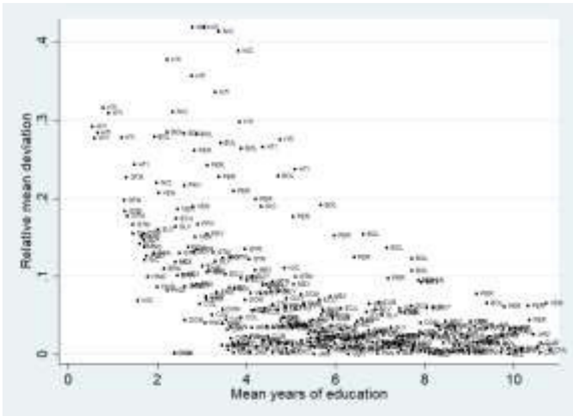
(Note) Same as Figure 3a.
(Source) Same as Figure 1.

Figure 3c. Relationship between relative mean deviation and mean years of education for Europe and Central Asia (ECA)



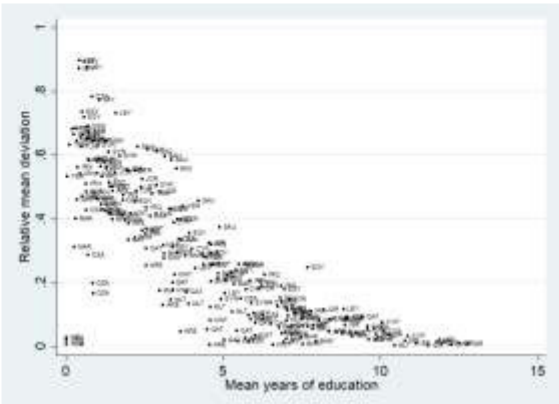
(Note) Same as Figure 3a.
(Source) Same as Figure 1.

Figure 3d. Relationship between relative mean deviation and mean years of education for Latin America and the Caribbean (LAC)



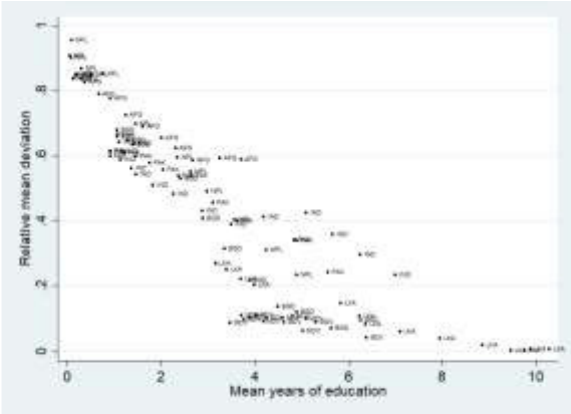
(Note) Same as Figure 3a.
(Source) Same as Figure 1.

Figure 3e. Relationship between relative mean deviation and mean years of education for Middle East and North Africa (MENA)



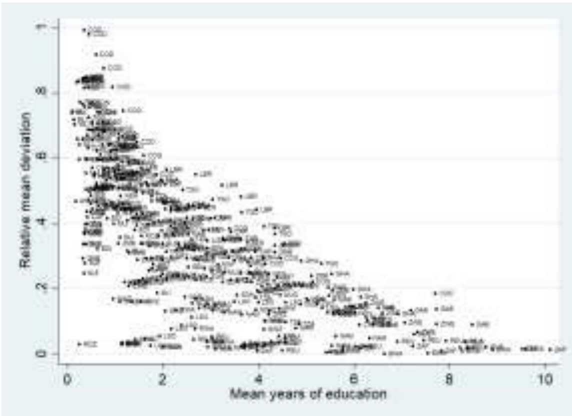
(Note) Same as Figure 3a.
(Source) Same as Figure 1.

Figure 3f. Relationship between relative mean deviation and mean years of education for South Asia (SA)



(Note) Same as Figure 3a.
(Source) Same as Figure 1.

Figure 3g. Relationship between relative mean deviation and mean years of education for Sub-Saharan Africa (SSA)



(Note) Same as Figure 3a.
(Source) Same as Figure 1.

In ECA, including former Soviet Union countries, a V-shaped pattern is observed (Figure 3c). The relative mean deviation declines steadily until mean years of education reach 12, after which it begins to rise sharply. In LAC, there appear to be two groups of countries and economies: Bolivia, Haiti, Nicaragua, and Peru form the first group, while the remaining countries and economies make up the second (Figure 3d). The first group exhibited higher levels of the relative mean deviation than the second group. In the second group, the relative mean deviation was relatively small, clustering around 0-0.1 with mean years of education ranging from 4 to 10.

