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Human genetic diversity and income inequality

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Abstract

This paper examines whether human genetic diversity is relevant to understand income inequality differences across countries. It extends the existing genetics-development studies in the literature to the relationship between genetics and inequality. The results obtained from more than 140 countries indicate a statistically significant U-shaped relationship between genetic diversity and inequality. An essential mediating factor in this relationship can be the level of trust in society. Genetic homogeneity can increase mutual support, aid, and cooperation in society. Hence, higher levels of genetic homogeneity can be associated with higher trust levels, which improves income equality. In addition, the relationship between genetics and the innovation capacity of societies can be another causal mechanism relating genetics to inequality.

Keywords: development, income inequality, genetic diversity, genetic homogeneity
JEL Classification Codes: D63, N10, N30, O15, Z10

1. Introduction

The determinants of economic development are among the main questions in economics and social sciences. In addition to the proximate causes of economic growth, such as investments, savings, trade, and foreign direct investments, the literature considers various factors such as institutions, statehood, culture, and geography as more fundamental determinants of economic development (Acemoglu et al., 2005). A relatively recent strand of literature in this context also considers the possible role of human genetics in explaining the development differences of modern economies (Spolaore and Wacziarg, 2009; Ang and Kumar, 2014). In an important study on the economic effects of genetics, Ashraf and Galor (2013) argue that genetic diversity

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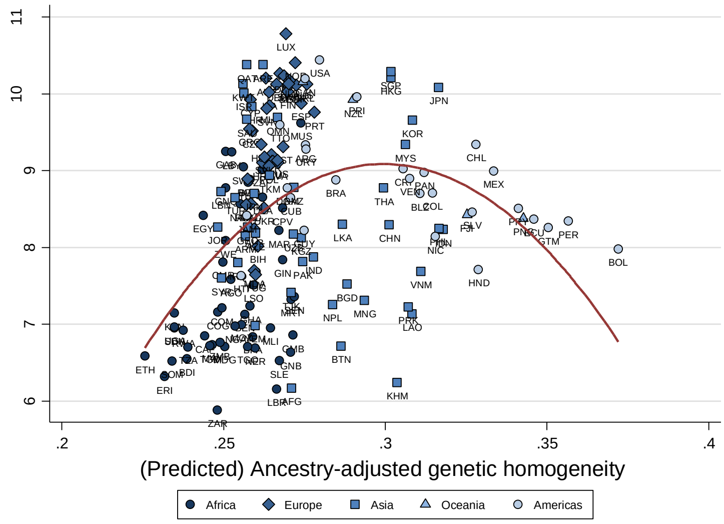
can create an inverse U-shaped impact on economic development as genetic homogeneity can support trust in society, while genetic diversity would be helpful for innovation. This case is illustrated in Figure 1, where the relevant data are obtained from Ashraf and Galor (2013). The y-axis shows the log GDP per capita levels in 2000, while the x-axis shows a measure of genetic homogeneity. The quadratic fit line shows a clear inverse U-shape in the relationship between development and human genetics.

Figure 1. Genetic diversity and economic development



Source: Ashraf and Galor (2013).

The present paper argues that the role of human genetics can be extended to the topic of income inequality. There is already a large body of literature examining the relationship between development and inequality, starting from the seminal work of Kuznets (1955). While the shape of the development-inequality nexus is not very clear, relevant studies generally find strong causal relationships between these two variables (Piketty, 2006). There are also studies looking at the genetics-inequality relationship from different perspectives. For example, Meisenberg (2008) investigates the association between racial diversity and income inequality through the impact of racial diversity on increased variance in intellectual ability in the population and less solidarity in society. The author examines the case of more than 130 firms and finds evidence for the channel from racial diversity to less solidarity. In a relevant paper, Selita and Kovas (2019) show that the gene-inequality relationship can be important for the heritability of educational outcomes. A very recent paper by Houmark et al. (2024) also shows that genetics play an important role in skill formation and family investments in children. A more relevant paper to the present study is Amini and Jogani (2023). In this paper, the authors examine the relationship between patrilineal genetic diversity (as proxied by the genetic distance between Y-DNA haplogroups in a country) for more than 120 countries. The construction of this genetic diversity index is a novel contribution of the authors. Their results show a statistically significant effect of this genetic diversity on income inequality. While these papers provide important evidence on the gene inequality index, they do not examine the possibility of a nonlinear relationship in this nexus. Specifically, they do not consider the possibility that genetic diversity can increase innovation and creativity. In addition, they do not control for macroeconomic factors in the empirical analysis. Hence, our study extends the existing literature by looking at the nonlinear relationship in the gene-inequality nexus after controlling the major macroeconomic indicators.

