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Barriers to the international diffusion of technological innovations

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A B S T R A C T

This paper examines the role of diffusion barriers in explaining differences in technological innovation across countries through an index of economic complexity. The barriers are captured by genealogical distance from the world's technology frontier. We hypothesize that greater the genetic distance between a country's population and the technology innovator the lower will be levels of technological innovations. Utilizing data for 100 countries, our empirical estimates offer solid support for the negative influence of genetic distance from the global frontier on innovation. A number of sensitivity checks also confirm that our findings are robust. Overall, the evidence lends strong support to the barriers effect of genetic distance from the frontier whereby it prevents the diffusion of productivity enhancing innovations across countries by affecting the country's capability to imitate and adopt frontier innovations and technologies.

1. Introduction

This paper seeks to bring forth empirical evidence to highlight the significance of barriers that hold back technological innovations from spreading across countries. In particular, it focuses on human barriers which are measured using genetic distance between a laggard country and the global technology frontier. To this end, the study analyses the influence that genetic distance has on country specific economic complexity index (ECI). Following Sweet and Eterovic Maggio (2015), we used ECI as proxy of innovation because an improvement in ECI implies that a country is improving its production capacity as well as creating innovation that is essential for its prosperity (Hausmann et al., 2013). More importantly, innovation is an accumulative process, which is obtained by accumulation of both "tacit" and "explicit" knowledge; using patent as an indicator of innovation reflects only the "explicit" component of innovative activities (Nelson, 2005; Sweet and Eterovic Maggio, 2015). On the contrary, genetic links promotes progressive accumulation of "tacit" knowledge through a series of social relationships and networks. Hence, the impact of genetic distance on innovation could be more effectively captured through ECI as a measure of technological progress compared to any other indicator.

Technological innovation is essential for supporting economic growth and development (Romer, 1986; Lucas, 1988). Recently, a number of studies have tried to explore the determinants of innovation in developed as well as developing countries (Aghion and Howitt, 1998; Guloglu et al., 2012; Ang and Kumar, 2014; Chen et al., 2018; Zhou et al., 2019). Some of these studies suggest that factors such as organizational ability of a firm, resources available for research purpose and spillover across business entities and nations as well as quality of institutions are crucial for innovation. While other studies argue that factors such as interest rates, foreign capital, and domestic income are important determinant of innovation. Despite the extensive literature, there is lack of consensus on what limits the diffusion and adaptation of productivity-improving technologies across different societies.

More recently, a stream of researchers on innovation, such as Lundvall (1988) and Alvarez et al. (2013) argue that creative and innovative learning takes place through interactive activities. Studies such as Jovanovic and Rob (1989), Ang (2018) and Azis (2019) attribute formulation of new innovation to interaction between agents with diverse prior knowledge. Cattani and Ferriani (2008) and Buera and Oberfield (2016) argue that social networks shape an individual's ability to generate creative outcomes. Mejia (2018) using a case study of Colombia demonstrates that individuals that have better capacity to engage with different components of social web have better chances of emerging as industrial entrepreneurs in the initial stage of industrialization. Likewise, Dudley (2012) finds similar evidence for the British industries. However, a series of literature identify genetic link as an important factor in formulation of a social network among individuals. According to the inclusive fitness theory (Hamilton, 1964), people are generally able to detect those who have similar traits as themselves and prefer to interact with those that resemble themselves. Individuals and societies prefer to form social networks and they are willing to cooperate

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with other people or groups that share similar genetics. This literature highlights that genetics and a series of social relationships are highly related.

Moreover, there is ample evidence to show that some countries share close genetic links while there is significant genetic distances among other countries. In line with inclusive fitness theory, countries that share similar genetic links with frontier countries will most probably have high levels of social interaction and collaboration with frontier countries which is likely to transfer innovation more easily to laggard countries. Moreover, genetically linked countries are expected to cooperate more because of similar language, comparable commercial operation, common economic and social interest (Chaudhry and Ikram, 2015). In contrast, populations which are very different genetically from each other incline to differ in many of these attributes, which can potentially hold back the free flow of technology and knowledge because it imposes costs on adaptation and imitation. Moreover, a laggard country which is not genetically close to a frontier country is likely to receive less social interaction and cooperation from firms and citizens of a frontier country, and hence their overall innovation will be less. Generally, there can be a lack of trust between firms and citizens of frontier country and laggard country whose citizens do not share similar cultural and genetic traits.

Using the insight from the above literature, we hypothesize that dissimilarities in these genetic attributes between societies limit the sharing and communication of new ideas. Limited flow of ideas lowers the prospects for learning, copying and embracing new technology, thereby serving as an obstacle to the dissemination of technology from the frontier to laggard countries. Contrarily, countries that share similar genetic characteristics with the technology leader can facilitate the dissemination of knowledge more effectively as there is more significant interaction between genetically similar countries due to common ethnic and cultural characteristics, languages, beliefs and practices. Effective social interaction between frontier and laggard countries facilitate greater flow of ideas and innovation from the frontier country which increases product innovation in the laggard country.