MENA includes a wide range of countries and economies, from low-income to high-income. In MENA, except for Yemen in the early years, the relative mean deviation declines gradually as mean years of education increase (Figure 3e). In MENA, Libya recorded a relatively high relative mean deviation in the early years, exceeding 0.7. As in MENA, the relative mean deviation in SA declines gradually as mean years of education increase (Figure 3f). In SA, Afghanistan and Nepal recorded relatively high relative mean deviations, exceeding 0.7 in the early years. Overall, mean years of education in SA were relatively low, with Sri Lanka registering the highest in 2015 at 10.4. SSA does not include any high-income countries or economies; most countries and economies are low-income. In SSA, the relative mean deviation shows a generally declining trend (Figure 3g). However, due to the diversity of countries and economies, there were considerable variations, particularly in the early years. Like SA, mean years of education in SSA were relatively low, with South Africa recording the highest in 2015 at 10.1.

5. Relationship between the relative mean deviation and mean years of education: A dynamic panel data analysis

As shown in Figures 3a–3g, gender disparity in educational attainment, as measured by the relative mean deviation, varies considerably across countries and economies. Additionally, aggregate time-specific shocks may affect all countries and economies. To account for country-specific and time-specific effects, as well as the persistent nature of gender disparity in educational attainment over time, we conduct a two-way dynamic panel data regression analysis to examine the relationship between gender disparity in educational attainment and mean years of education, based on the following model.[2]

$$RD_{it} = \delta_1 RD_{it-1} + \delta_2 RD_{it-2} + \beta_0 + \beta_1 ME_{it} + \beta_2 ME_{it}^2 + \alpha_i + \mu_t + u_{it}. \qquad (9)$$

RD_{it} denotes the relative mean deviation for country i at time t, while RD_{it-1} and RD_{it-2} are its first-order and second-order lags ($|\delta_1| < 1$ and $|\delta_2| < 1$), respectively. ME_{it} is the mean years of education for country i at time t. To account for potential nonlinearity, we also include the squared mean years of education (ME_{it}^2). Finally, α_i and μ_t are the country- and time-specific fixed effects, respectively, while u_{it} is the usual error term. α_i represents unobservable time-invariant country heterogeneity, while μ_t denotes aggregate shocks that affect all countries.

The dynamic panel data model in Equation (9) is estimated by both the two-step difference GMM and two-step system GMM estimators (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Table 1 summarizes the descriptive statistics of the dependent and independent variables, while Table 2 presents the results of the dynamic panel data analysis.

Table 1. Descriptive statistics

Variable	No. of observations	Mean	Standard deviation	Min	Max
Relative mean deviation	2,043	0.191	0.214	0.000	0.990
Mean years of education	2,043	5.579	3.501	0.000	13.633

(Source) Barro and Lee dataset on educational attainment for individuals aged 25-64 for 146 countries and economies over the period 1950-2015 (Barro and Lee, 2013).

[2] According to the test for autocorrelation in panel data indicates that gender disparity in educational attainment, as measured by the relative mean deviation, is highly serially correlated with its own lagged terms.

Table 2. Relationship between relative mean deviation and mean years of education: A dynamic panel data regression analysis

Dependent variable = relative mean deviation

	Difference GMM estimator		System GMM estimator	
	Coefficient		Coefficient	
Relative mean deviation (-1)	0.7619	***	0.7562	***
	(0.1747)		(0.1652)	
Relative mean deviation (-2)	-0.1479	*	-0.1268	
	(0.0784)		(0.0805)	
Mean years of education	-0.0654	***	-0.0620	***
	(0.0193)		(0.0176)	
Mean years of education (squared)	0.0039	***	0.0036	***
	(0.0012)		(0.0010)	
Constant	0.2675	***	0.2635	***
	(0.0771)		(0.1412)	
Time-specific effects	Yes		Yes	
No. of observations	1,749		1,749	
Sargan test				
Chi-squared value	63.5371		74.9540	
p-value	0.4928		0.5124	
Arellano-Bond test				
AR(1) *p*-value	0.0433	**	0.0392	**
AR(2) *p*-value	0.2747		0.4388	
Mean years of education at minimum between-gender Gini	8.5		8.7	

(Note) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Values in parenthesis are robust standard errors.
(Source) Same as Table 1.