We combine the genetics dataset of Ashraf and Galor (2013) with the inequality dataset of Solt (2016) and the macroeconomic factors from the World Development Indicators database of the World Bank (2023). Our results show a statistically significant U-shaped relationship between genetic diversity/homogeneity and inequality. Namely, rising genetic diversity is initially associated with declining inequality levels, whereas higher genetic diversity after a threshold is related to increasing inequality levels. Regarding the causal mechanisms of this genetics-inequality relationship, the same channels as those of Ashraf and Galor (2013) can be at play. Specifically, genetic homogeneity can increase mutual support, aid, and trust in society, in return improving economic equality. However, rising genetic diversity levels would be useful for innovation and development as well. The role of human genetics in development can also be connected to historical studies such as the Muqaddimah of Ibn Khaldun (2015[1337]). In this important work, Khaldun argues that blood relationship is at the root of "asabiyah", which is translated as "group feeling". In return, a broader concept of asabiyah is argued as the root cause of social, economic, and political development by Ibn Khaldun (2015[1337]). Specifically, Khaldun (2015[1337], p.172) argues that "Compassion and affection for one's blood relations and relatives exist in human nature as something God put into the hearts of men. It makes for mutual support and aid, and increases the fear felt by the enemy." Hence, these arguments also support the mutual support, aid, and trust dimensions of genetics.

2. Data and methods

The main variables on the genetic diversity of countries are directly obtained from Ashraf and Galor (2013). Genetic diversity relies on the 'expected heterozygosity', which is defined as "the probability that two individuals, selected at random from the relevant population, differ genetically from one another with respect to a given spectrum of traits" (Ashraf and Galor, 2013, p.4). The data on the heterozygosity is available for 53 ethnic groups from the database of the Human Genome Diversity Cell Line Panel. Ashraf and Galor (2013) use this 'observed' genetic diversity for ethnic groups and the migratory distance from East Africa to create 'predicted' genetic diversity for modern countries. Then, this index is adjusted using ancestry weights for the shares of the year 2000 population that can be traced back to their ancestral origins in different source countries in the year 1500. So, this is the first genetic diversity indicator used in the present study, i.e., 'predicted genetic diversity (ancestry adjusted)'. In another relevant variable, i.e., 'mobility index-predicted genetic diversity (ancestry adjusted)' the predicted genetic diversity is adjusted using the mobility index that measures optimal land-restricted routes for the spread of populations from East Africa. Finally, the third indicator looks at 'predicted genetic homogeneity (ancestry adjusted)', which is defined as one minus the genetic diversity.

The dependent variable of income inequality is obtained from the Standardized World Income Inequality Database (SWIID) of Solt (2016). The relevant variables used in the empirical analysis are summarised in Table 1. To avoid the impact of a specific year on the results, macroeconomic variables, including the inequality indicator of Gini, are estimated as the averages for the 2001-2020 period. Regarding human genetics, three leading indicators from Ashraf and Galor (2013) are utilized. These measures are predicted genetic diversity, mobility index-predicted genetic diversity, and predicted genetic homogeneity. All these three indicators are adjusted for ancestry effects.

The empirical analysis also includes control variables for the leading determinants of inequality following the relevant literature (Kus, 2012; Furceri and Ostry, 2019). In this context, the table includes macroeconomic variables of GDP growth, unemployment, female labour force participation (LFP), trade ratio, financial development (as measured by the ratio of banking credits to GDP), and inflation as control variables. Among these variables, the literature argues that unemployment and female labour force participation can be associated with higher inequality, while the impact of international trade would depend on the comparative advantages and resource abundance of countries. The impact of financial development on inequality is widely studied in the literature, with mixed results on this effect (Chletsos and Sintos, 2023), while inflation is generally found to increase inequality (Sintos, 2023). As another important control variable, the table also includes the ethnic fractionalization variable from Ashraf and Galor (2013). Table 1 shows that the Gini indicator and the macroeconomic control variables are included as the averages for the 2001-2020 period in order to avoid the idiosyncratic behaviour of the variables in specific years.