Using data on the index of economic complexity from 2000 to 2015 for 100 countries, we find genetic distance from the technological frontier (that is, USA) exerts a significant negative influence on innovations across countries. Our results hold even after controlling for many other variables which are found influential in the literature on innovation. Moreover, additional analysis using cross-country panel data further confirm the consistency of the evidence provided. In general, our results lend strong support to the notion that the diffusion barrier effect of genetic distance from the frontier reduces innovation.

The balance of the paper is as follows: Section 2 examines the literature on genetic distance and innovation. Section 3 lays out the empirical specification and strategy of this study and also discusses the data. Section 4 uncovers the main empirical results. Section 5 performs sensitivity checks to confirm robustness of the core results. Final conclusion and remarks are provided in the last section.

2. Literature review

2.1. Genetic distance and technological innovation

A growing number of studies investigate the underlying drivers of technological innovation. The initial studies suggest that increasing investment in new technology is vital to ensure continuous improvement in country's technological advancement (Schumpeter, 1942; Abramovitz, 1956; Solow, 1956; Romer, 1990; Jones, 2002; Rath and Hermawan, 2019). Few studies have recently examined the capacity of nations to create and market a series of new innovation over the years (e.g., Wu et al., 2017; Furman et al., 2002; Furman and Hayes, 2004; Hu and Mathews, 2005). The insight from this strand of literature is that in addition to financial and human resources invested in innovation, factors such as innovative environment in a country's industrial sector, the linkage between common innovative infrastructure and strength of relationships between a nation's industrial sector are essential for improving a country's creativity and technological advances (Porter and Stern, 2002; Furman and Hayes, 2004).

On the other hand, scholars such as Lundvall (1988) and Sweet and Eterovic (2019) highlight that innovation partly takes place through the tacit learning process. These studies further emphasize that collaboration, a series of social relationships and social networks are essential drivers of the tacit learning process. Cattani and Ferriani (2008) argue that social networks shape individuals ability to generate creative outcomes. However, there is conclusive evidence in the literature that genetic link is a critical determinant of the strength of social relationships between individuals. According to Kin-selection theory, animals improve their wellbeing more by cooperating with their relations than to non-relations. Hamilton (1964) in an animal study shows that individual animals identify close relations through a number of channels such as familiarity and imprinting self on others. Hamilton (1975) extended his study to humans and deduced that level of cooperation between persons is to a large extent determined by genetic relatedness. Hamilton's theory is generally known as "inclusive-fitness theory." More recently, some studies applied inclusive-fitness theory to human studies and broadly find conclusive evidence that individuals maximize their inclusive fitness by engaging with those that have similar genetic traits. For instance, Rushton et al. (1984) find that individuals maximize their benefit by marrying others similar to themselves and by assisting neighbors who are most similar to them. Similarly, DeBruine (2002), Bereczkei et al. (2004) and DeBruine et al. (2008) noted that people turn to trust other people more when they have a similar face as theirs. Likewise, Malat and Hamilton (2006) noted that individuals have a preference for health workers from their own race. In other related literature, Ang and Kumar (2014) examine the influence of cultural barriers due to genetic distance relative to the global frontier on cross-country financial development and demonstrate that genetic distance reduces financial development by impeding the diffusion of cross border financial technology from the global frontier. Similarly, Kodila-Tedika and Asongu (2016) suggest that genetic distance relative to the technology frontiers negatively influences human capital levels across countries. However, there are very few studies which have examined direct effects of genetic distance between frontier countries and laggard countries on laggard countries' technological innovation, and evidence is mostly inconclusive. Hence, a further analysis is required to uncover the direct effects of genetic distance on technological innovation.

2.2. Technological innovation

Most of the studies working to identify factors explaining innovation use patent and disbursement on R&D as indicators of innovation. The shortcomings of these two measures are well known. Innovation is an accumulative process, which is obtained by accumulation of both "tacit" and "explicit" knowledge; using patent as an indicator of innovation reflects only the explicit component of innovative activities (Nelson, 2005; Sweet and Eterovic Maggio, 2015). Moreover, given stringent criteria for patenting and high application and enforcement cost of patent, many patentable innovations are not patented. Studies on innovation argue that recent evidence on patents suggest that "firms" use of patents has shifted to encompass far more complex tasks than merely protecting the right of the innovators" (Sweet and Eterovic, 2019, pg80).

Similarly, the critics of disbursement on R&D to innovation argue that quality of domestic institutions will most likely affect the effectiveness and efficiency of same resources. Economies with good institutions and effective firm management is likely to use resources more efficiently then economies with poor institutions. Moreover, there is lack of R&D data from small firms and thus understates some of the innovation realized by small firms. Similarly, there is lack of reliable data from small countries. Given the limitations of patent and disbursement on R&D, we examine the effects of genetic distance on innovation by using "economic complexity index" (ECI) to capture innovation. ECI indicates a country's export sophistication. Calculation of ECI is based on diversity and ubiquity of the output of a country (Hausmann et al., 2013). The diversity reflects different kinds of goods produced by a country. A country's production of many distinct products reflects its embedded knowledge and its ability to use tacit and explicit bundle of creative knowledge across its production assembly. In other words, the quantity of knowledge possessed by a country is reflected by its production diversity. Ubiquity can be measured by the proportion of countries that process a product. A lower ubiquity implies that product is processed by only few countries. A complex product requires a large bundle of tacit and explicit knowledge; its production is limited to a few countries that possess required knowledge for production of the product. For instance, products like medical imaging devices require large bundle of specialist and organizational skills and as a result, it is manufactured in a few countries only. On the other hand, goods such as wood logs and coffee require less specialist skills and therefore they can be provided by a larger number of countries. Increasing economic complexity expresses a country's ability to advance new knowledge and apply it across its production structure.