The Sargan test results are satisfactory, as all p-values are around 0.50, meaning that we cannot reject the null hypothesis that the over-identifying restrictions are valid (Sargan, 1958). The results of the Arellano-Bond test are also satisfactory since we can reject the null hypothesis of no first-order serial correlation, but cannot reject the null hypothesis of no second-order serial correlation (Arellano and Bond, 1991). The coefficient associated with the first-order lag of the dependent variable is significant with $|\hat{\delta}_1| < 1$. This result indicates the persistent nature of gender disparity in educational attainment as measured by the relative mean deviation.

The coefficients for mean years of education and its square are significant at the 1% level and have expected signs regardless of whether the model is estimated using the two-step difference or two-step system GMM estimator. In other words, the relative mean deviation follows a U-shaped pattern with the expansion of education. According to the result of the two-step system GMM estimator, the relative mean deviation reaches its minimum at an estimated 8.7 mean years of education, after which it begins to rise. This suggests that once the average education level reaches the senior secondary stage, the female-to-male (F/M) ratio of mean years of education begins to exceed one, that is, females attain higher mean years of education than males.

6. Conclusion

This study proposed the relative mean deviation as an alternative to the between-gender education Gini derived from the decomposition of the education Gini coefficient by gender. Through a dynamic panel data regression analysis, the study found that gender disparity, as measured by the relative mean deviation, follows a U-shaped relationship with mean years of education. Specifically, gender disparity initially declines as education expands, but after reaching a minimum at an estimated mean years of education of 8.7, it begins to increase. This result is consistent with the findings based on the between-gender education Gini.

The expansion of education has not been gender neutral. At low levels of education, males benefited disproportionately from educational opportunities; however, as education expanded, females caught up with males. Consequently, gender disparity in educational attainment declined, a pattern reflected in the declining portion of the relative mean deviation. However, in recent years, the expansion of education has been accompanied by a reversal of gender disparity (or gender gap) in education in favor of females in many developed countries (Esteve et al., 2012; van Bavel et al., 2018; Saadat et al., 2022). Our results — showing that females have higher mean years of education than males once the average level of education reaches the senior secondary stage — appear to reflect this recent reversal.

References

Akita, T. (2025) "Measuring Gender Disparity in the Structure of Educational Attainment in Asia based on Grouped Data" *Economics Bulletin* 45(1), 1-10.

Anand, S. (1983) *Inequality and Poverty in Malaysia: Measurement and Decomposition*, Oxford University Press: New York.

Arellano, M. and S. Bond (1991) "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations" *Review of Economic Studies* 58, 277–297.

Arellano, M. and O. Bover (1995) "Another Look at the Instrumental Variable Estimation of Error-components Models" *Journal of Econometrics* 68(1), 29–51.

Barro, R.J. and J.W. Lee (2013) "A New Data Set of Educational Attainment in the World, 1950–2010" *Journal of Development Economics* 104, 184–198.

Baten, J., M. de Haas, E. Kempter and F. M. zu Selhausen (2021) "Educational Gender Inequality in Sub-Saharan Africa: A Long-term Perspective" *Population and Development Review* 47(3), 813-849.

Blundell, R. and S. Bond (1998) "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models" *Journal of Econometrics* 87(1), 115–143.

Castello-Climent, A. and R. Domenech (2021) "Human Capital and Income Inequality Revisited" *Education Economics* 29(2), 194-212.

Coady, D. and A. Dizioli (2018) "Income Inequality and Education Revisited: Persistence, Endogeneity and Heterogeneity" *Applied Economics* 50(25), 2747–2761.

Esteve, A., J. Garcia-Roman and I. Permanyer (2012) "The Gender-gap Reversal in Education and Its Effect on Union Formation: The End of Hypergamy?" *Population and Development Review* 38(3), 535-546.

Fordvari, P. and B. van Leeuwen (2011) "Should Less Inequality in Education Lead to a More Equal Income Distribution?" *Education Economics* 19(5), 537–554.

Lee, J.W. and H. Lee (2018) "Human Capital and Income Inequality" *Journal of the Asia Pacific Economy* 23(4), 554-583.
Lim, A.S.K. and K. K. Tang (2008) "Human Capital Inequality and the Kuznets Curve" *The Developing Economies* 46(1), 26-51.
Meschi, E. and F. Scervini (2014) "Expansion of Schooling and Educational Inequality in Europe: the Educational Kuznets Curve Revisited" *Oxford Economic Papers* 66(3), 660–680.
Saadat, Z., S. Alam and M. Rehman (2022) "Review of Factors Affecting Gender Disparity in Higher Education" *Cogent Social Sciences* 8(1), 1-16.
Sargan, J. D. (1958) "The Estimation of Economic Relationships using Instrumental Variables" *Econometrica* 26(3), 393-415.
Thomas, V., Y. Wang and X. Fan (2001) "Measuring Educational Inequality: Gini Coefficient of Education" World Bank Policy Research Working Paper 2525.
van Bavel1, J., C. R. Schwartz and A. Esteve (2018) "The Reversal of the Gender Gap in Education and Its Consequences for Family Life" *Annual Review of Sociology* 44, 341-360.
van der Vleuten, L. (2016) "Mind the Gap! The Influence of Family Systems on the Gender Education Gap in Developing Countries, 1950–2005" *Economic History of Developing Regions* 31(1), 47-81.

