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Unbundling the roles of human capital and institutions in economic development

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ABSTRACT

This research uses predicted genetic diversity unadjusted for the ancestral composition of current populations, as a plausible source of exogenous variations for indicators of economic institutions. While genetic diversity has a robust, concave and significant effect on economic institutions, reduced-form regressions and numerous falsification tests ostensibly suggest that genetic diversity affects development only via indices of multidimensional measures of economic institutions. Second-stage results indicate that allowing for cognitive skills, latitude and ethno-diversity, economic institutions exert a positive and strongly statistically significant effect on development. These findings are robust to the inclusion of deep and proximate growth determinants, different measures of geography, institutions, and horse races between cognitive skills and economic freedom, as well as to the use of different estimators. Human capital, gauged by cognitive skills, in most specifications is not significant in the second stage; however, it is positive and a strong significant predictor of economic institutions in the first stage. The empirical evidence unveiled in this study lends credence to the primacy of economic institutions hypothesis to ignite long-term growth and highlights the crucial role of human capital in enhancing economic institutional quality.

1. Introduction

In this paper, we attempt to disentangle the role of human capital and economic institutions in development. There is considerable controversy in the literature on comparative economic development over the treatment of human capital in growth regressions. For example, North and Thomas (1973) contested other work by claiming that human capital, physical capital, and total factor productivity are not causes of growth but rather *embody* growth—they should be considered measures of growth, or highly proximate determinants of development. "The factors we have listed (innovations, economies of scale, capital accumulation, etc.) are not causes of growth; they are growth" (North and Thomas 1973, p. 2). Subsequent papers by Acemoglu et al. (2001, 2002, and 2012) and Acemoglu and Johnson (2005) argue that institutions are the driving factor spurring technological innovation, as well as human and physical capital accumulation. Following North and Thomas, Acemoglu and his coauthors consider

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technological innovation and both types of capital accumulation to be proximate determinants of growth and thus exclude them from their regression models.

Further controversy has stemmed from the observation that human capital and institutions themselves are considerably interwoven. Institutions are essentially ideas, which are generated by human capital. The production of ideas in turn is at least partially stimulated by institutions that protect intellectual property rights; also, the portion of human capital generated in schools, which appears to be substantial, depends partly on the institutional quality that governs the schooling system.[1] Empirically, both human capital and institutions have been shown to affect long-term growth, to be endogenous to development, and to be correlated. Moreover, a simultaneous causality bias may afflict the relationship between these two covariates.[2]

To surmount the challenge of unbundling the role of human capital and institutions on long-term growth, we draw from three distinct but related strands of the comparative economic development literature information on institutional quality, human capital and deep growth determinants. First, we educe from the institutions literature the Economic Freedom of the World index (EFW) published by the Fraser Institute and developed by Gwartney, Lawson and Hall (2014), as our main indicator of institutional and policy quality. As a robustness check we also use the Social Infrastructure index (SII) introduced by Hall and Jones (1999) and the Worldwide Governance Indicators (WGI) of the World Bank advanced by Kaufmann, Kraay and Mastruzzi (2010) which contains some dimensions of political institutions. These indices, in particular EFW, are more informative for policy decision making than are unidimensional indicators, such as constraints on the executive, risk of expropriation, and rule of law.

Second, from the recent human capital research strand and following Hanushek and Woessmann, we use cognitive skills as our proxy for human capital. Hanushek and Woessmann (2008, 2012a, 2012b) provide compelling evidence in growth regressions indicating that cognitive skills are a better predictor of growth than years of schooling.[3] At issue is the appropriate measurement of human capital to cast light on the disappointing performance of years of schooling in explaining economic growth (Pritchett 2001 and 2006). However, using acquired skills rather than time in school dramatically improves the explanatory power of long-run cross-country growth variation.

Third, from the literature on deep determinants of growth, we use latitude, ethno-linguistic fractionalization, and genetic diversity, the last being determined tens of thousands year ago and therefore representing the deepest known development channel other than geography.[4] This paper uses genetic diversity—the probability that two randomly selected individuals from the relevant population differ genetically from one another—as an instrumental variable (IV) for institutions. Specifically, henceforth we use either predicted genetic diversity unadjusted for the ancestral composition of current populations, or, precolonial-predicted genetic diversity.

An IV approach is necessary because proxies for institutions in cross-country OLS regressions are potentially afflicted by endogeneity biases stemming from correlation of institutions with the error term due to measurement errors, reverse causality, and omitted variable bias, which renders OLS estimates biased and inconsistent. The objective is for precolonial-predicted genetic diversity, to induce exogenous variation in institutions, variation that is thus in principle uncorrelated with the error term, and then to use this exogenous variation to calculate the parameter estimate for institutions.[5] Unlike OLS estimates, IV estimates are consistent if the IVs are exogenous, that is, uncorrelated with the error term.

But is precolonial- predicted genetic diversity itself correlated with the error term? If so, it could be affecting development through channels other than economic institutions, which would invalidate our identification strategy. In an attempt to prevent this potential violation of the orthogonality condition, we control for human capital, ethno-linguistic fractionalization, and latitude.[6] We allow for cognitive skills, given that genetic diversity is inseverable from human capital and that there is a growing body of evidence suggesting that human capital has a direct effect on development (see Glaeser et al., 2004, Putterman and Weil, 2010, and Gennaioli et al., 2013). Ethnolinguistic fractionalization, based on evidence supplied by Ashraf and Galor (2013b), suggests that genetic diversity underlies multiple manifestations of cultural and ethnic fragmentation, which in turn may have an effect on development.[7] We also control for latitude because the level of genetic diversity is dependent upon migratory distance from East Africa to the geographic region being examined, and geography may in turn potentially affect growth directly (Dell, Jones and Olken, 2014).

Additional results that strengthen our confidence on the exogeneity of predicted-precolonial genetic diversity are based on reduced-form regression results and on falsification tests performed on measures of institutions that have received substantial scrutiny in the comparative development literature. These tests suggest that precolonial- predicted genetic diversity, after allowing for our control variables, neither affects development nor operates through political nor constitutional institutions

[1] For example, West and Woessmann (2010) and Hanushek and Woessmann (2012b) document that improving the institutional structure of the school system to provide for more competition matters for the quality of human capital measured by cognitive skills test scores.

[2] Glaeser et al. (2004) find that initial years of schooling are a strong predictor of improving political institutions, while political institutions have no impact on human capital. Conversely, Acemoglu et al. (2014), allowing for historical determinants of institutions, do not uncover evidence of years of schooling predicting institutions.

[3] An intuitive criticism of school attainment is offered by Hanushek and Woessmann (2012b): “For example, a year of schooling in Peru is assumed to create the same increase in productive human capital as a year of schooling in Japan” (p. 269).

[4] Spolaore and Wacziarg (2013) provide a survey of the recent literature on deep determinants of growth inclusive of geography. Nunn (2009) brings a related survey on the role of history on economic development.

[5] As will be explained later, we use a quadratic functional form of precolonial-predicted genetic diversity providing two instrumental variables, one given by the linear term and the other one by the quadratic term.

[6] For the instruments to be exogenous they cannot be correlated with the error term in the structural equation given by the second-stage regression. If the instruments are uncorrelated with the error term, the orthogonality condition (also known as the exclusion restriction) is satisfied.

[7] See Alesina and La Ferrara (2005) for a survey the literature on ethnic diversity and economic performance.

such as democracy, constraints on the executive, constitutional review, judicial independence, autocracy, plurality, proportional representation and government effectiveness. Additional falsification tests conditioning for our controls also indicate that precolonial-predicted genetic diversity does not affect human capital, social capital nor risk of expropriation, the latter being a unidimensional measure of economic institutions.

In short, our baseline specification allows for cognitive skills, latitude and ethno-linguistic fractionalization to control for possible correlation of the instruments with variables that have been shown in the growth literature to affect development. We hasten to add that not allowing for these covariates may violate the exclusion restriction, compromising the exogeneity of the instruments.[8]

This study finds that the cross-country variation part of EFW, which can be traced back to our instrumental variables, exhibits a positive and statistically significant effect on development in the second-stage regression.[9] Furthermore, cognitive skills do not have a statistically significant effect in the second-stage regression. Moreover, horse race regressions between economic institutions and human capital, in which both are treated endogenously, suggest that clusters of economic institutions exert a first-order effect on development, whereas cognitive skills do not appear to matter directly for development.[10] This finding reinforces our results based on the treatment of economic institutions as the sole endogenous covariate instrumented which are congruous with recent evidence provided by Young and Sheehan (2014) and Compton et al. (2014).

Our baseline estimates, obtained from a parsimonious yet informative specification, prove to be robust to the inclusion of a wide range of control variables. These variables are deep determinants of growth rooted in geography and long-term history, adjusted for the ancestral composition of current populations, natural resource endowments, climate and proximate growth determinants such as legal origin, social capital and different measures of economic institutions. In addition, the main results also survive different samples, continent fixed effects, horse races between cognitive skills and economic institutions, different IV estimators and two-step bootstrapped standard errors.

Finally, our empirical analysis reveals that a first-stage quadratic equation in genetic diversity affects development through economic institutions, but not directly.[11] Based on first-stage regressions, we also determine that cognitive skills exert a robust, strong and significant effect on institutional quality in accordance with the notion of human capital promoting institutions (Glaeser et al., 2004; Galor et al., 2009 and Galor, 2011). This finding, coupled with second-stage results, suggests that human capital has an indirect effect on development influencing the quality of institutions.

The remainder of the paper has the following structure: The next section presents recent literature in the area of comparative economic development related to our paper. Section 3 discusses our identification strategy and presents evidence consistent with the IVs exogeneity and relevancy assumptions. The fourth section displays our main results, and their robustness is analyzed in Section 5. Section 6 reports findings based on specifications that treat both EFW and school achievement as endogenous variables. The last section offers concluding remarks.

2. Review of the recent literature

The role that human capital and institutions play in the growth process is a contentious and intensely debated issue in the recent comparative economic development literature. The seminal empirical contributions of Knack and Keefer (1995), Hall and Jones (1999) and Acemoglu et al. (2001 and 2002) provided a major impetus to the primacy of the institutions hypothesis. However, Glaeser et al. (2004) report evidence suggesting that years of schooling, a proxy for human capital, is a better predictor of development than Constraints on the Executive, which is a main measure of political institutions used by Acemoglu et al. (2001 and 2005) and Acemoglu and Johnson (2005).

Acemoglu and Dell (2010) document in a sample of the Americas that approximately half of between-country and between-municipality income differences can be ascribed to human capital variations and that institutions play a more modest role. More recently, Gennaioli et al. (2013) disclose that human capital plays a first-order role in explaining regional differences in development, whereas institutions lack predictive power of per capita income in regions within countries.

Acemoglu et al. (2014) show that institutions gauged by rule of law outperform years of school attainment when both variables are treated as endogenous or when controlling for historical determinants of both human capital and institutions. For concreteness, in Two-Stage Least Squares (TSLS) regressions, institutions become a robust predictor of development, allowing for historical determinants of human capital. However, in regressions that control for historical determinants of institutions, estimates associated with human capital either decline to levels consistent with Mincerian microeconomic evidence or become insignificant.