Moreover, Sweet and Eterovic Maggio (2015) observed that ECI is closely correlated with disbursement on R&D and patent. They argued that ECI provides a measure of innovation that captures not only tangible innovative output or input, but intangible inputs and advancements are reflected. An increase in complexity index reflects an economy's ability to combine enormous quantities of knowledge across individuals and societies to create number of innovative products. In contrast, laggard countries possess fewer creative ideas and generate less sophisticated output. In light of the above literature, this study uses ECI as a proxy for innovation.

3. Estimation strategies and the data

3.1. Empirical model

The effect of genetic distance from the frontier on the innovation levels across countries is explored using the following model:

$$Innovation_i = \alpha + \beta GD_{i,US} + \gamma Z_i + \varepsilon_i \quad (1)$$

where *Innovation* refers to the level of innovation of country i measured by economic complexity index, $GD_{i,US}$ refers to the genetic distance of country i relative to the world's technology frontier (i.e., United States), Z represents a set of control factors for innovation, and ε represents the error term. In general, we are mostly concerned about the sign, size, and significance of the coefficient β. It is expected to be negative based on our barriers to the diffusion interpretation. Furthermore, in all the tables we report beta coefficients of GD as it lets us to interpret the impact of genetic distance on innovation in terms of standard deviations[1]. We estimate Equation (1) with and without considering the control factors to see if our empirical results are sensitive due to their addition. The sample in our study contains 100 countries from 5 continents, that is 31 countries from Europe, 20 countries from America, 23 countries from Asia, 24 countries from Africa, and 2 countries from Oceania.

The control factors taken into account in the empirical equation are standard in the literature and are chosen from among the variables suggested as determinants of innovation (Romer, 1992; Dahlman, 1994; Wang, 2013). They include human capital (H_cap), openness to trade (Openc), a measure of the quality of institutions and per capita real GDP. We also introduce other control variables when performing robustness check in section 5.

We estimate Equation (1) using the ordinary least squares (OLS) method. However, we cannot ignore the possibility that genetic distance from the frontier may be endogenous with respect to the current levels of technological innovation, i.e., GD and ε are likely to be correlated with each other and thus the estimates from Equation (1) cannot be taken as representing a causal effect of genetic distance on technological innovation. This is because technological innovation in the country may impact one's conduct, norms, ideals, beliefs, etc., and so causality may flow in reverse direction. Moreover, the coefficients maybe affected by some unobserved factors that are also correlated with technological innovation and genetic distance to the frontier, or the indicator for genetic distance to the frontier may be measured with error. Accordingly, we use instrumental variable method to estimate the causal effect of genetic distance from the frontier on innovations. The current genetic distance from the USA is instrument using genetic distance from the United Kingdom in 1500 AD. Our choice of instrument is consistent with Spolaore and Wacziarg (2009) and Ang and Kumar (2014). The genetic distance from the United Kingdom in 1500 AD reflects genetic distance between the societies that existed prior to the great migrations.

Consequently, in the instrumental variable regressions, the genetic distance from the USA is taken as endogenous and the specification of genetic distance from the USA is as follows:

$$GD_{i,US} = \pi + \rho GD_{i,UK} + \sigma X_i + \mu_i \quad (2)$$

where $GD_{i,UK}$ is the genetic distance of country i relative to the UK in 1500 AD and μ represents the error term. In this approach, the exogenous deviation in genetic distance from the USA due to the genetic distance from the UK in 1500 AD gets isolated by $GD_{i,UK}$ from the endogenous deviation in $GD_{i,US}$ caused by the unobserved error term. Our identification approach will be appropriate provided $GD_{i,UK}$ is not correlated with the error term. Put differently, the exclusion restriction suggested by instrumental variable method is that genetic distances from the UK in 1500 AD do not affect current technological innovation directly, other than through influencing the genetic distance from the USA.

3.2. Data

A detailed description of the variables utilized including their data sources and the correlation coefficients of the key indicators are provided in Tables A1, A2 and A3 of the appendix.

3.2.1. Measure of innovation

Conventional approach to measure innovation is through data on patent granted or research and development (R&D) expenditure. However, the effectiveness of these data sources as a true representation of innovative activity has been increasingly questioned (see Griliches, 1998; Kleinknecht et al., 2002; Sweet and Eterovic Maggio, 2015). In light of the limitations, innovation will be measured using an index of economic complexity. ECI provides information about a country's economic complexity (Hartmann et al., 2017). ECI reflects capabilities accumulated by a country. The idea following ECI is that more sophisticated economies have better capabilities to produce differentiated goods and create less ubiquitous products for export. Hence, ECI which measures a country's diversity and ubiquity of its products reflect accumulated "tacit" and "explicit" bundle of innovation that a country has and their interaction. Cross-country differences in ECI can effectively capture variation in innovation of countries.