Appendix

Table A1. Classification of countries and economies and their World Bank country codes

Advanced Economies (AE)	
Australia	AUS
Austria	AUT
Belgium	BEL
Canada	CAN
Switzerland	CHE
Germany	DEU
Denmark	DNK
Spain	ESP
Finland	FIN
France	FRA
United Kingdom	GBR
Greece	GRC
Ireland	IRL
Iceland	ISL
Italy	ITA
Japan	JPN
Luxembourg	LUX
Netherlands	NLD
Norway	NOR
New Zealand	NZL
Portugal	PRT
Sweden	SWE
Turkey	TUR
United States	USA

East Asia and the Pacific (EAP)	
Brunei	BRN
China	CHN
Fiji	FJI
China, Hong Kong	HKG

Latin America and the Caribbean (LAC)	
Argentina	ARG
Belize	BLZ
Bolivia	BOL
Brazil	BRA
Barbados	BRB
Chile	CHL
Colombia	COL
Costa Rica	CRI
Cuba	CUB
Djibouti	DOM
Ecuador	ECU
Guatemala	GTM
Guyana	GUY
Honduras	HND
Haiti	HTI
Jamaica	JAM
Mexico	MEX
Nicaragua	NIC
Panama	PAN
Peru	PER
Paraguay	PRY
El Salvador	SLV
Trinidad and Tobago	TTO
Uruguay	URY
Venezuela	VEN

Middle East and North Africa (MENA)	
United Arab Emirates	ARE
Bahrain	BHR
Cyprus	CYP

Indonesia	IDN
Cambodia	KHM
Republic of Korea	KOR
Laos	LAO
China, Macao	MAC
Myanmar	MMR
Mongolia	MNG
Malaysia	MYS
Philippines	PHL
Papua New Guinea	PNG
Singapore	SGP
Thailand	THA
Tonga	TON
Taiwan	TWN
Vietnam	VNM
Europe and Central Asia (ECA)	
Albania	ALB
Armenia	ARM
Bosnia and Herzegovina	BWA
Bulgaria	BGR
Czech Republic	CZE
Estonia	EST
Croatia	HRV
Hungary	HUN
Kazakhstan	KAZ
Kyrgyzstan	KGZ
Lithuania	LTU
Latvia	LVA
Poland	POL
Republic of Moldova	ROM
Romania	ROU
Russia	RUS
Serbia	SER
Slovakia	SVK
Slovenia	SVN
Tajikistan	TJK
Ukraine	UKR

Algeria	DZA
Egypt	EGY
Iran	IRN
Iraq	IRQ
Israel	ISR
Jordan	JOR
Kuwait	KWT
Libya	LBY
Morocco	MAR
Malta	MLT
Qatar	QAT
Saudi Arabia	SAU
Syria	SYR
Tunisia	TUN
Yemen	YEM
South Asia (SA)	
Afghanistan	AFG
Bangladesh	BGD
India	IND
Sri Lanka	LKA
Maldives	MDV
Nepal	NPL
Pakistan	PAK
Sub-Saharan Africa (SSA)	
Burundi	BDI
Benin	BEN
Central African Republic	CAF
Cote d'Ivoire	CIV
Cameroon	CMR
Congo (Kinshasa)	COD
Congo (Brazzaville)	COG
Gabon	GAB
Ghana	GHA
Gambia	GMB
Kenya	KEN
Liberia	LBR
Lesotho	LSO
Mali	MLI
Mozambique	MOZ
Mauritania	MRT
Mauritius	MUS
Malawi	MWI
Namibia	NAM
Niger	NER
Reunion	REU
Rwanda	RWA
Sudan	SDN
Senegal	SEN
Sierra Leone	SLE
Swaziland	SWZ
Togo	TGO
Tanzania	TZA
Uganda	UGA
South Africa	ZAF
Zambia	ZMB
Zimbabwe	ZWE

(Source) Barro and Lee dataset on educational attainment (Barro and Lee, 2013).