In a sequence of papers, Hanushek and Woessmann (2008, 2012a and 2012b) use cognitive skills, also known as school achievement, as a proxy for human capital. Applying TSLS and Limited Information Maximum Likelihood (LIML) estimators,

[8] Although cognitive skills and ethno-linguistic diversity are potentially endogenous to income, inclusion of these controls variables does not invalidate our analysis, provided that we do not interpret as causal parameter estimates associated with these controls in the second stage. The coefficient on the variable of interest, EFW, may have a causal interpretation in so far, the exogeneity assumption of the instruments is satisfied.

[9] This result is robust to the employment of the social infrastructure index (SII) as another proxy for a cluster of economic institutions. In the robustness section we will summarize results pertaining to the SII and WGI indices, which are available in Sections F and G of the online Appendix.

[10] Cognitive skills are instrumented using the identification strategy developed by Hanushek and Woessmann (2012a, b))

[11] As mentioned above, falsification tests and reduced-form regression results lend credence to the notion that precolonial- predicted genetic diversity impacts development through the channel of clusters of economic institutions in congruence with our theoretical reasoning.

Hanushek and Woessmann find that cognitive skills are a better predictor of development than institutions. By contrast, Ang (2013), using ancestry-adjusted deep determinants of growth as instrumental variables for institutions, which are measured by multidimensional indices such as the World Bank's World Wide Governance Indicators, finds in a TSLS empirical framework that institutions predict development, even allowing for years of schooling, which are not significant. Thus most papers in the comparative development literature generally find that either institutions or human capital matter for development, but not both, in spite of empirical evidence suggesting that these two variables are important determinants of long-term growth.

Ashraf and Galor (2013a) are the first to use genetic diversity data in the economic development literature, and they propose the existence of a genetic channel that impacts long-term economic growth. In reduced form regressions Ashraf and Galor find that genetic diversity determined tens of thousands of years ago has a hump-shaped impact on precolonial population density as well as on contemporary income. This non-monotonic and concave effect reflects the trade-off emanating from inimical and favorable consequences of diversity on productivity. High levels of heterogeneity raise the probability that a society will be dysfunctional due to distrust and diminished cooperation. But production efficiency and technological innovation in a society can be enhanced by the presence of a wide array of complementary traits. Thus low diversity levels within indigenous South American populations and high levels of diversity in African populations seem to have hindered economic progress, while the intermediate diversity levels of Asian and European populations appear to be more propitious for economic development.

Following Ashraf and Galor (2013a, b), a burgeoning body of empirical work has emerged to study the influence of genetic diversity on comparative economic performance of nations and societies. We will refer to the three papers most closely related to ours. Arbatli, Ashraf and Galor (2015), document the incidence of genetic diversity on the emergence of civil conflict, intensity of social unrest and intragroup factional conflict over the last half-century.

Depetris-Chauvin and Ozak (2015), uncover an influential channel from population diversity to economic specialization and trade among pre-modern societies. They also provide empirical evidence suggesting that pre-modern societies displaying high levels of economic specialization, today show larger occupational heterogeneity and greater development as well. Finally, Galor and Klemp (2015), empirically show that genetic diversity contributed to the emergence of autocratic political institutions, conditioning on potentially confounding effects of geographical factors as well as unobserved heterogeneity at the continent level. These authors also uncover an effect of genetic diversity on contemporary variation of autocracy, consistent with the persistence of institutions, culture and genetic traits. For an extended survey of this nascent and vibrant literature, see Ashraf and Galor, forthcoming.

3. Identification strategy

3.1. A plausible exogenous source of economic institutional variation: Genetic diversity

Genetic diversity of any given population—for example, an ethnic group—is measured by population geneticists using an index of *expected heterozygosity*. That is, expected heterozygosity measures "the extent of diversity in genetic material across individuals within a given population" (Asraf and Galor 2013a, p. 13). This index may be construed as the probability that two randomly selected individuals differ from one another in relation to an array of genetic traits like eye and hair colors. Thus, expected heterozygosity has an interpretation formally similar to that of the index of ethno-linguistic fractionalization and to most measures of diversity (see Ashraf and Galor, 2013a).

The Human Genome Diversity Cell Line Panel assembled by the Human Genome Diversity Panel (HGDP) and the Centre d' Etudes du Polymorphisme Humain (CEPH) is the most reliable and consistent source of genetic diversity data. Fifty-three ethnic groups are covered, spanning 21 countries. These groups are aboriginal to their contemporary geographical location and have been mostly isolated from interregional population movements as well as from genetic flows induced by other ethnic groups.

To avoid restricting the research to a sample of only 21 countries, Ashraf and Galor (2013a) exploit prehistoric migratory distance out of Addis Ababa in Ethiopia of anatomically modern humans.[12] Specifically, given the high explanatory power of migratory distance to account for observed genetic diversity within the aforementioned 21 countries, they generated predicted values of genetic diversity for all countries of the world, employing migratory distance to overcome the paucity of data.[13]

We claim that genetic diversity of precolonial ethnic groups, which was determined tens of thousands of years ago in the course of the exodus of *Homo sapiens* out of East Africa, is a good instrumental variable for clusters of economic institutions, viz., those measured by indices such as EFW. In fact, the humans who left East Africa seventy to ninety thousand years ago did not know that as they settled in regions farther removed from Addis Ababa, measured by migratory distance, that their genetic diversity was being diminished and that this variation in diversity would have an effect on measures of development such as population density in 1500 and contemporary income levels. This line of reasoning provides the foundation for our assertion that

[12] Ashraf and Galor appeal to the "Out of Africa" hypothesis, which holds that the human species evolved to its modern form in East Africa some 150,000 years ago, then subsequently—circa 70,000-90,000 years ago—commenced an exodus from Ethiopia that populated the earth "in a series of stages where subgroups left initial colonies to create new colonies farther away, carrying with them only a portion of the overall genetic diversity of their parental colonies" (Ashraf and Galor, 2013a, p. 6) and therefore diminishing genetic diversity of contemporary indigenous ethnic groups with increasing distance from East Africa. Population geneticists have found empirical evidence strongly supportive of this so-called serial founder effect (see Prugnolle et al., 2005, Ramachandra et al., 2005, and Wang et al., 2007).

[13] Migratory distance explains close to 86% of the cross-group genetic diversity observed among the 53 ethnic groups which span 21 countries.

genetic diversity is a plausible source of exogenous variation and therefore potentially complies with the instrument exogeneity assumption which is one of the two conditions that a valid instrument must satisfy.

Yet, after the onset of the Neolithic revolution circa ten thousand years ago, some regions of the earth experienced greater economic development (as measured by population density in 1500) than others. One channel conducive for greater development was the luck of being dealt more favorable biogeographic conditions; this is the Diamond (1997) hypothesis.

Another channel is genetic diversity, as proposed by Ashraf and Galor (2013a): the regions that prospered the most were those whose inhabitants exhibited intermediate levels of genetic diversity. Further, a positive and high correlation exists between EFW and measures of prosperity such as population density in 1500 and contemporary income. Thus, unsurprisingly, a strong correlation is found between EFW and genetic diversity. This is the basis for the relevancy of genetic diversity, contributing to satisfy the second condition for instruments' validity.

Notwithstanding our arguments on exogeneity of precolonial- predicted genetic diversity, the identifying assumption used in this paper is that predicted genetic diversity, unadjusted for ancestral composition of the current population, affects income today only via clusters of economic institutions, in particular EFW, after conditioning for human capital, geography, and ethno-linguistic fractionalization. We use these controls to avoid invalidating our identification strategy by virtue of omitting variables correlated with genetic diversity (our IV), which also impact development. In other words, if genetic diversity affects contemporary economic development, either directly or via some other omitted channel, then our study would be ascribing to EFW the influence of either the omitted covariate or of genetic diversity or both. That is, our IV would be correlated with the error term in the second-stage structural regression.

Accordingly, we control first for human capital because genetic diversity is "innately related to the very dawn of humankind itself" (Ashraf and Galor, 2013a p. 2), and recent research studies highlight a direct influence of human capital on development, (see Glaeser et al., 2004; Hanushek and Woessmann, 2012a, b; and Gennaioli et al., 2013).

Second, we allow for latitude as a measure of geography because as previously indicated in footnotes 12 and 13, migratory distance from East Africa had a detrimental linear effect on genetic diversity, implying that ethnic groups located farther away from East Africa exhibited lower levels of genetic diversity. However, the migratory routes adopted were highly influenced by geographic factors that may also have a persistent effect on today's income.[14]

Moreover, Diamond (1997) stresses the importance of initial bio-geographical and geographical conditions as important timing determinants of the transition from hunter-gatherer societies into settled agrarian societies in which agricultural activity became the main source of a population's sustenance. Thus, geographic variables in the Diamond hypothesis are ultimate determinants of economic development, with a potential to affect development directly.[15]

Finally, we also account for ethno-fragmentation because Ashraf and Galor (2013b) have established empirically that genetic diversity is a major determinant of numerous expressions of diversity, including ethnic diversity. In turn, the literature of comparative economic development documents that ethnic diversity is a robust determinant of growth (see Alesina et al., 2003 and Alesina and La Ferrara, 2005). Thus, to increase confidence that variation on EFW induced by precolonial-predicted genetic diversity is uncorrelated with the error term in the second-stage regression (which will allow the estimate of EFW to be interpreted causally), we control for human capital, ethno-diversity and geography. Accordingly, our goal is to provide for conditionally exogenous instrumental variables.[16]

3.2. Accounting for the concave effect of genetic diversity on EFW

Ashraf and Galor (2013a), seeking to explain the hump-shaped effect of genetic diversity on development, provide evidence consistent with the notion that such diversity has both adverse and beneficial effects on development. The detrimental effects of heterogeneity are the consequence of increased levels of mistrust, disarray, and diminished cooperation, i.e., lower social capital, which reduces productivity. The beneficial effects of diversity are derived from the greater specialization and innovation possible when a wider variety of traits are present in the population—productivity gains driven by more rapid knowledge creation. Accordingly, given the implicit hypothesized diminishing returns to both diversity and homogeneity, the theory predicts an optimal level of diversity conditional on the development level.

However, we argue and present evidence strongly suggesting that after allowing for our control variables, predicted genetic diversity unadjusted for the ancestral composition of current populations, i.e., precolonial-predicted genetic diversity, affects development only through clusters of economic institutions and policies, which define the rules of the game in the economic arena. We contend that mistrust, prejudice and group infighting, driven by too much genetic diversity, inhibit agreements on institutional traits that lead to evenhanded treatment of the population and that foster voluntary transactions. This is the case for many sub-Saharan nations. Intermediate levels of diversity require sophisticated institutional arrangements to coordinate the multiplicity of complementary traits. Such arrangements promote technological advancements, efficiency gains and high levels of voluntary transactions. This level of genetic diversity would contribute to induce low and simplified taxation, regulations that promote well-functioning markets, trade openness, protection of property rights and rules leading to sound money, among other

[14] Engermann and Sokoloff (2012) advance a hypothesis suggesting that geographical differences in the Americas had a critical effect on shaping institutional heterogeneity between North and South America, contributing to account for the income differences between the North and South. Dell et al. (2012 and 2014) provide evidence of a direct effect of temperatures on income per capita and growth rates.