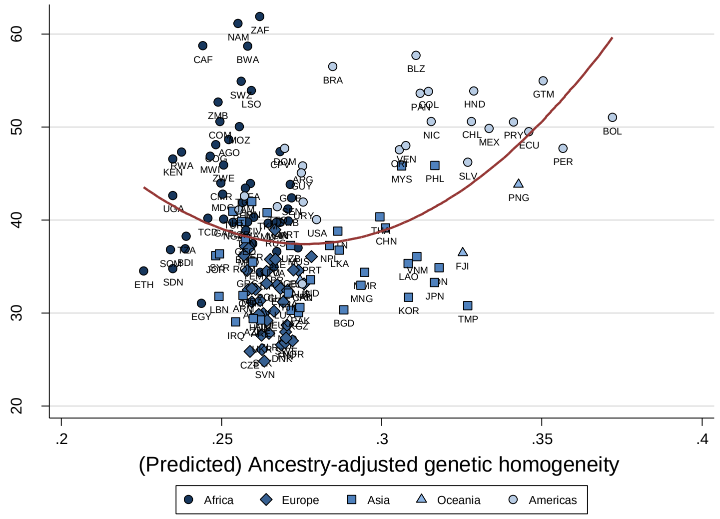
Table 1. Summary statistics

	Obs	Mean	Std.Dev.	Min	Max
Gini (Disposable Income) (2001-2020)	147	39.462	8.502	24.18	66.382
Predicted Genetic Diversity (ancestry adjusted)	147	.727	.027	.628	.774
Mobility Index-Predicted Genetic Diversity (ancestry adjusted)	121	.722	.029	.618	.783
Predicted Genetic Homogeneity (ancestry adjusted)	147	.273	.027	.226	.372
GDP Growth (2001-2020)	147	3.625	2.023	-.919	9.387
Unemployment (2001-2020)	147	7.88	5.641	.457	29.464
Female LFP (2001-2020)	147	50.438	15.304	11.78	84.013
Trade Ratio (2001-2020)	147	86.811	53.581	21.574	364.297
Bank Credit/GDP (2001-2020)	145	48.007	39.519	4.945	188.549
Inflation (2001-2020)	144	6.327	9.442	.138	75.609
Ethnic Fractionalization	147	.446	.252	0	.93

Source: Ashraf and Galor (2013); Solt (2016); World Bank (2023).

Before moving to the empirical analysis, Figure 2 presents the scatter plot between the predicted genetic homogeneity and income inequality, following the same convention of Ashraf and Galor (2013). A U-shaped relationship is observed in the graph. Namely, for very low levels of predicted genetic homogeneity, the inequality level is relatively high. When predicted homogeneity increases, inequality declines. However, as genetic homogeneity increases further, the graph shows that inequality starts to increase as well.

Figure 2. Genetic diversity and income inequality



Source: Ashraf and Galor (2013).

To see whether the U-shaped relationship observed in Figure 2 is statistically significant, the following regression model is estimated using the OLS technique, which is very similar to the methodology of Ashraf and Galor (2013):

$$Inequality_i = \alpha + \beta_1 Genetics_i + \beta_2 Genetics_i^2 + \gamma Controls_i + \varepsilon_i \qquad (1)$$

In the above equation, countries are represented by i, and a cross-country analysis is conducted. The relevant genetics indicators are assumed to have both linear and quadratic terms that would encompass a nonlinear relationship between inequality and genetic homogeneity/diversity.

3. Results

Table 2 presents the regression results for the relationship between genetic homogeneity and inequality. The first column only includes the genetic measure as the independent variable and does not find a statistically significant regression coefficient. Then, the second column includes the quadratic term, and it is found that both the linear term and the quadratic term are statistically significant at the 1% level. The negative sign of the linear term and the positive sign of the quadrative term imply a U-shaped relationship between inequality and genetic homogeneity. In the following columns from (2) to (6), the relevant control variables are added in a stepwise fashion. When the macroeconomic variables are included initially, the linear and quadratic terms of genetic homogeneity do not display major changes in their sizes and maintain the same signs. The signs and statistical significances are retained when the control variables on credit, inflation, and ethnic fractionalization are added; however, both coefficient sizes decline in absolute value. The results are still economically significant, as well, as discussed in the following parts.