Data for ECI are taken from the MIT's Observatory of Economic complexity[2]. For empirical estimation, average ECI over the period 2000–2015 are used. Other periods are also used when performing robustness checks of the results. In our sample the average level of economic complexity is 0.057. Details about the construction of ECI measure is provided in Appendix B. Fig. 1 reports the distribution of ECI across the

[1] The beta coefficients are estimates obtained from regressions after standardizing all variables so that their mean is zero and the standard deviation is one.

[2] ECI data is accessible online at https://atlas.media.mit.edu/en/rankings/country/eci/.

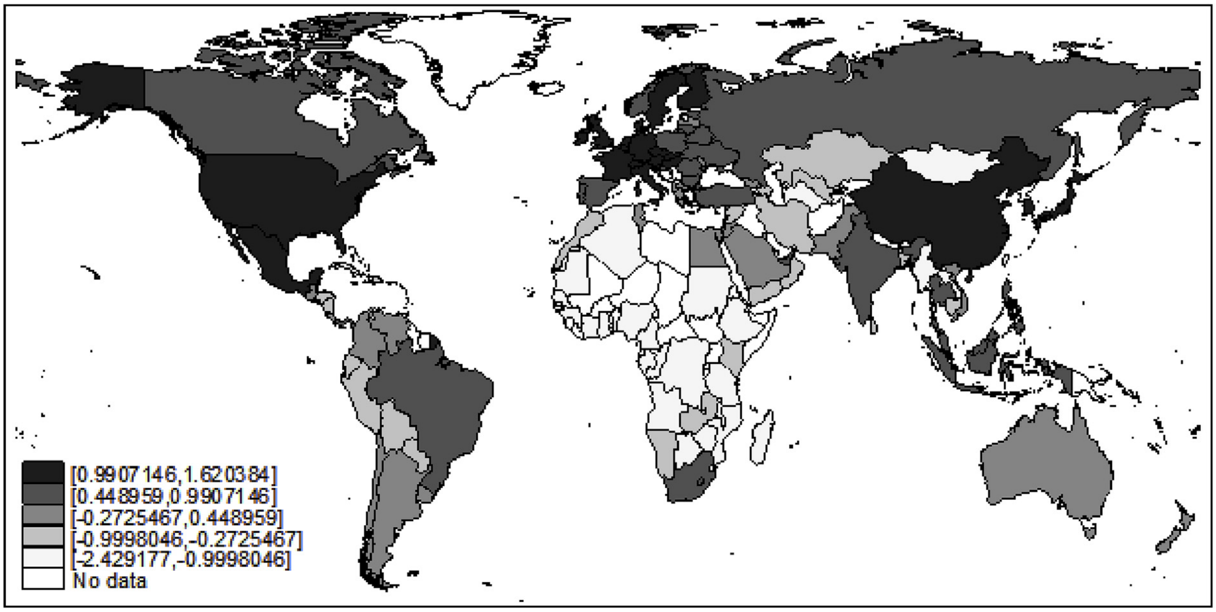

Fig. 1. Distribution of ECI across 119 countries. Notes: Economic Complexity Index (ECI) shows the extent of technological complexity of products each country exports where larger values (corresponding to darker areas) imply greater complexity. The data are averaged over the years 2000–2015. The data is taken from MIT's Observatory of Economic Complexity (Simoes and Hidalgo, 2011).

countries using data for all available countries from Simoes and Hidalgo (2011). It is evident that the level of economic complexity varies extensively across countries.

3.2.2. Genetic distance from the frontier

Diffusion barriers of innovation across borders are measured via the level of genealogical dissimilarities or historical unrelatedness between populations of two countries using genealogical distance. The data are obtained from Spolaore and Wacziarg (2009). They stress that, on average, genealogical distance can be taken as an ideal measure that captures divergence in a number of human characteristics and traits such as languages, norms of behaviour, beliefs, values, customs, cultures, etc., which are vertically transmitted through generations of populations over the long term. These deviations in characteristics works as development barriers by preventing flow of technological advances from the technological frontier. That is to say, countries with characteristics fairly different from the frontier face obstacles and higher costs to adopt one another's innovations.

Genetic distance is captured through a fixation index (*Fst*). Following the approach of Spolaore and Wacziarg (2009), we measure genetic distance of a particular country relative to the United States (Fst_gd_{US}) where the United States is taken as the frontier country. The Fst_gd_{US} is rescaled to range between 0 and 1, where 0 implies that the populations of the country under study and the frontier country (US) are genetically similar and 1 implies that there is no similarity between the two countries population. Here, a larger value of Fst_gd_{US} indicates more genetic dissimilarities between populations of the US and the country under study. The mean value of Fst_gd_{US} in the sample is 0.422[3]. The strength of the association between Fst_gd_{US} and ECI for the countries in our sample is shown in Fig. 2. There is a negative relationship between Fst_gd_{US} and ECI, with an estimated correlation coefficient of −0.60, a pattern that supports our argument that genetic distance limits the flow of innovation across countries.