[15] See Olson and Hibbs (2005), Putterman (2008) and Ashraf and Galor (2011) for supporting empirical evidence.

[16] See Section A of the online Appendix for variables' definition, summary statistics and simple correlations among the variables.

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institutional traits. This is the case for Australia, the U.S., Canada, Western Europe and Japan. Finally, low levels of diversity do not require complex multidimensional institutional arrangements to tackle a low number of tasks occurring in the economy. This is the case for Bolivia, Paraguay, Venezuela and Central America.

This theoretical line of reasoning is advanced to explain the empirically supported non-monotonic hump-shaped effect of genetic diversity on EFW which is disclosed below. That is, intermediate levels of genetic diversity are associated with higher levels of EFW, while both high and low levels of diversity are associated with low levels of EFW.

3.3. First-stage functional form

Before presenting evidence consistent with genetic diversity satisfying the two assumptions of valid instruments, relevancy (strong instruments) and exogeneity (affecting development only through EFW), we discuss the first-stage functional form of the two-stage least square estimator and of other IV estimators used in this research. This study exploits a quadratic first-stage regression in which the higher order term is genetic diversity squared, i.e., a higher order polynomial of a continuous instrument. Several considerations have led us to use a non-linear transformation of genetic diversity in the first stage. First, it is consistent with our theoretical outline, which explains the role of predicted and precolonial genetic diversity in shaping different qualitative clusters of economic institutions.

Second, we obtain an improvement of the fit between clusters of economic institutions and genetic diversity, alleviating functional form misspecification problems. This fit improvement may also lead to a greater precision, statistical significance, of the estimate of interest in the second stage.[17] This is particularly relevant for the TSLS estimator, which delivers large standard errors, given that only the variation in the endogenous variable that can be traced back to the instruments is used in the second stage. In addition, greater variation of the endogenous regressor induced by the excluded instruments contributes to alleviate the bias inherent to the TSLS estimator, which is consistent but not unbiased.[18]

Third, using a higher order polynomial in genetic diversity in the reduced form equation allows us to perform over-identification tests. Failure to reject the null of the Hansen test suggests that the TSLS estimates calculated using each instrument separately are similar.

In summary, controlling for the influence of human capital, geography and ethno-linguistic fractionalization, we use a quadratic equation in genetic diversity first-stage regression to predict EFW. The intent is to uncover a causal link between economic institutions and development, alleviating endogeneity concerns induced by simultaneity, (reverse causality), attenuation (due to measurement errors) and omitted variable biases.

3.4. Formalization of our identification strategy

The following equations formalize our TSLS identification strategy described above:

First stage:

$$\begin{aligned} EconInst = {} & \alpha_0 + \alpha_1(GenDiv) + \alpha_2(GenDiv)^2 \\ & + \psi_1 Latitude + \psi_2 ELF + \psi_3 CogSkills \\ & + X'\psi + \in \end{aligned} \tag{1}$$

Second stage:

$$\begin{aligned} \mathrm{l}GDP = {} & \beta_0 + \beta_1 EconInst \\ & + \gamma_1 Latitude + \gamma_2 ELF + \gamma_3 CogSkills \\ & + X'\gamma + u \end{aligned} \tag{2}$$

Eqs. (1) and (2) represent our first-stage and second-stage regressions, respectively. As aforementioned, we allow for Latitude, Ethno Linguistic Fractionalization (ELF) and Cognitive Skills (CogSkills) and justify inclusion of these control variables to provide for conditional exogeneity of the IVs.[19] The vector X contains additional control variables such as deep growth determinants, different samples dummies, continent fixed effects, additional geographic covariates such as island dummies, climate and natural resources, colonial origin, culture, armed conflicts gauged by an index of terrorism and an indicator for peace, as well as other covariates commonly used in the empirical development literature. These variables are optionally added to our most parsimonious

[17] Using only the linear term in genetic diversity in our base specification, the R-square of the excluded instrument is 0.114 Adding the quadratic term increases the R-square of the excluded instruments to 0.2981 These results also alleviate concerns about the potential presence of weak instruments Angrist and Pischke (2008). Finally, both parameter estimates on economic institutions are relatively close, 0.78 instrumenting only with the linear term versus 0.69 instrumenting with both the linear and quadratic terms.

[18] See Wooldridge (2010), inter alia.

[19] More precisely, our identifying assumption implies conditional mean independence, meaning that the conditional mean of the structural error term does not depend on our IVs.

specification to provide additional credence and robustness to the main results. Predicted Genetic Diversity ancestry unadjusted (GenDiv) and its square make for the two-dimensional vector of excluded instruments, that is, excluded from the second-stage structural equation model. This implies, as previously indicated, that it is assumed that they don't affect development directly after controlling for all other included variables. We provide test results consistent with the exclusion restriction assumption using several strategies based on reduced equations and numerous falsification tests, as well as conditional exogeneity tests.

Our endogenous variable of interest is clusters of Economic Institutions (EconInst). We use the Economic Freedom of the World (EFW) index as our main proxy for clusters of Economic Institutions. Our main dependent variable in this model is the logarithm of Gross Domestic Product per capita (lGDP), which is our proxy for contemporaneous economic development.

The first coefficient of interest, β_1, measures the estimated direct and marginal impact of economic institutions on development. The second coefficient of interest, γ_3, represents the marginal direct effect of human capital on development, after controlling for the quality of economic institutions and other covariates. The third coefficient of interest,ψ_3, estimates the direct effect of human capital shaping economic institutional quality and thus its indirect effect on development. Therefore, if β_1 is positive and significant, γ_3 is not statistically significant, and ψ_3 is positive and significant, we interpret this result as providing empirical support to the claim made by this study of disclosing distinct roles for human capital and institutions in economic development, that is, evidence of an unbundling effect.

All other coefficients are of interest as well, but they are not central to the research questions of this paper. Particularly important, however, are α_1 and α_2. They determine the form of the polynomial in the first-stage and thus they are fundamental for interpreting our identification strategy. For a hump-shaped effect of GenDiv on EconInst, which is predicted by our theory, we expect $\alpha_1 > 0$ and $\alpha_2 < 0$.In addition, it is expected that the corresponding estimates are jointly statistically significant, to the point of mitigating weak instrument concerns, which can be further lessened based on results delivered by alternative IV estimators which are robust to weak instruments. Moreover, allowing for the correct functional form enhances internal validity of the statistical analysis. Finally, the terms ϵ and u are idiosyncratic error terms.

An additional consideration is in order, which pertains to the use of predicted genetic diversity as a regressor. We employ in our reduced-form equations, falsification tests and first-stage regressions predicted-genetic diversity instead of observed genetic diversity, basically to overcome the small sample size problem previously mentioned. However, use of predicted genetic diversity, a generated regressor, in our regressions corresponds to the second step of a two-step OLS estimation procedure in which the first step consisted of applying migratory distance to estimate a regression coefficient for genetic diversity.[20] The second step consists in using this coefficient along with migratory distance to estimate genetic diversity of all countries of the world. Pagan (1984) and Murphy and Topel (1985) show that coefficient estimates in the second step are consistent but that inferences are invalid due to inconsistently estimated standard errors. It is necessary to account for the extra variability by using predicted diversity instead of observed diversity. We follow Ashraf and Galor (2013a) and apply a two-step bootstrap procedure to obtain consistent standard errors in regression specifications that use precolonial-predicted genetic diversity. That is, we first resample ethnic groups to predict genetic diversity with migratory distance and then resample predicted genetic diversity unadjusted for the ancestral composition of current populations, to estimate standard errors in regressions that use predicted genetic diversity as an explanatory variable.[21]

3.5. Exogeneity evidence of our IVs

Turning to the evidence, column 1 of Table 1 in Panel A shows the unconditional effect of predicted genetic diversity, unadjusted for the ancestry composition of current population, on log of income per capita in 2010. The results from this reduced equation suggest a hump-shaped relationship between income and genetic diversity. Both the linear and quadratic terms are statistically significant at the 1% level. This evidence is qualitatively similar to the findings of Ashraf and Galor (2013a).

Column 2 investigates the robustness of the hump-shaped result between income and genetic diversity when we allow for EFW. Revealingly, genetic diversity does not impart a statistically discernible effect on development when the regression model accounts for EFW. In effect, parameter estimates associated with the linear and quadratic terms of genetic diversity are not statistically significant, whereas the coefficient estimated for EFW is positive and significant at the 1% level.

Reassuringly, these results suggest that predicted genetic diversity ancestry unadjusted and EFW belong to the same channel of influence on development, in which genetic diversity and economic institutions are ultimate and proximate determinants, respectively, of the log of income per capita 2010. However, most of the explanatory power of development allowing for genetic diversity is captured by EFW, providing support to the claim that genetic diversity affects development indirectly using economic institutions as an intermediating channel.

Results disclosed in columns 3, 4 and 5, which correspond to extended specifications, lend additional credence to the claim that genetic diversity does not exert a direct effect on income when human capital, ethno-diversity and latitude are accounted for in the regression models. Our measure of human capital is added in column 3, showing that genetic diversity remains not statistically significant, whereas institutions and human capital are positively strongly statistically linked to development.

Column 4 adds ethno-diversity, which is negative and statistically significant, and column 5 additionally includes latitude, which exerts a positive and statistically significant effect on income per capita. In both columns 4 and 5, genetic diversity does

[20] See Ashraf and Galor, 2013a, pp. 15–16, and footnote 23 for details.

[21] The algorithm used, data, and codes to replicate the results of the entire paper are available in the Replication Key folder located in the online Appendix.

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Table 1
Evidence on exogeneity of the instrumental variables.

Panel A. Reduced-form equations. Dependent variable is PWT 2010 log income pc

	1	2	3	4	5
Genetic diversity ϟ	254.556***	18.263	−57.765	−7.235	21.989
	[66.934]	[50.842]	[47.952]	[39.487]	[42.850]
Genetic diversity squared ϟ	−191.969***	−14.454	42.425	5.027	−17.737
	[49.196]	[37.822]	[35.700]	[29.619]	[32.299]
Economic Freedom 1985–2010		1.030***	0.593***	0.566***	0.507***
		[0.087]	[0.126]	[0.117]	[0.117]
Cognitive skills			0.527***	0.374**	0.298**
			[0.114]	[0.146]	[0.147]
Ethno diversity				−1.255***	−0.974**
				[0.367]	[0.380]
Latitude					1.068**
					[0.478]
Constant	−74.610***	−3.174	22.799	6.964	−2.013
	[22.596]	[16.703]	[15.639]	[12.803]	[13.791]
Optimum genetic diversity	0.663***	0.632	0.681*	0.72	0.62
	[0.008]	[0.926]	[0.405]	[1.952]	[0.597]
Adj. R-sq.	0.115	0.601	0.657	0.742	0.756
Observations	139	121	75	66	66
Replications	1000	1000	1000	1000	1000