Table 2. Regression results for genetic homogeneity and inequality

	Dependent Variable: Gini Measure					
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Genetic Homogeneity	35.34 (25.81)	-1,499*** (401.7)	-1,417*** (389.3)	-1,169*** (395.2)	-853.8** (408.3)	-765.7* (402.4)
(Predicted Genetic Homogeneity)^2		2,634*** (688.3)	2,540*** (666.8)	2,128*** (675.8)	1,600** (696.3)	1,455** (686.1)
GDP Growth			0.835** (0.338)	0.811** (0.333)	0.486 (0.366)	0.427 (0.361)
Unemployment			0.402*** (0.126)	0.469*** (0.131)	0.430*** (0.128)	0.449*** (0.126)
Female LFP				0.0575 (0.0452)	0.0549 (0.0444)	0.0385 (0.0441)
Trade Ratio				-0.0273** (0.0123)	-0.00957 (0.0126)	-0.00939 (0.0124)
Credit Ratio					-0.0708*** (0.0203)	-0.0520** (0.0213)
Inflation					0.00482 (0.0692)	0.0110 (0.0680)
Ethnic Fractionalization						6.943** (2.819)
Constant	29.80*** (7.091)	250.4*** (58.06)	229.0*** (56.50)	191.3*** (57.44)	148.5** (59.08)	132.2** (58.38)
Observations	147	147	147	147	144	144
R-squared	0.013	0.104	0.177	0.215	0.303	0.333

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: Based on data from Ashraf and Galor (2013); Solt (2016); World Bank (2023).

To check whether the results are robust to the selection of specific measures of human genetics, Table 3 estimates the full regression specification for the three leading genetic indicators of Ashraf and Galor (2013). In addition to the predicted genetic homogeneity, the authors also use two other indicators in their analysis, which are predicted genetic diversity adjusted for ancestry effects and the mobility index-predicted genetic heterogeneity adjusted for ancestry effects. Table 3 presents the regression result for these three different genetic indicators for the full regression specification. In all specifications, the linear term has a negative sign, and the quadratic term has a positive sign, implying a U-shaped relationship between inequality and genetic diversity/homogeneity. Hence, these regression results imply that as genetic homogeneity/diversity increases, inequality first declines and then increases after a threshold.

Table 3. Regression results for different genetic measures

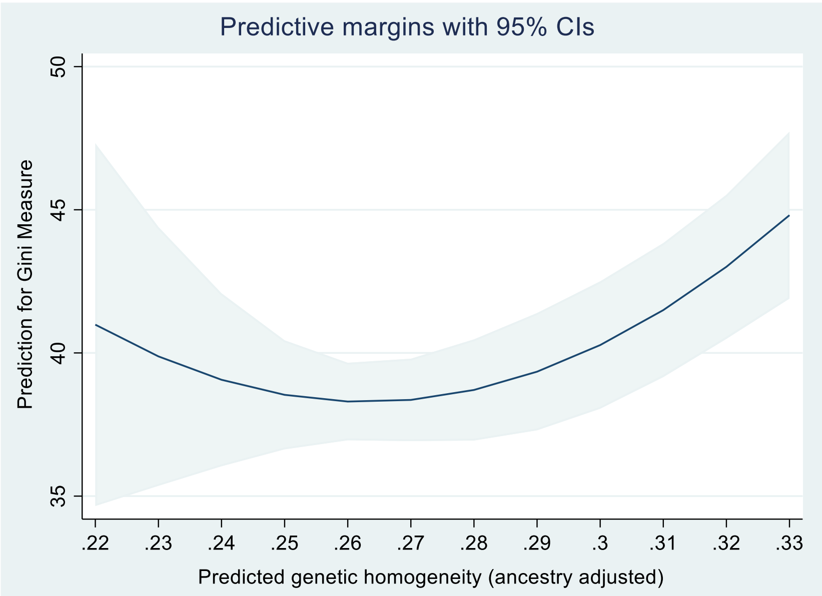
	Dependent Var: Gini Measure		
	(1)	(2)	(3)
(Predicted Genetic Diversity)	-2,145**		
	(970.8)		
(Predicted Genetic Diversity)^2	1,455**		
	(686.1)		
(Mobility Index-Predicted Genetic Diversity)		-1,461*	
		(745.1)	
(Mobility Index-Predicted Genetic Diversity)^2		973.8*	
		(528.1)	
(Predicted Genetic Homogeneity)			-765.7*
			(402.4)
(Predicted Genetic Homogeneity)^2			1,455**
			(686.1)
GDP Growth	0.427	0.502	0.427
	(0.361)	(0.387)	(0.361)
Unemployment	0.449***	0.523***	0.449***
	(0.126)	(0.130)	(0.126)
Female LFP	0.0385	0.0445	0.0385
	(0.0441)	(0.0461)	(0.0441)
Trade Ratio	-0.00939	-0.0399**	-0.00939
	(0.0124)	(0.0178)	(0.0124)
Credit/GDP	-0.0520**	-0.0391	-0.0520**
	(0.0213)	(0.0256)	(0.0213)
Inflation	0.0110	0.0178	0.0110
	(0.0680)	(0.0682)	(0.0680)
Ethnic Fractionalization	6.943**	9.320***	6.943**
	(2.819)	(3.081)	(2.819)
Constant	821.8**	577.9**	132.2**
	(342.7)	(262.2)	(58.38)
Observations	144	118	144
R-squared	0.333	0.364	0.333

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Based on data from Ashraf and Galor (2013); Solt (2016); World Bank (2023).