Fig. 3 presents the distribution of Fst_gd_{US} using data for all available countries from Spolaore and Wacziarg (2009). It is clear that the Fst_gd_{US} shows a large disparity across the globe.

3.2.3. Control variables

The control variables chosen includes per capita GDP, openness to trade, an indicator of institutional quality and human capital. In the empirical estimate, initial values for control variables in year 2000 or else the year when data first exist are used so to minimize the potential reverse causality problems.

We used per capita GDP to capture the economic development of the economy whereas exports plus import as a ratio of GDP is used to capture openness to trade. The data are obtained from the World Bank (2018). Greater openness to international trade can support innovation through higher domestic productivity as more open economies might benefit from diffusion of new technology (Grossman and Helpman, 1991; Romer, 1994; Coe and Helpman, 1995; Edwards, 1997). Furthermore, openness to trade may lead to more innovation through improved market access and increased competition. Better market access abroad increases profits and a more competitive marketplace promote innovation due to a greater threat to monopoly rents, which may force incumbent firms to innovate more to escape competition (Aghion et al., 1997, 2005).

To measure the quality of institutions, we utilized six indicators from the Worldwide Governance Indicators (WGI) of the World Bank (2018), i.e, regulatory quality, rule of law, government effectiveness, control of corruption, political stability and voice and accountability (see Kaufmann et al., 2010). We construct an aggregate indicator of the quality of institutions using the average of the six governance indicators. Institutions are important drivers of innovative capacity of nations (Clarke, 2001; Tebaldi and Elmslie, 2013; Wang, 2013). Countries with better institutions (i.e., less red tape, less corruption, stronger rule of law) on average can be expected to be more innovative as the costs of investment needed to introduce new products are significantly lower while at the sametime returns on investment in new technologies become more certain.

To measure human capital, we use human capital index from Penn World Tables 9.0 (Feenstra et al., 2015). The index for human capital is derived using mean years of schooling and returns to education. It is understood that the human capabilities determine the structure and progress of the economy. The accumulation of knowledge brings new ideas and enhance the products quality. Greater human capital can

[3] See Ang and Kumar (2014, p.55) for illustration on how the genetic distance measure is constructed.

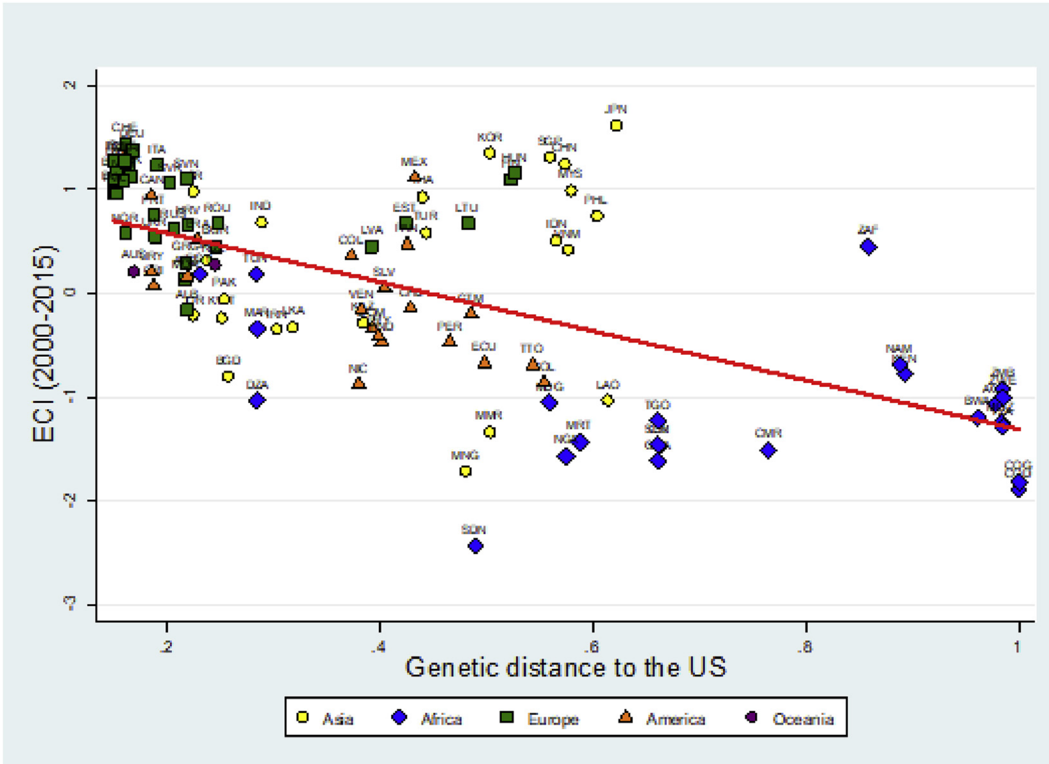

Fig. 2. Correlation between ECI and genetic distance to the frontier.