Panel B. Falsification test. Dependent variable is cognitive skills

	1	2	3	4	5
Genetic diversity ϟ	148.587**	20.672	32.784	61.272	
	[59.520]	[53.381]	[54.301]	[50.318]	
Genetic diversity squared ϟ	−106.536**	−10.926	−20.076	−42.704	
	[43.572]	[39.613]	[40.512]	[37.554]	
Genetic diversity ϟϟ					274.606***
					[51.242]
Genetic diversity squared ϟϟ					−190.114***
					[38.193]
Economic freedom 1985–2010		0.403***	0.378***	0.285***	0.279***
		[0.072]	[0.091]	[0.099]	[0.103]
Ethno diversity			−0.827**	−0.462	−0.015
			[0.360]	[0.412]	[0.403]
Latitude				1.137**	1.255**
				[0.508]	[0.543]
Constant	−47.099**	−7.36	−10.993	−19.67	−96.952***
	[20.212]	[17.541]	[17.601]	[16.335]	[16.684]
Optimum genetic diversity	0.697**	0.946	0.816	0.717	0.722
	[0.353]	[4.060]	[1.613]	[1.326]	[0.765]
Adj. R-sq.	0.265	0.463	0.543	0.573	0.609
Observations	83	75	66	66	65
Replications	1000	1000	1000	1000	1000

Two-step bootstrapped standard errors in brackets * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
ϟ Predicted Genetic Diversity Ancestry Unadjusted.
ϟϟ Predicted Genetic Diversity Ancestry Adjusted.

not predict development. In the specification including all of the controls and displayed in column 5, EFW remains statistically significant at the 1% level, whereas human capital, ethno-diversity and latitude appear significant at the 5% level..[22]

In Sections 4, 5 and 6 we show that in the first-stage regressions, some of which allow for a rich set of controls, the link between EFW and genetic diversity exhibits a statistically significant hump-shaped functional form consistent with the hypothesis that genetic diversity's channel of influence on development is through multidimensional measures of economic institutions and policies. However, it is possible that genetic diversity's true channel of influence is through human capital. To analyze this possibility, we perform a falsification exercise whereby cognitive skills are unconditionally regressed on genetic diversity, followed by extended specifications that allow for economic institutions and other covariates used in our baseline specification.

Results in column (1) of Panel B indicate that precolonial-predicted genetic diversity is statistically significant at the 5% level, exerting a hump-shaped effect on cognitive skills. However, accounting for EFW, shown in column (2), genetic diversity ceases to

[22] Reduced-form equation results using SII, reported in Section E of the online Appendix, are qualitatively similar to those using EFW. However, as shown in Section F of the online Appendix, pre-colonial and predicted genetic diversity remains a statistically significant predictor of income per capita, allowing for WGI, cognitive skills, ethno diversity and latitude. Thus, genetic diversity appears not to be a good IV for WGI, which is consistent with the hypothesis, proposed in this paper that unadjusted for the ancestry composition of current population genetic predicted by migratory distance out Africa only influences development through measures of multidimensional economic institutions.

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confer a statistically significant effect on cognitive skills, which is now captured by EFW. Columns (3) and (4) add ethno-diversity and latitude, respectively, and genetic diversity remains not statistically significant. This evidence lends additional credence to the hypothesis advanced by this study whereby the effect of precolonial-predicted genetic diversity on development occurs through the multidimensional economic institutional channel.

Ashraf and Galor (2013b) also construct a contemporary measure of genetic diversity which is predicted by migratory distance out of Africa and adjusted for the ancestry composition of current population. This is the indicator of genetic diversity used in column 5 of Panel B. Revealingly, in spite of controlling for EFW, ethno-diversity and latitude, genetic diversity exerts a statistically significant concave functional form effect on cognitive skills. This result is instructive because it is consistent with the notion that genetic diversity adjusted for post-1500 population flows across national borders may also affect development through human capital, leading us to discard this metric of genetic diversity as a good instrumental variable for EFW.

We also perform tests on indicators of political institutions, specifically on constraints on the executive, democracy, autocracy, and government effectiveness, as well as on constitutional indicators namely, judicial independence, constitutional review, plurality, and proportional representation.[23] The results are qualitatively similar. Genetic diversity does not exert a robust statistical effect on any of these indicators after allowing for economic institutions, latitude and ethno-diversity. However, when the dependent variable is EFW, genetic diversity is statistically linked with EFW in a non-monotonic concave shape. These falsification test findings are reported in Section B of the online Appendix.

We also inquired whether genetic diversity affects risk of expropriation, which is a unidimensional indicator of economic institutions.[24] Once again, the results, shown in Section B of the online Appendix, remain unaltered. That is, after allowing for EFW, latitude and ethno-diversity, genetic diversity has no significant effect on risk of expropriation.

We investigated as well, whether genetic diversity may be influencing development through social capital. For concreteness, we use distrust as a proxy for culture.[25] We find that only in the extended specification which controls simultaneously for EFW, human capital, ethno-diversity and latitude does genetic diversity significantly predict distrust. However, it does so at the 10% significance level. These results are also reported in Section B of the online Appendix. Overall, we interpret these findings as reinforcing the hypothesis that the channel through which precolonial and predicted genetic diversity affects development is multidimensional indices of economic institutions.

Finally, we performed similar tests using SII, which is a multidimensional measure of economic institutions, and the WGI index of the World Bank, which is a multidimensional index of economic and political institutions, as explained in the Introduction. On the whole, we find that results for the SII, available in the in Section E of the online Appendix, are similar although somewhat weaker than those obtained using EFW. The results for the WGI, available in Section F of the online Appendix are generally weak. These findings also contribute to bolster the hypothesis that predicted and precolonial genetic diversity affects development only through multidimensional measures of economic institutions.

4. Main results

Table 2, which portrays our basic development findings, offers the following structure. Panel A presents second-stage results. Panel B shows first-stage regressions using two-step bootstrapped standard errors. Panel C displays findings delivered by the Limited Information Maximum Likelihood estimator (LIML), controlling for the same variables as in Panels A and B and using the same IVs. Panel D contains OLS benchmark estimates, allowing for the same and corresponding controls used in Panel A.

Column 1 in Panel A contains results corresponding to our most parsimonious specification. The parameter estimate on EFW is 0.695, positive and highly significant at the 1% level. The estimate on cognitive skills is 0.165, positive and not significant. However, regression coefficients on latitude and ethno-linguistic fractionalization are positive and negative, respectively, and both are significant.

Column 1 in Panel B indicates that precolonial-predicted genetic diversity is strongly correlated with EFW. Both the linear and quadratic terms are significant at the 1% level, indicating that genetic diversity has a significant humped-shaped linkage with EFW. Latitude is also statistically linked with EFW, consistent with the notion that on average, countries located in latitudinal bands farther from the equator possess better institutions. Ethno-diversity appears statistically unrelated to economic institutional quality, which can be explained by the presence of genetic diversity, which is a determinant of ethno-diversity (see Ashraf and Galor, 2013b).

Interestingly, the coefficient on cognitive skills in column (1) of Panel B is positive and highly significant at the 1% level on the first-stage regression. This evidence lends credence to the hypothesis of human-capital promoting institutions discussed in Glaeser et al. (2004), Galor, Moav and Vollrath (2009) and Galor (2011).

Panel C discloses results delivered by the LIML estimator. If the instruments are weak, the LIML estimator is "median-unbiased," whereas the bias of the TSLS estimator can be severe, particularly when there are over-identifying restrictions. However, when instruments are strong, the LIML and TSLS estimators deliver similar estimates in large samples. Column 1 of Panel C evinces parameter estimates on EFW (0.70) and cognitive skills (0.16) quantitatively similar as those extracted by the TSLS estimator in Panel A.

[23] These political and constitutional variables were employed by Glaeser et al. (2004).

[24] Risk of expropriation was used by Acemoglu et al. (2001 and 2012)

[25] The measure of distrust was originally used by Aghion et al. (2010)

Importantly, the combined evidence provided in Panels A through C supports the view that the exogenous component of EFW exerts a direct effect on development, whereas human capital, gauged by cognitive skills, has a strong effect on economic institutional and policy qualities. However, the non-significant performance of cognitive skills in the second stage suggests that human

Table 2
Unbundling human capital and institutions in development allowing for deep determinants of growth.

Panel A. Second-stage results. Dependent variable is PWT 2010 log income pc

	1	2	3	4	5	6	7	8	9
Economic freedom 1985–2010	0.695***	0.737***	0.696***	0.639***	0.647***	0.683***	0.655***	0.646***	0.646***
	[0.191]	[0.192]	[0.184]	[0.137]	[0.187]	[0.184]	[0.184]	[0.148]	[0.148]
Cognitive skills 1963–2003	0.165	0.08	0.093	0.012	0.189	0.179	0.117	0.071	−0.025
	[0.172]	[0.178]	[0.189]	[0.210]	[0.167]	[0.165]	[0.171]	[0.170]	[0.239]
Ethno-linguistic fractionalization	−1.079***	−0.907***	−1.017***	−1.044***	−0.854***	−0.830**	−1.033***	−1.056***	−1.040***
	[0.338]	[0.317]	[0.320]	[0.294]	[0.318]	[0.323]	[0.324]	[0.295]	[0.310]
Latitude	0.709**	0.807**	0.789**	0.644**	0.674*	0.439	0.676**	0.722**	0.870**
	[0.319]	[0.353]	[0.349]	[0.328]	[0.350]	[0.411]	[0.340]	[0.358]	[0.386]
Agricultural transition		0.066							0.037
		[0.054]							[0.047]
State history			0.502						0.058
			[0.345]						[0.382]
Technology adoption				1.017					0.776
				[0.749]					[1.000]
Geo proximity to regional frontier					0.601				0.025
					[0.469]				[0.489]
Gen proximity to global frontier						0.629			−0.147
						[0.429]			[0.407]
Population density in 1500							0.015**		0.004
							[0.007]		[0.006]
Principal component								0.197	
								[0.131]	
Observations	66	64	65	58	65	65	65	56	56
p(OID)	0.459	0.537	0.375	0.788	0.638	0.737	0.666	0.986	0.887
p(UID)	0.001	0.006	0.001	0.001	0.001	0.001	0.001	0.002	0.012
p(CLR)	0	0	0	0	0	0	0	0	0.003
Robust standard errors in brackets	$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$								

Panel B. First-stage with two-step bootstrapped standard errors. Dependent variable is economic freedom