Regarding the causal mechanisms behind this U-shaped relationship between genetics and inequality, the proposed mechanisms of Ashraf and Galor (2013) can be considered to be relevant in the present case, as well. For example, as genetic homogeneity increases, the trust level, along with compassion and affection, in society also increases. Therefore, genetic homogeneity could support equality in an economy, and there are studies in the literature showing this positive association between economic equality and trust (Barone and Mocetti, 2016; Jordahl, 2017). However, as genetic homogeneity increases further (or genetic diversity declines), innovative capacity would decrease, thereby affecting economic development negatively. While these channels provide possible causal explanations for the U-shaped relationship (as shown by Ashraf and Galor (2013)), detailed analyses would be needed to establish them more firmly.

The results in Tables 2 and 3 provide evidence of the robustness and statistical significance of the nonlinear relationship between genetics and income inequality. It would also be informative to see the economic impact of these statistical results. In this context, Figure 3 shows the linear predictions of the Gini measure based on the mean values of the independent variables. Namely, the regression coefficients in the last column of Table 2 (or Table 3) are used with the mean values of the dependent variables from Table 1 to produce a linear prediction for the dependent variable of the Gini indicator. Then, the delta method is utilized to see how this prediction changes when the genetic indicator varies, holding other variables fixed at their mean values. The analysis also computes the 95% confidence intervals (CIs) for these predictions. Then, these linear predictions are used to produce a graph on the relationship between inequality and genetic homogeneity in Figure 3.

Figure 3. Predicted impact of genetic homogeneity on inequality



Source: Based on the last column of Table 3.

It is seen that as the predicted homogeneity moves from 0.22 (mean – 2*standard deviation) to 0.27 (the mean value), the predicted Gini level declines from around 0.41 to 0.38. However, as the predicted homogeneity increases from 0.27 to 0.33 (mean + 2*standard deviation), the predicted Gini level increases from 0.38 to 0.45. Hence, these movements are in the magnitudes of 3 and 7 points. Table 1 shows that the standard deviation of the Gini variable is 8.5; therefore, these changes imply the economically significant effects of human genetics on income inequality.

4. Concluding remarks

A new strand of economics literature provides evidence of the role of human genetics in certain economic outcomes such as technology transfer and economic development. These papers, as well as the present paper, do not imply that genetic properties directly affect economic outcomes. However, there can be underlying associated factors, such as trust and innovation, that can mediate the impact of genetics on economics. In this context, the present paper has examined the role of human genetics in explaining income inequality. The relevant empirical results show that genetic homogeneity and diversity are related to income inequality in a U-shape. Namely, as genetic homogeneity increases, inequality declines first but increases after a certain threshold of homogeneity. An important mediating factor in this relationship can be the level of trust in society. Genetic homogeneity can increase mutual support, aid, and cooperation in society. Hence, higher levels of genetic homogeneity can be associated with higher trust levels, which improves income equality. In addition, the relationship between genetics and the innovation capacity of societies, as articulated by Ashraf and Galor (2013), can be another causal mechanism relating genetics to inequality. The present study can be extended data-wise and methodologically by incorporating other genetic markers to measure genetic diversity, collecting longitudinal datasets, and employing panel data econometrics.

While the newly emerging literature on the role of human genetics provides valuable information on the long-term determinants of current economic outcomes, they do not necessarily imply that genetics fully determines the economic fate of human civilization. Societies (and their properties such as social cohesion, group feelings, trust, mutual support, or fractionalization) evolve significantly (albeit generally slower than economic developments), and their interaction levels have increased greatly in the context of globalization. Therefore, it can be expected that the role of genetics will be limited, possibly to a declining extent, over the coming periods. The literature already discusses effective interventions to raise awareness of other groups, counter stereotypes, provide positive contact opportunities, and improve intergroup relations (Orazani et al., 2023). As Ibn Khaldun (2015[1337]) argues in detail, blood relations or genetics is one of the factors driving group feelings, and societies can develop other sources (such as culture, bureaucracy, statehood, and institutions) for their successful social and economic development processes. These arguments are broad speculations but imply a productive research area on the role of genetic and non-genetic factors in economic outcomes for future research.

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