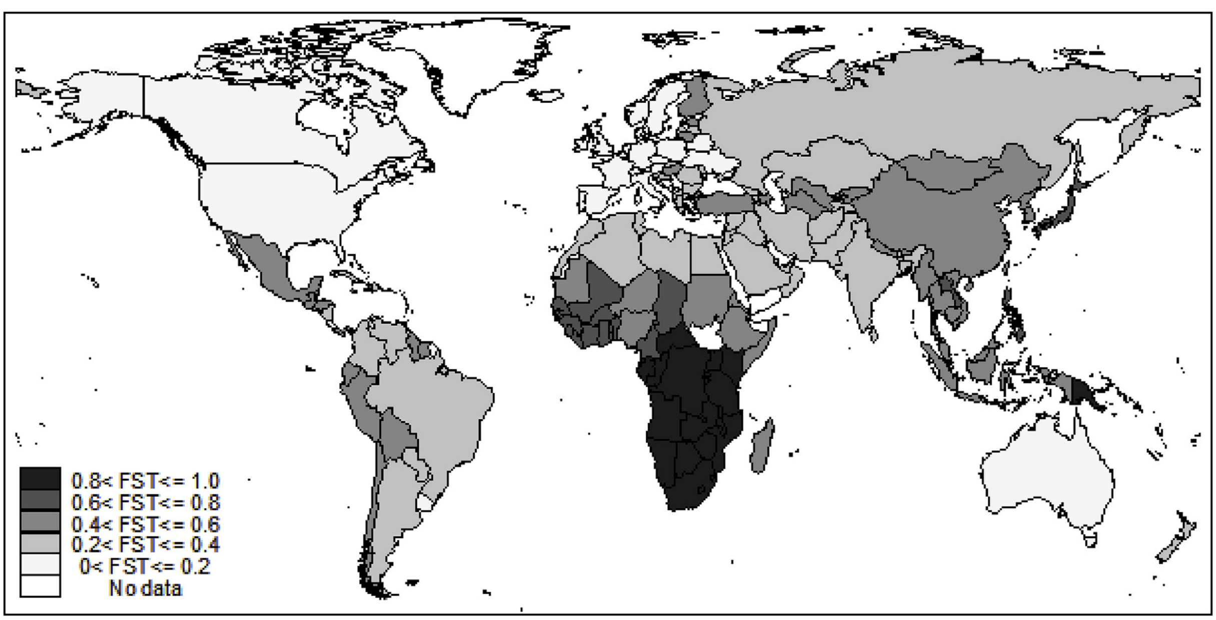

Fig. 3. Distribution of genetic distance from the frontier for 180 countries. Notes: Fst_gd_{US} data are rescaled to range between 0 and 1, where higher values (corresponding to darker areas) represent larger genetic distance from the United States. The data is obtained from Spolaore and Wacziarg (2009).

potentially increase innovation, bring improvement in productivity, and encourage entrepreneurship (Nelson and Phelps, 1966; Dakhli and De Clercq, 2004).

4. Empirical estimates

4.1. Ordinary least squares (OLS) results

The regression results for Equation (1) are presented in Table 1. Column (1) reports coefficient estimates of our variable of interest

Table 1
OLS estimation.

DV: *ECI*	(1)	(2)	(3)	(4)	(5)	(6)
Fst_gd_{US}	−2.370***	−0.828**	−2.396***	−1.108***	−1.322***	−0.752**
	(-9.802)	(-2.534)	(-9.699)	(-3.711)	(-4.844)	(-2.238)
Per capita GDP, log		0.548***				0.250**
		(6.763)				(2.203)
Openc			0.483***			0.0871
			(3.477)			(0.671)
H_cap				0.860***		0.398***
				(7.419)		(3.083)
Institutions					0.559***	0.179*
					(7.293)	(1.831)
Constant	1.057***	−4.583***	0.689***	−1.569***	0.546***	−2.960***
	(10.22)	(-5.429)	(4.688)	(-4.158)	(4.578)	(-2.864)
Beta coefficient (%)	−60.4	−21.1	−61.0	−28.2	−33.7	−19.2
R^2	0.365	0.605	0.417	0.591	0.586	0.660
N	100	100	100	100	100	100

Notes: The dependent variable (DV) is economic complexity index (ECI), averaged over the years 2000–2015, Openc is trade openness and H_cap is human capital. Figures in the round brackets represent *t*-statistics generated by heteroskedasticity-robust standard errors. *, ** and *** suggest that p value is less than 0.1, 0.05 and 0.01 respectively. Beta coefficient refers to standardized coefficient of genetic distance from the USA.

(Fst_gd_{US}) when excluding the control variables. The result indicates a significant negative association between Fst_gd_{US} and our measure of innovation (ECI), i.e., countries who are genetically distant from the US show relatively lower innovation levels. The aforesaid relationship is strongly significant at 1% level. The R^2 statistic indicates that Fst_gd_{US} can solely explain 37% of the deviation in cross-country innovation levels. The standardized coefficient on Fst_gd_{US} reveals that one standard deviation increase in Fst_gd_{US} results in 60.4% of a standard deviation reduction in innovation level.