	1	2	3	4	5	6	7	8	9
Genetic diversity ϟ	215.664***	222.284***	213.683***	227.482***	220.193***	217.706***	222.440***	223.368***	231.745***
	[57.608]	[65.785]	[57.359]	[58.546]	[58.788]	[57.517]	[60.278]	[61.689]	[70.860]
Genetic diversity squared ϟ	−164.979***	−169.972***	−163.550***	−174.249***	−168.126***	−166.258***	−169.873***	−171.115***	−176.902***
	[42.636]	[49.030]	[42.568]	[43.479]	[43.510]	[42.645]	[44.707]	[45.774]	[52.743]
Cognitive skills	0.517***	0.491***	0.519***	0.518**	0.493***	0.512***	0.457**	0.508***	0.638**
	[0.163]	[0.180]	[0.169]	[0.233]	[0.167]	[0.172]	[0.194]	[0.192]	[0.311]
Ethno-linguistic fractionalization	0.138	0.185	0.124	0.237	0.304	0.287	0.158	0.272	0.279
	[0.403]	[0.445]	[0.449]	[0.514]	[0.474]	[0.488]	[0.451]	[0.491]	[0.695]
Latitude	1.622**	1.789**	1.542**	1.797**	1.667**	1.269	1.696**	1.683**	1.226
	[0.693]	[0.821]	[0.741]	[0.786]	[0.773]	[0.785]	[0.778]	[0.801]	[1.120]
Agricultural transition		0.01							−0.018
		[0.073]							[0.140]
State history			0.054						−0.24
			[0.456]						[0.655]
Technology adoption				0.038					−0.655
				[0.968]					[2.030]
Geo proximity to regional frontier					0.465				0.289
					[0.726]				[1.304]
Gen proximity to global frontier						0.458			0.633
						[0.664]			[1.388]
Population density in 1500							0.008		0.004
							[0.009]		[0.011]
Principal component								0.033	
								[0.191]	
Constant	−65.881***	−68.058***	−65.215***	−69.717***	−67.791***	−66.919***	−68.072***	−68.312***	−71.734***
	[19.237]	[21.965]	[19.060]	[19.462]	[19.740]	[19.136]	[20.060]	[20.438]	[23.473]
Optimum genetic diversity	0.654***	0.654***	0.653***	0.653***	0.655***	0.655***	0.655***	0.653***	0.655***
	[0.010]	[0.061]	[0.012]	[0.012]	[0.014]	[0.012]	[0.017]	[0.029]	[0.016]
Adj. R-sq.	0.496	0.476	0.491	0.505	0.496	0.491	0.494	0.486	0.442
Obs.	66	64	65	58	65	65	65	56	56
Replications	1000	1000	1000	1000	1000	1000	1000	1000	1000

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Table 2 (*continued*)

Panel C. LIML estimator. Dependent variable is PWT 2010 log income pc

	1	2	3	4	5	6	7	8	9
Economic freedom 1985–2010	0.70***	0.74***	0.70***	0.64***	0.65***	0.68***	0.66***	0.65***	0.65***
	[0.19]	[0.19]	[0.19]	[0.14]	[0.19]	[0.18]	[0.19]	[0.15]	[0.15]
Cognitive skills	0.16	0.08	0.09	0.01	0.19	0.18	0.12	0.07	-0.02
	[0.17]	[0.18]	[0.19]	[0.21]	[0.17]	[0.17]	[0.17]	[0.17]	[0.24]
Observations	66	64	65	58	65	65	65	56	56
p(OID)	0.46	0.538	0.378	0.789	0.638	0.737	0.666	0.986	0.887
p(UID)	0.001	0.006	0.001	0.001	0.001	0.001	0.001	0.002	0.012

Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel D. OLS estimator. Dependent variable is PWT 2010 log Income pc.

	1	2	3	4	5	6	7	8	9
Economic freedom 1985–2010	0.56***	0.57***	0.54***	0.56***	0.54***	0.55***	0.54***	0.56***	0.56***
	[0.11]	[0.11]	[0.10]	[0.09]	[0.09]	[0.09]	[0.10]	[0.09]	[0.10]
Cognitive skills	0.25**	0.19	0.19	0.06	0.26**	0.27**	0.19	0.12	0.02
	[0.12]	[0.15]	[0.16]	[0.21]	[0.12]	[0.12]	[0.13]	[0.16]	[0.25]
Observations	66	64	65	58	65	65	65	56	56
Adj. R-sq.	0.757	0.754	0.765	0.828	0.763	0.768	0.768	0.824	0.809

Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
ᓭ Predicted Genetic Diversity Ancestry Unadjusted.

capital impinges on development mostly indirectly through its influence on institution building. A major endeavor of this study is to assess the robustness of this result, which disentangles the role of human capital and economic institutions in development and, more generally, to evaluate the robustness of our parsimonious basic specification.

Columns 2 to 7 of Panel A add one at a time a different deep determinant of long-term growth, adjusted for population movements across national borders. The only deep determinant with a statistically significant regression coefficient is population density in 1500, shown in column 7. The coefficient estimate is positive and statistically significant at the 5% level.

Results shown in Panel A of Table 2, corresponding to columns 2 to 7, reveal that in all cases, parameter estimates associated with EFW are positive, statistically significant at the 1% level and stable across the six different specifications. Ethno-linguistic fractionalization in every specification is negative and statistically significant at the 1% level. Latitude is statistically significant in the six specifications considered except in column 6. Cognitive skills in no case are significant in the second-stage regression.

Analyzing first-stage results in Panel B indicates a statistically significant non-monotonic relationship with EFW of genetic diversity, which is preserved in all first-stage regressions reported in columns 2 to 7. Cognitive skills are also positive and significant at the 5% level or better in columns 2 to 7 of Panel B in Table 2. Latitude also is positive and significant, except in column 6, generally suggesting that geography has both an indirect and a direct influence on long-term development. Finally, none of the deep determinants, other than latitude, are significant.

In column 8 of Panel A, we add the first principal component of the deep determinants, and the results are qualitatively and quantitatively very similar to those in columns 2 to 7. Column 9 exploits the coalesced explanatory power of the deep growth determinants used in Table 2, which are simultaneously included. Reassuringly, results remain virtually intact when compared to those of our most parsimonious specification. Indeed, in the second stage, the exogenous component of EFW is positive and significant, with a parameter estimate of 0.646, nearly identical to the estimate found in column 1 of 0.695. Cognitive skills do not predict development, whereas ethno-diversity is significantly negative and latitude is significantly positive. Furthermore, LIML estimates displayed in Panel C are very similar to those delivered by the TSLS estimator, buttressing confidence in our findings.

The first-stage regressions shown in columns 1 to 9 of Panel B offer an identical pattern. The linear as well the quadratic terms of genetic diversity are statistically significant at the 1% level, and the optimal level of diversity, optimum genetic diversity, remains virtually unchanged across all nine columns and statistically significant at the 1% level. Cognitive skills, in columns (1) to (9), predict better institutional quality, with coefficient estimates significant at the 5% level or better.

We also find that in all specifications, the *p*-value for the over-identifying restrictions using Hansen's test is >10%, supporting the notion of conditional exogeneity of the instruments, and the null of under-identification is rejected in all nine columns at the 1% level or better. In addition, we performed a conditional likelihood ratio test (CLR), introduced by Morreira (2003) and further refined by Andrews et al. (2007), which is robust to the presence of weak and strong instruments. The inferential Morreira test results reconfirm the TSLS findings.

Results are statistically significant and economically significant as well. Indeed, in Table 2, panel A, the estimated coefficient of EFW ranges from 0.639 to 0.737 and the number of the observations ranges from 56 (column 9, including all controls) to 66 (base specification). For the countries included in the regressions, the sample standard deviation of both EFW and the logarithm of income per capita in 2010 are close to one. The model predicts that a one standard deviation increase in EFW translates into 0.7 standard deviation increase in the log of income per capita (0.67 is the number for column 1 and 0.71 is the number for column 2). A 0.7 standard deviation is the approximate difference in per capita income between the United States and Portugal. A unitary EFW distance is approximately the difference between the United States and Norway (8.26–7.28, respectively, for the average EFW from 1985 to 2010).

In the case of Table 2, panel B, the standard deviation of cognitive skills is slightly less than one. Therefore, the standardized coefficients range from 0.4 to 0.53 rather than 0.5 to 0.64, as is shown in the table, which shows the non-standardized coefficients. That is, for columns 1 to 8, a one standard deviation increase in cognitive skills is associated with about 0.4 standard deviation increase of EFW. For column 9, this number is 0.53. To give some perspective, the level of cognitive skills in Canada is 5.038 and that of India is 4.281. The difference of 0.76 is near one standard deviation of the sample of cognitive skills. About one standard deviation below India follow Botswana and Morocco, with values of cognitive skills of 3.575 and 3.327, respectively.

Overall, the findings emerging from Table 2 suggest that, accounting for a rich set of covariates drawn from the deep determinants of growth literature, EFW retains its economic and statistical significance, exerting a strong effect on development along with ethno-diversity and geography. Moreover, human capital measured by cognitive skills has a consequential influence on economic institutional quality, thereby influencing development indirectly. These findings are consistent with the hypothesis of an unbundling effect suggested by this research. Finally, predicted-precolonial genetic diversity confers a clearly defined hump-shaped impact on EFW in congruence with the assumptions of relevancy and exogeneity of our IVs.

5. Robustness checks

5.1. Different samples and continent fixed effects

To save space we present a summary of the main findings, focusing on the parameter estimates of EFW, cognitive skills and genetic diversity, the latter in the first stage. Additional robustness checks results can be found in Section C of the online Appendix.

Tables 3 and 4 offer a similar structure to Table 2. Table 3 investigates the sensitivity of our main findings to different samples, exclusion of Neo-UK and Africa, and to continent-fixed effects. The major findings are that parameter estimates on EFW remain positive and statistically significant predictors of development. However, the magnitude decreases somewhat when excluding Africa, column (3), and allowing for continent fixed effects, column (4). A result different from those reported on Table 2 is that cognitive skills enters positive and statistically significant at the 5% level in column (3) and at the 10% level in column (4) in the second stage. These findings are corroborated by the LIML estimator in Panel C.

Panel B results suggest that the hump-shaped effect of genetic diversity on EFW remains statically significant at the 1% level in the new samples and controlling for fixed effects at the continent level. Similarly, cognitive skills remain positive and statistically linked to EFW at the 1% level, allowing for different samples and for unobserved heterogeneity at the continent level. Finally, in no case is the null of instruments' exogeneity rejected at conventional levels, the null of under-identification is rejected in all cases at the 1% level, and reassuringly, the CLR inferential test results are congruous with those delivered by the TSLS estimator.

5.2. Additional geographic covariates

Findings reported in Tables 2 and 3 suggest that geography, gauged by latitude, has a direct effect on development. Given these results, Table 4 probes further the issue of geographic legacy on modern development, attempting to establish whether the data largely support the view of a direct effect on development or an indirect effect working largely through the channel of institutions and human capital.[26] Meanwhile, Table 4 explores the robustness of our most parsimonious specification to other widely used geographic covariates, namely, distance to major markets, coastal populations, tropical climate and malaria ecology.

A reassuring finding provided by this exercise, shown in Panel A, is that parameter estimates on EFW are positive, statistically significant at the 1% level and relatively stable. Coefficient estimates on cognitive skills are not significant. These results are reinforced by LIML estimates reported in Panel C.

Latitude only enters significantly and at the 10% level in column (4), suggesting that it is not a robust predictor of development when controlling for other geographic variables. Similarly, no other geographic determinant of development enters statistically significant in the second-stage regressions.

Panel B findings corroborate the persistent concave effect of genetic diversity on EFW, and the salutary impact of cognitive skills and latitude on the quality of economic institutions. Larger shares of coastal population also appear to affect positively the quality of economic institutions.

The Hansen test supports the claim that the IVs are exogenous except in column (1), in which the null of orthogonality of the instruments to the sample errors in the structural second-stage regression can be rejected but at the 10% level. Moreover, the null of under-identified instruments is rejected in all columns at the 1% level except in column (5), in which rejection is at the 5% level. Taken together, the findings from Table 4 strengthen the view whereby geography's major effect on long-run growth is indirect and that our main results remain qualitatively unaltered.[27]

[26] Sachs (2003a, b) has argued that geography has a direct impact on development even allowing for institutions and other growth determinants. Bennett, Faria, Gwartney and Morales (2015), allowing for several geographic indicators, report evidence that lends credence to a direct, as well as indirect, effect of geography on development. Spolaore and Wacziarg (2013) provide a summary of this discussion.

[27] Section C of the online Appendix, reports additional robustness checks controlling for climatic, land productivity, natural resources, colonial and culture covariates, as well as presence of Islands and conflicts. The unbundling role of human capital and institutions in development remains qualitatively robust.

5.3. Comments on OLS results and alternative measures of institutional quality

This study's methodological focus is on IV estimators. Nonetheless, we also briefly comment on reported OLS estimates which can be construed as benchmark results. Stability of OLS estimates on EFW is remarkable. Only five OLS estimates, out of thirty-six,

Table 3
Unbundling human capital and institutions in development using different samples and continent fixed effects.

Panel A. Second-stage results. Dependent variable is PWT 2010 log Income pc

	Base sample	Base sample w/o Neo-UK	Base sample w/o Africa	Base sample with continent fixed effects
	1	2	3	4
Economic freedom 1985–2010	0.695***	0.758***	0.413**	0.487**
	[0.191]	[0.241]	[0.207]	[0.198]
Cognitive skills 1963–2003	0.165	0.136	0.362**	0.318*
	[0.172]	[0.190]	[0.182]	[0.166]
Ethno-linguistic fractionalization	−1.079***	−1.037***	−0.866**	−0.690**
	[0.338]	[0.357]	[0.354]	[0.326]
Latitude	0.709**	0.737**	0.657**	0.617
	[0.319]	[0.349]	[0.321]	[0.467]
Africa				−0.643***
				[0.249]
Asia				−0.231
				[0.197]
Other				−0.124
				[0.273]
Constant	4.134***	3.836***	5.194***	4.929***
	[0.784]	[1.022]	[0.834]	[0.945]
Observations	66	62	58	66
p(OID)	0.459	0.325	0.645	0.55
p(UID)	0.001	0.003	0.005	0.002
p(CLR)	0	0.001	0.036	0.035

Robust standard errors in brackets *$p < 0.10$,** $p < 0.05$,***$p < 0.01$

Panel B. First-stage with two-step bootstrapped standard errors. Dependent variable is economic freedom

	1	2	3	4
Genetic diversity ϟ	215.664***	208.316***	188.933***	217.352***
	[57.608]	[58.994]	[61.617]	[61.689]
Genetic diversity squared ϟ	−164.979***	−159.119***	−145.264***	−165.872***
	[42.636]	[44.079]	[45.980]	[46.271]
Cognitive skills	0.517***	0.493***	0.651***	0.533***
	[0.163]	[0.184]	[0.190]	[0.193]
Ethno diversity	0.138	0.115	0.358	0.171
	[0.403]	[0.456]	[0.453]	[0.461]
Latitude	1.622**	1.583**	1.340*	1.444
	[0.693]	[0.780]	[0.715]	[0.891]
Africa				−0.039
				[0.451]
Asia				−0.126
				[0.378]
Other				0.19
				[0.270]
Constant	−65.881***	−63.511***	−57.421***	−66.604***
	[19.237]	[19.638]	[20.382]	[20.431]
Optimum genetic diversity	0.654***	0.655***	0.650***	0.655***
	[0.010]	[0.015]	[0.067]	[0.010]
Adj. R-sq.	0.496	0.42	0.455	0.473
Obs.	66	62	58	66
Replications	1000	1000	1000	1000

Panel C. LIML estimator. Dependent variable is PWT 2010 log income pc.

	1	2	3	4
Economic freedom 1985–2010	0.698***	0.772***	0.414**	0.487**
	[0.195]	[0.255]	[0.210]	[0.201]
Cognitive skills 1963–2003	0.162	0.127	0.362**	0.318*
	[0.174]	[0.198]	[0.183]	[0.167]
Observations	66	62	58	66

Robust standard errors in brackets *$p < 0.10$,** $p < 0.05$,***$p < 0.01$

(*continued on next page*)

Table 3 (*continued*)

Panel D. OLS estimator. Dependent variable is PWT 2010 log income pc.				
	1	2	3	4
Economic freedom 1985–2010	0.563***	0.569***	0.393***	0.502***
	[0.107]	[0.115]	[0.063]	[0.095]
Cognitive skills 1963–2003	0.251**	0.246*	0.377***	0.309*
	[0.124]	[0.124]	[0.103]	[0.163]
Observations	66	62	58	66

Robust standard errors in brackets *$p < 0.10$,** $p < 0.05$,***$p < 0.01$.
ᒣ Predicted Genetic Diversity Ancestry Unadjusted.

fall outside the 0.5–0.6 open interval. For those exceptions, the estimates are 0.393, 0.462, 0.623, 0.623 and 0.616.[28] Yet even these estimates are not far apart from the aforementioned interval. This notable stability of point estimates allays concerns for selection on unobservables. Moreover, all OLS estimates are statistically significant at the 1% level and generally lower in modulus than corresponding IV estimates, consistent with IV estimators correcting for attenuation bias. Finally, OLS estimates on cognitive skills are more volatile and frequently are not statistically significant.

Another robustness check performed in this study pertains to different measures of institutions. Results uncovered using the SII, reported in Section E of the online Appendix, are generally qualitatively similar to those using EFW, albeit weaker. Indeed, for all specifications reported in Table E2 which allow for deep determinants of growth, the test of over-identification rejects the null of conditional exogeneity at the 10% level in six out of nine different specifications, and at the 5% level in the three remaining specifications.

Robustness checks performed using the WGI of the World Bank, reported in Section F of the online Appendix, are also in general qualitatively equivalent to those obtained using the EFW index, though weaker than those generated using the SII. As reported in Table F1, income reduced-form equations suggest that in some specifications genetic diversity directly impacts development. Moreover, first-stage results indicate that genetic diversity is not persistently statistically linked to WGI, as it is to EFW and SII. Given that WGI contains political dimension measurements, this evidence reinforces the hypothesis presented in this paper that predicted-precolonial genetic diversity impacts development mainly through multidimensional measures of economic institutions and policies.

An additional salient difference, shown in Table F12 in Section F of the online Appendix, is that cognitive skills in three second-stage specifications significantly affect development but with a negative coefficient estimate. This result is corroborated by LIML estimates which are also negative, statistically significant at the 10% level and of a similar magnitude to corresponding TSLS estimates.

6. Horse race results

Summing across estimators and specifications, we have 72 s-stage estimates, of which only four cognitive skills estimates are positive and statistically significant at the 5% level or better in predicting development. However, only three coefficient estimates on EFW are not statistically significant at the 5% level or better. Nonetheless, these three estimates are positive and significant at the 10% level.[29]

In spite of this overwhelming evidence supportive of a direct effect of EFW on development and scant direct impact on development of cognitive skills, to cast further light on the issue of which development strategy matters most for a direct effect on long-term growth, in this section we perform horse races between institutions and human capital. Thus, EFW and cognitive skills are treated as endogenous regressors. EFW is instrumented with pre-colonial genetic diversity predicted by migratory distance from Ethiopia, while cognitive skills are instrumented with the identification strategy developed by Hanushek and Woessmann (2012a, b). We use their two most frequently employed instruments, namely years of education in the 1960 and the population share of Catholics in 1900.

Before discussing the results, we briefly summarize the advantages and shortcomings of alternative estimators and tests applied in this section. In the presence of weak identification, the TSLS estimator is afflicted by a finite sample bias and a non-normal sample distribution. Consequently, the *t*-test for hypothesis testing and confidence intervals are unreliable. One possibility to surmount this problem in the presence of two endogenous variables is the Anderson-Rubin test. Using this test, we report the joint significance of the parameter estimates associated with the two endogenous variables.

We also make use of other IV estimators, which tend to be more centered on the true value of parameters under weak identification. One such estimator has already been used in this paper, the Limited Information Maximum Likelihood Estimator (LIML). A shortcoming of LIML is a considerable dispersion in the estimates, generating extreme outliers. The Anderson-Rubin confidence intervals are more reliable than confidence intervals built with LIML standard errors and parameter estimates.

The GMM generalization of the LIML estimator is known as the Continuously Updated Estimator (CUE), developed by Hansen, Heaton and Yaro (1996). The CUE estimator provides for simultaneous estimation of population parameters and the weighting matrix. Simulation results indicate that this estimator generally offers a better performance than does the GMM two-step

[28] OLS estimates, reported in Section C of the online Appendix, are included among the indicated thirty-six estimates.
[29] These results include those in Section C of the online Appendix.

Table 4
Unbundling human capital and institutions in development allowing for additional geographic covariates.

Panel A. Second-stage results. Dependent variable is PWT 2010 log income pc

	1	2	3	4	5
Economic freedom 1985–2010	0.659***	0.748***	0.738***	0.666***	0.736***
	[0.178]	[0.228]	[0.181]	[0.223]	[0.237]
Cognitive skills 1963–2003	0.178	0.148	0.075	0.199	0.068
	[0.168]	[0.180]	[0.167]	[0.206]	[0.206]
Ethno-linguistic fractionalization	−1.028	−1.171	−1.053	−0.999	−1.026
	[0.330]	[0.365]	[0.307]	[0.400]	[0.371]
Latitude	0.565	0.493	−0.022	0.630*	−0.756
	[0.383]	[0.387]	[0.659]	[0.338]	[0.870]
Distance to major markets	−0.027				−0.046
	[0.029]				[0.032]
Coastal population		−0.136			−0.135
		[0.274]			[0.262]
Tropical climate			−0.474		−0.624
			[0.326]		[0.394]
Malaria ecology				−0.011	0.001
				[0.017]	[0.016]
Observations	66	63	64	66	62
p(OID)	0.087	0.535	0.79	0.479	0.15
p(UID)	0.001	0.01	0.002	0.001	0.015
p(CLR)	0	0	0	0.001	0.001

Robust Standard errors in brackets $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B. First-stage with two-step bootstrapped standard errors. Dependent variable is economic freedom.

	1	2	3	4	5
Genetic diversity ϟ	236.005***	159.033***	226.640***	215.831***	193.595**
	[67.042]	[59.732]	[63.275]	[58.575]	[83.797]
Genetic diversity squared ϟ	−179.784***	−122.989***	−173.171***	−165.108***	−148.443**
	[49.282]	[44.364]	[46.955]	[43.417]	[61.806]
Cognitive skills	0.496***	0.516***	0.480***	0.517***	0.444**
	[0.174]	[0.162]	[0.181]	[0.162]	[0.200]
Ethno diversity	0.019	0.481	0.162	0.136	0.269
	[0.442]	[0.448]	[0.449]	[0.429]	[0.567]
Latitude	1.777**	1.930***	1.227	1.626**	2.009**
	[0.742]	[0.709]	[0.922]	[0.728]	[1.013]
Distance to major markets	0.029				0.032
	[0.058]				[0.069]
Coastal population		0.706**			0.700**
		[0.333]			[0.343]
Tropical climate			−0.265		−0.155
			[0.442]		[0.471]
Malaria ecology				0	0.011
				[0.049]	[0.066]
Constant	−72.849***	−47.532**	−69.142***	−65.933***	−58.903**
	[22.554]	[19.744]	[20.804]	[19.533]	[27.770]
Optimum genetic diversity	0.656***	0.647***	0.654***	0.654***	0.652
	[0.064]	[0.075]	[0.012]	[0.011]	[0.433]
Adj. R-sq.	0.491	0.541	0.488	0.488	0.518
Obs.	66	63	64	66	62
Replications	1000	1000	1000	1000	1000

Panel C. LIML estimator. Dependent variable is PWT 2010 log income pc.