Columns (2) to (5) introduce control variables one at a time. It is evident that while the effects of individual control variables are significant and carry the correct signs, the estimated coefficients of Fst_gd_{US} remain strongly significant in all the regressions, hence the latter finding remains intact. Column (6) introduces all the control variables together to account for their joint influence. Importantly, this consideration has no effect on our key findings, implying that the relationship uncovered in the previous columns is not due to omitted variables. However, the estimated size of the beta coefficient reduces compared to column (1). Specifically, a one standard deviation increase in genetic distance from the frontier results in about 19.2% of a standard deviation decrease in innovation level. The model estimated in column (6) is now able to explain 66% of the differences in cross-country innovation levels.

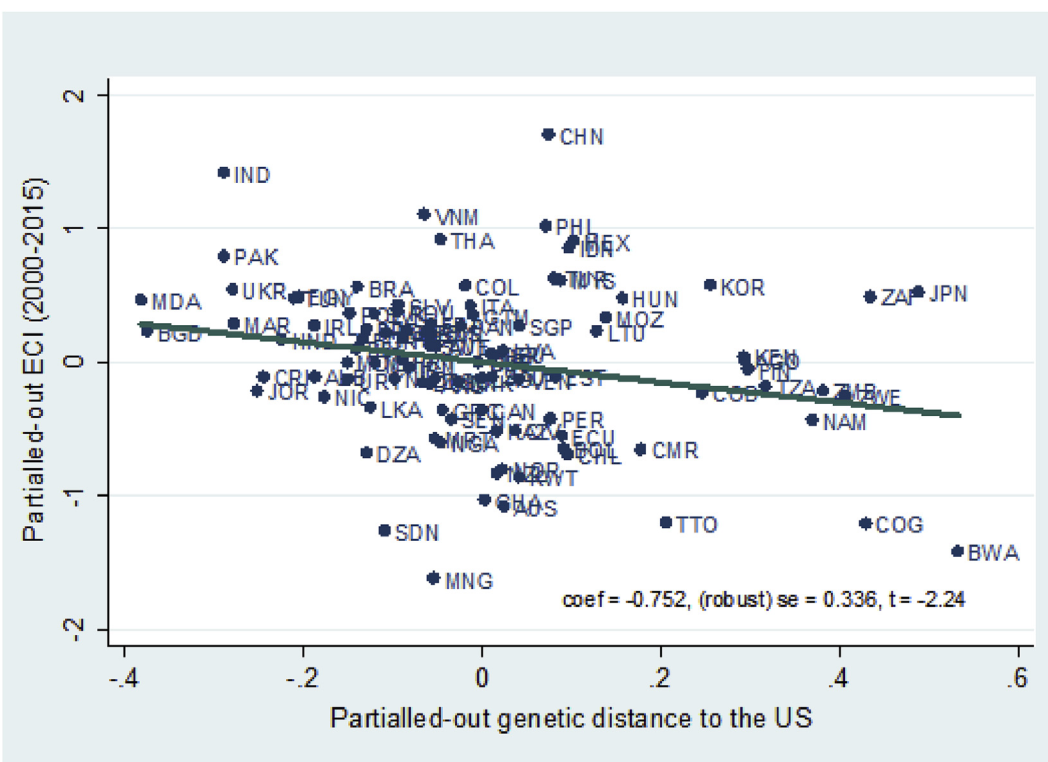

Fig. 4. Partial-effect of genetic distance from the frontier on ECI. Notes: The scatter plot illustrates the effects of genetic distance to the frontier on ECI when the effects of all control variables are partialled-out. The partial regression line is derived from regression in column (6) of Table 1.

Considering the control variables, except for trade openness, all other control variables are significant. Our finding is consistent with Spolaore and Wacziarg (2009) and Bove and Gokmen (2018) who find genetic distance impact cross-country income convergence.

Fig. 4 presents the orthogonalized residual plot for results in column (6) while controlling for the effect of the included control variables. As observed, the associated partial regression line of the effect of Fst_gd_{US} on innovation is largely consistent with the above findings.

4.2. Instrumental variable (IV-2SLS) results

Thus far, our analysis has assumed genetic distance is exogenous. Nonetheless, we cannot ignore the likelihood that our results might be due to the endogeneity of ECI with respect to genetic distance from the frontier. To deal with this concern, we also estimate Equation (1) using instrumental variable estimator. It also allows us in part to address the measurement errors in current genetic distance, arising from pairing genetic groups to populations and to countries as highlighted by Spolaore and Wacziarg (2009), which can cause attenuation bias in OLS coefficient estimates. Hence, we utilize data on genetic distance from the United Kingdom in 1500 AD (Fst_gd_{UK}) as an instrument to separate the exogenous source of variation in genetic distance from the United States so to estimate its effects on current innovations. The Fst_gd_{UK} is highly correlated with Fst_gd_{US}, with a correlation coefficient of 0.87, thus it meets the requirements of a valid instrument.