	1	2	3	4	5
Economic freedom 1985–2010	0.674***	0.754***	0.739***	0.669***	0.769***
	[0.197]	[0.234]	[0.182]	[0.227]	[0.269]
Cognitiveskills 1963–2003	0.168	0.145	0.075	0.196	0.047
	[0.179]	[0.183]	[0.167]	[0.209]	[0.220]
Observations	66	63	64	66	62

Robust Standard errors in brackets $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel D. OLS estimator. Dependent variable is PWT 2010 log income pc.

	1	2	3	4	5
Economic freedom 1985–2010	0.560***	0.531***	0.564***	0.551***	0.521***
	[0.103]	[0.109]	[0.101]	[0.116]	[0.112]

(continued on next page)

Table 4 *(continued)*

Panel D. OLS estimator. Dependent variable is PWT 2010 log income pc.					
	1	2	3	4	5
Cognitive skills 1963–2003	0.242*	0.269**	0.189	0.281**	0.198
	[0.130]	[0.125]	[0.136]	[0.136]	[0.171]
Observations	66	63	64	66	62

Robust Standard errors in brackets *$p < 0.10$,**$p < 0.05$,***$p < 0.01$.
ʖ Predicted Genetic Diversity Ancestry Unadjusted.

estimator, to the extent of exhibiting a smaller median bias and inducing more reliable over-identification tests. Finally, the CUE estimator is efficient under general non-spherical disturbances. In our cross-sectional regressions, the major concern is with heteroscedastic disturbances.

Table 5 displays horse race results between our measures of economic institutions (EFW) and human capital (Cognitive skills). As indicated above, we instrument EFW with genetic diversity and cognitive skills with School Attainment (Years of Schooling) in 1960 and the Share of Catholic Population in 1900. In addition, we control for deep determinants of growth.

Panel A, which presents TSLS results, indicates a clear dominance of EFW. In fact, parameter estimates associated with EFW are positive and statistically significant at the 1% level. These results are reconfirmed by LIML estimates, except in column 9, and by CUE estimates reported in Panels C and D, respectively.

The Anderson-Rubin (AR) test, which is robust to weak instruments, rejects the null of no joint significance of the two endogenous variables at the 1% level. In addition, the fractionally resampled Anderson-Rubin (FAR) test, which provides valid inferences under weak identification and mild violations of the exclusion restriction, indicates that rejection of joint no significance of EFW and cognitive skills occurs at the 5% level.[30]

First-stage results for EFW and cognitive skills are displayed in Panels B1 and B2, respectively, of Table 5. For the EFW regression, we highlight that regression coefficients corresponding to both terms of genetic diversity are statistically significant at the 1% level in specifications shown in columns (1) to (8), and in column (9), which includes a rich array of deep determinant covariates, the significance of both terms is at the 5% level. The share of Catholics coefficient is not significant in any specification. However, years of schooling are positive and statistically significant in all nine first-stage regressions, consistent with the human capital promoting institutions view. Latitude and ethno-linguistic fractionalization are not statistically significant in any specification. In relation to the deep determinants of growth adjusted for post-1500 migrations, no regression coefficient is statistically significant.

For the cognitive skills first-stage regression, years of education in 1960 is positive and significant at the 1% level in columns 1 to 8, and in column 9, significance is at the 5% level. Catholic share in 1900 is negative and statistically significant at the 5% level in columns 2, 4, 7 and 8 and at the 10% level in columns 1, 5 and 6. However, in columns 3 and 9 the coefficients on Catholic share are not significant. Genetic diversity is statistically significant but not as robustly as in the EFW regression. For example, in columns 8 and 9, neither term is statistically significant.

Several coefficients on deep determinants of growth are statistically significant at the 1% level. This is true of years since agricultural transition, state antiquity, and technology adoption in columns 2, 3 and 4, respectively, as well as population density in 1500 and the first principal component of the six indicators of early development as reported in columns 7 and 8, respectively. In column 9, which includes all the controls, the coefficient estimate of technology adoption is positive and significant at the 1% level, while the point estimate on genetic proximity is significant but with the wrong sign.

Finally, in the vast majority of cases, the null of exogenous instruments cannot be rejected at the 10% level. Over-identification test results using the CUE estimator, which provides the most reliable test of exogenous instruments, indicate that the null of conditional exogeneity cannot be rejected at the 10% level in any of the nine specifications. Yet the null of under-identification can be rejected at the 5% level or better in all specifications except in column 9, but can be rejected at the 10% level, with a p-value of 0.052.

Based on the results from this section, the overall conclusion is that EFW, our main measure of economic institutions and policies, outperforms cognitive skills, arguably the best extant indicator of human capital, in predicting development. This conclusion is bolstered by EFW's robustness to the application of different IV estimators, to the Anderson-Rubin as well as to the FAR inferential tests. The statistically significant concave effect on EFW of genetic diversity predicted and precolonial (unadjusted for inter-regional migration flows in the colonial era) is also remarkable. Finally, we also highlight the positive role of human capital, in this section measured by years of education, on economic institution building.[31]

7. Concluding remarks

Three major findings emerge from this investigation. First, economic institutions and policies are strongly linked to development. In effect, after accounting extensively for deep and proximate growth determinants, parameter estimates associated with

[30] This test was developed by Berkowitz, Caner and Fang (2008 and 2012).
[31] Additional robustness checks, qualitatively corroborative of the horse race results between EFW and cognitive skills presented in Table 5, are reported in Section D of the online Appendix.

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Table 5
Economic development horse race between human capital and institutions allowing for deep growth determinants (with competing identification strategies).

Panel A. Second-stage results. Dependent variable is PWT 2010 log income pc

	1	2	3	4	5	6	7	8	9
Economic freedom 1985–2010	0.865***	0.980***	0.820***	0.729***	0.788***	0.811***	0.797***	0.735***	0.765***
	[0.226]	[0.243]	[0.228]	[0.148]	[0.240]	[0.235]	[0.205]	[0.163]	[0.184]
Cognitive skills	−0.031	−0.186	0.01	−0.122	0.079	0.052	−0.049	0.013	−0.129
	[0.312]	[0.326]	[0.335]	[0.278]	[0.326]	[0.311]	[0.278]	[0.215]	[0.417]
Ethno diversity	−1.192***	−0.987***	−1.083***	−1.092***	−0.935**	−0.967**	−1.133***	−1.144***	−1.247***
	[0.387]	[0.377]	[0.362]	[0.320]	[0.406]	[0.385]	[0.360]	[0.326]	[0.345]
Latitude	0.825	0.918	0.714	0.684*	0.64	0.544	0.783	0.652	1.022*
	[0.502]	[0.565]	[0.542]	[0.367]	[0.534]	[0.603]	[0.484]	[0.400]	[0.613]
Agricultural transition		0.114**							0.091
		[0.050]							[0.056]
State history			0.584						0.165
			[0.388]						[0.375]
Technology adoption				1.226					0.659
				[0.771]					[1.337]
Geo. proximity to regional frontier					0.561				−0.103
					[0.463]				[0.485]
Gen. proximity to global frontier						0.507			−0.404
						[0.431]			[0.637]
Population density in 1500							0.015**		0.002
							[0.007]		[0.007]
Principal component								0.206*	
								[0.121]	
Constant	3.835***	3.036***	3.658***	4.266***	3.458***	3.508***	4.176***	4.472***	4.177***
	[0.802]	[0.859]	[0.787]	[0.597]	[0.838]	[0.807]	[0.772]	[0.651]	[0.798]
Observations	64	62	63	56	63	63	63	54	54
p(OID)	0.079	0.114	0.045	0.193	0.066	0.147	0.156	0.277	0.011
p(UID)	0.005	0.034	0.031	0.01	0.003	0.004	0.002	0.003	0.052
p(AR)	0	0	0	0	0	0	0	0.001	0.001
p(FAR)	0.015	0.023	0.02	0.038	0.019	0.025	0.018	0.02	0.041
Reps	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Kappa(FAR)	3	3	3	3	3	3	3	3	3

Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fractionally Resampled Anderson Rubin (FAR) performed using parameters kappa = 3 and 10,000 repetitions.

Panel B1. First-stage with two-step bootstrapped standard errors. Dependent variable is economic freedom

	1	2	3	4	5	6	7	8	9
Genetic diversity ϟ	215.848***	223.289***	205.710***	179.953***	214.357***	217.151***	210.088***	186.956***	153.255**
	[61.371]	[67.049]	[57.291]	[58.337]	[58.491]	[57.852]	[60.533]	[55.331]	[66.075]
Genetic diversity squared ϟ	−162.448***	−168.260***	−155.254***	−135.686***	−161.294***	−163.369***	−158.606***	−140.552***	−115.131**
	[45.481]	[50.139]	[42.692]	[43.711]	[43.488]	[42.821]	[45.180]	[41.412]	[49.450]
Ethno diversity	−0.014	0.031	0.066	0.308	0.204	0.191	0.044	0.249	0.508
	[0.380]	[0.397]	[0.387]	[0.446]	[0.396]	[0.407]	[0.403]	[0.439]	[0.688]
Latitude	1.057	1.179	1.029	0.586	0.996	0.672	1.09	0.318	−0.225
	[0.907]	[1.018]	[0.897]	[1.081]	[0.966]	[0.902]	[0.939]	[1.150]	[1.374]
Years of schooling	0.157***	0.154**	0.155***	0.174***	0.155***	0.151***	0.135**	0.195***	0.173**
	[0.050]	[0.061]	[0.053]	[0.063]	[0.056]	[0.047]	[0.056]	[0.062]	[0.074]
Catholic 1900	−0.109	−0.131	−0.168	−0.215	−0.209	−0.178	−0.243	−0.25	−0.398
	[0.288]	[0.293]	[0.306]	[0.299]	[0.327]	[0.290]	[0.322]	[0.301]	[0.398]
Agricultural transition		0.016							−0.144
		[0.067]							[0.136]
State history			0.436						−0.114
			[0.420]						[0.835]
Technology adoption				0.867					1.216
				[0.836]					[1.680]
Geo. proximity to regional frontier					0.632				0.813
					[0.709]				[1.339]
Gen. proximity to global frontier						0.626			0.341
						[0.582]			[1.170]
Population density in 1500							0.016		0.012
							[0.010]		[0.014]
Principal component								0.196	
								[0.198]	
Constant	−65.387***	−67.844***	−62.055***	−53.999***	−65.364***	−66.183***	−63.326***	−55.932***	−45.564**
	[20.554]	[22.390]	[19.107]	[19.348]	[19.663]	[19.392]	[20.073]	[18.374]	[21.790]
Optimum genetic diversity	0.664***	0.664***	0.662***	0.663***	0.664***	0.665***	0.662***	0.665***	0.666***
	[0.010]	[0.010]	[0.010]	[0.015]	[0.010]	[0.009]	[0.011]	[0.013]	[0.050]

(continued on next page)

Table 5 *(continued)*

Panel B1. First-stage with two-step bootstrapped standard errors. Dependent variable is economic freedom

	1	2	3	4	5	6	7	8	9
Adj. R-sq.	0.471	0.444	0.469	0.516	0.473	0.471	0.484	0.496	0.471
Obs.	64	62	63	56	63	63	63	54	54
Replications	1000	1000	1000	1000	1000	1000	1000	1000	1000

Panel B2. First-stage with two-step bootstrapped standard errors. Dependent variable is cognitive skills

	1	2	3	4	5	6	7	8	9
Genetic diversity ϟ	104.687**	122.791***	85.153**	44.779	104.157**	106.584**	93.423**	71.851	5.173
	[46.301]	[44.490]	[38.483]	[42.489]	[42.204]	[42.901]	[36.586]	[44.821]	[40.868]
Genetic diversity squared ϟ	−75.729**	−89.871***	−61.194**	−30.998	−75.325**	−77.168**	−67.861**	−50.722	−1.646
	[33.982]	[32.903]	[28.303]	[31.973]	[31.018]	[31.626]	[26.971]	[33.638]	[30.834]
Ethno diversity	−0.693	−0.428	−0.446	−0.039	−0.549	−0.605	−0.616*	−0.302	0.046
	[0.430]	[0.386]	[0.383]	[0.330]	[0.404]	[0.394]	[0.355]	[0.374]	[0.409]
Latitude	0.741	0.975	0.683	0.038	0.715	0.626	0.7	0.067	0.295
	[0.610]	[0.656]	[0.591]	[0.637]	[0.676]	[0.663]	[0.619]	[0.801]	[0.693]
Years of schooling 1960–2010	0.119***	0.110***	0.128***	0.101***	0.117***	0.115***	0.089***	0.128***	0.092**
	[0.034]	[0.035]	[0.034]	[0.036]	[0.038]	[0.039]	[0.034]	[0.044]	[0.044]
Catholic 1900	−0.332*	−0.336**	−0.266	−0.342**	−0.400*	−0.377*	−0.513**	−0.458**	−0.217
	[0.190]	[0.167]	[0.181]	[0.158]	[0.210]	[0.205]	[0.219]	[0.191]	[0.211]
Agricultural transition		0.098***							−0.059
		[0.038]							[0.067]
State history			0.894***						0.089
			[0.321]						[0.518]
Technology adoption				2.030***					3.066***
				[0.536]					[0.776]
Geo. proximity to regional frontier					0.412				0.475
					[0.401]				[0.584]
Gen. proximity to global frontier						0.276			−1.358**
						[0.346]			[0.593]
Population density in 1500							0.024***		0.011
							[0.008]		[0.009]
Principal component								0.355***	
								[0.129]	
Constant	−32.095**	−38.435**	−26.147**	−13.469	−32.218**	−32.865**	−28.188**	−21.39	−0.31
	[15.583]	[14.949]	[12.921]	[13.967]	[14.238]	[14.392]	[12.245]	[14.823]	[13.337]
Optimum genetic diversity	0.691***	0.683	0.696***	0.722	0.691***	0.691***	0.688**	0.708	1.571
	[0.165]	[0.931]	[0.078]	[10.968]	[0.145]	[0.200]	[0.275]	[1.776]	[3.515]
Adj. R-sq.	0.604	0.635	0.659	0.733	0.602	0.596	0.665	0.679	0.764
Obs.	64	62	63	56	63	63	63	54	54
Replications	1000	1000	1000	1000	1000	1000	1000	1000	1000

Panel C. LIML estimator. Dependent variable is PWT 2010 log income pc

	1	2	3	4	5	6	7	8	9
Economic freedom 1985–2010	1.003***	1.163***	0.984**	0.759***	0.941**	0.906***	0.884***	0.755***	0.993
	[0.330]	[0.376]	[0.386]	[0.171]	[0.410]	[0.325]	[0.268]	[0.182]	[0.615]
Cognitive skills	−0.22	−0.433	−0.209	−0.169	−0.121	−0.069	−0.155	−0.009	−0.653
	[0.493]	[0.540]	[0.615]	[0.326]	[0.599]	[0.456]	[0.373]	[0.243]	[1.732]
Observations	64	62	63	56	63	63	63	54	54
p(OID)	0.149	0.22	0.115	0.221	0.14	0.189	0.216	0.296	0.086
p(UID)	0.005	0.034	0.031	0.01	0.003	0.004	0.002	0.003	0.052

Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. To save space, just pertinent Horse Race variables shown.

Panel D. CUE estimator. Dependent variable is PWT 2010 log income pc

	1	2	3	4	5	6	7	8	9
Economic freedom 1985–2010	1.087***	1.240***	1.122***	0.807***	1.061***	1.016***	0.954***	0.812***	1.403***
	[0.230]	[0.267]	[0.245]	[0.145]	[0.256]	[0.245]	[0.198]	[0.163]	[0.419]
Cognitive skills	−0.387	−0.549	−0.513	−0.262	−0.337	−0.268	−0.263	−0.091	−0.413
	[0.348]	[0.394]	[0.393]	[0.275]	[0.384]	[0.352]	[0.285]	[0.220]	[0.756]
Observations	64	62	63	56	63	63	63	54	54
p(OID)	0.158	0.19	0.145	0.218	0.147	0.191	0.232	0.305	0.2
p(UID)	0.005	0.034	0.031	0.01	0.003	0.004	0.002	0.003	0.052

Robust standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. To save space, just pertinent Horse Race variables shown, estimated by the Continuously Updated Estimator.

ϟ Predicted Genetic Diversity Ancestry Unadjusted the exogenous component of economic institutions, extracted by predicted genetic diversity unadjusted for global migrations in the colonial era, are found to be persistently positive, statistically significant, and relatively stable.

Second, human capital gauged by cognitive skills exerts a strong effect on institutions. Indeed, in nearly all first-stage regressions, cognitive skills estimates are positive and statistically significant at the 1% level. This finding is congruous with the hypothesis of human capital promoting institutions. However, the data primarily suggests that cognitive skills' direct effect on development is nil after accounting in the first stage for its effect on institutions.

Third, the robustness of the hump-shaped relationship of predicted genetic diversity, unadjusted for cross-country population flows in the post-1500 era, on economic institutions is remarkable. In fact, in the vast majority of the first-stage regressions, both the linear and quadratic terms are statistically significant at the 1% level. This result is consistent with the notion of a genetic channel influencing the quality of economic institutions and attests to the relevancy (strength) of our instrumental variables.

Horse race results between economic institutions and human capital appear to reinforce the previously mentioned finding of economic institutions, but not human capital, exerting a direct effect on growth. Indeed, EFW seems clearly to dominate cognitive skills in predicting economic development. In most cases, cognitive skills are not statistically significant, whereas in an overwhelming number of cases, economic institutions are positively and statistically significantly linked to long-term development.

Overall, the main contribution of this research to the comparative economic development literature is to lend credence to the primacy-of-institutions-and-policies hypothesis for long-term economic growth. More specifically, it is to follow the policy suggestions embedded in the EFW index such as rule of law, sound money, regulations promoting well-functioning markets, openness, simplified and limited taxation, inter alia. Human capital appears to have no direct effect on development; nevertheless, it has a critical role—to promote economic institutions of better quality. Accordingly, our empirical evidence based on cross-country growth regressions unbundles the roles of multidimensional indices of economic institutions and human capital in development.

Three additional findings are worth mentioning. Ethno-linguistic fractionalization typically is negative and statistically significant at the 1% level in the second stage but, interestingly, it is never significant in the first stage. This is most likely due to the inclusion of genetic diversity (see Ashraf and Galor, 2013b). Geography seems to play a greater role in shaping the quality of institutions than in directly affecting development.

Statistical tests suggest that the IVs used in this paper are exogenous, which is to say they influence development only through EFW. Further, in all but two specifications, the null of under-identification is rejected at the 5% level or better (in the other two at the 10% level). In no regression model with a single endogenous variable is the null of the exclusion restriction rejected. Only in Table 4, column 1, however, can we reject the null of the IVs' influencing development exclusively through the institutional channel at the 10% level. In other words, statistical tests suggest that the IVs used in this paper are exogenous, which is to say they influence development only through EFW, our main multidimensional indicator of economic institutions and policies. Additional persuasive evidence consistent with the notion of using instruments that are a plausible source of exogenous variation for EFW is provided by numerous falsification tests and reduced-form regressions.

The results also decisively suggest that the critical policy lever informing policymakers to ignite long-term economic development is the quality of economic institutions and not genetic diversity. For example, our income reduced-form regressions clearly indicate that, in the presence of EFW, precolonial genetic diversity does not impart any statistically discernible effect on contemporary income. Moreover, even in the reduced-form regressions of Ashraf and Galor (2013a) genetic diversity has relatively little power to explain development. Indeed, after allowing for timing of the Neolithic transition, land productivity, and continent fixed effects (Ashraf and Galor do not control for EFW nor cognitive skills), they find that precolonial genetic diversity only explains 7% of population density (the appropriate measure of development during the Malthusian epoch) in the year 1500.[32]

Accordingly, attempts to alter genetic diversity *today*, for example, through a policy of enticing immigrants with certain genetic structures, would be not only ethically questionable but highly inefficient in terms of the time that would be required for this indirect procedure to improve the quality of institutions and policies. Augmenting the quality of human capital as measured by cognitive skills would be both more expeditious and salutary to the economy in terms of a better-educated workforce and potential positive spillover effects.

Importantly, although this paper has unveiled the existence of a channel from precolonial and predicted genetic diversity to economic institutions, consideration must be extended to an available channel from economic institutions to genetic traits. For example, Galor and Moav (2002, 2007) provide evidence supporting the view that the Neolithic transition—a change of the rules of the game—provoked an evolutionary process giving rise to a natural selection of some traits complementary to economic development, such as preference for higher-quality children and enhanced entrepreneurial spirit.

Given the primacy of economic institutions for sustained long-term growth, highlighted by empirical results revealed in this paper, and the apparent institutional incidence on modifying human traits, some of them potentially genetic, we suggest the following dynamic interpretation of our results. First, economic institutional quality is enhanced which, over a relatively short time period, starts to deliver increased growth. The population experiences rising living standards and "learns by doing" that the change of rules is mostly responsible for their augmented welfare. Improved future prospects and greater demands for skills associated with an expanding economy lead to more and better educational quality. This increase in human capital in turn promotes higher institutional quality. Thus a virtuous circle of enriched institutions and human capital is triggered by the initial

[32] In the wake of the Industrial Revolution, income per capita growth has accelerated, prompting a process characterized by numerous countries escaping the Malthusian trap of income stagnation. A critical ramification of the Industrial Revolution is the Grand Transition, which encompasses transitions to lower fertility rates, increased urbanism, diffusion of democratic rule, enhanced honesty (less corruption) and secularism. For a lucid explanation and documentation of these issues, see several contributions by Gundlach and Paldam (2009a, 2009b and 2012).

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institutional reform. If this initial institutional reform takes place under substantial backwardness and a relatively high level of human capital, e.g., China and India, growth may be explosive. Other countries with a development pattern broadly consistent with this virtuous circle are Hong Kong, Singapore, Chile and even the U.S. We leave the question of an existing virtuous circle as an issue to be researched in the future.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ejpoleco.2016.08.001.

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