The regression results using two-stage least squares (2SLS) technique is reported in Table 2. The findings are evident, the second-stage estimates presented in panel A show that in all cases the coefficients of Fst_gd_{US} are found to be precisely estimated at 1% significance level with the expected negative sign, thus lending strong support for our argument that genetic distance from the frontier impedes technological innovations across countries. The standardized coefficient on Fst_gd_{US} in column (6) when all control factors are included suggests that a one standard deviation increase in genetic distance from the frontier results in 31.6% of a standard deviation decrease in innovation levels. It is also noteworthy that the coefficients of Fst_gd_{US} (in absolute terms) using instrumental variable approach are consistently larger in all cases than those reported in Table 1. These findings are likely to reflect that either our genetic distance measure is measured with error or genetic distance may have an effect on technological innovation through other unobserved channels. Nevertheless, the evidence provided support the idea that genetic distance from the frontier matters for technological innovation.

A strong first-stage association between Fst_gd_{UK} and Fst_gd_{US} is further noted (see panel B). All coefficients of Fst_gd_{UK} are positive and strongly significant. The partial R^2 from the first-stage regression and the F-test statistics for the significance of the excluded instruments (markedly larger than the rule of thumb of 10) indicate our instrument is strong and valid in all cases and hence is relevant to explain the endogenous regressor. Furthermore, the subsequent endogeneity tests indicate that the null hypothesis that genetic distance from the frontier can be treated as exogenous is rejected nearly in all cases, thus providing credence that genetic distance from the frontier must be taken as endogenous and it is appropriate to use instrumental variable technique. Accordingly, the IV-2SLS estimates presented in column (6) of Table 2 will be considered as our benchmark results to perform a number of robustness check.

5. Robustness checks

This section performs a series of sensitivity analysis on the model in column (6) of Table 2 to test the robustness of the results. For this purpose, we consider different measures of ECI and genetic distance from the frontier, and control for influences of cultural and other factors.

5.1. Alternative measures of innovation

In the analysis so far, the baseline measure of innovation is taken as the average of the index of economic complexity over period 2000–2015. The results obtained can be sensitive to the way technological innovation is measured. To mitigate the bias, we consider the following strategies. First, average ECI over several alternative periods (1980–2015, 1985–2015, 1990–2015, and 1995–2015) are considered to examine how genetic distance from the frontier influences technological innovation over the years. Next, the default period considered also includes the period of global financial crisis that can also bias the result. To this end, we eliminate the crisis period by confining the sample period to 2000–2006. Lastly, average R&D spending as a ratio of GDP (R/Y) over the period 2000–2015 is used as an alternative measure of technological innovation.

Table 2
Instrumental variable (IV-2SLS) estimation.

DV: *ECI*	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second stage regressions						
Fst_gd_{US}	−2.660***	−1.302***	−2.620***	−1.491***	−1.744***	−1.238***
	(-8.804)	(-3.575)	(-8.834)	(-4.311)	(-5.681)	(-3.151)
Per capita GDP, log		0.482***				0.190
		(5.873)				(1.643)
Openc			0.487***			0.140
			(3.508)			(0.991)
H_cap				0.778***		0.354***
				(6.348)		(2.787)
Institutions					0.504***	0.189**
					(6.189)	(2.004)
Constant	1.179***	−3.784***	0.781***	−1.208***	0.731***	−2.144**
	(9.325)	(-4.381)	(4.893)	(-2.962)	(5.706)	(-1.998)
Beta coefficient (%)	−67.8	−33.2	−66.8	−38.0	−44.5	−31.6
R^2	0.359	0.596	0.414	0.585	0.577	0.651
N	100	100	100	100	100	100
Panel B: First stage regression (DV: Fst_gd_{US})						
Fst_gd_{UK}	0.695***	0.602***	0.697***	0.627***	0.642***	0.584***
	(19.410)	(11.920)	(19.650)	(13.240)	(14.530)	(11.100)
Partial R^2	0.758	0.655	0.761	0.678	0.707	0.648
F-test for excl. instruments	376.8	142.1	385.9	175.3	211.0	123.1
Endogeneity test [p-value]	3.278 [0.070]	4.446 [0.035]	2.385 [0.122]	3.174 [0.075]	4.662 [0.031]	4.198 [0.041]

Notes: See Table 1 notes and Section 3.1 for other details. The Fst_gd_{US} is instrumented by Fst_gd_{UK}. *F*-test is the test for excluded instrument with the null hypothesis that the coefficients of the instruments equal to zero in first stage regressions. Moreover, endogeneity test is the test for endogeneity of instrumented variable. The null hypothesis is Fst_gd_{US} is exogenous. Figures in square brackets report p-values for the Chi-squared statistics. *, ** and *** suggest that p value is less than 0.1, 0.05 and 0.01 respectively.

Table 3
Alternative innovation measures (IV-2SLS estimation).

DV:	(1) $ECI^{1980-2015}$	(2) $ECI^{1985\text{-}2015}$	(3) $ECI^{1990\text{-}2015}$	(4) $ECI^{1995\text{-}2015}$	(5) $ECI^{2000\text{-}2006}$	(6) R/Y
Fst_gd_{US}	−1.060***	−1.088***	−1.102***	−1.127***	−1.116***	−1.541**
	(-2.905)	(-2.936)	(-2.924)	(-2.932)	(-2.766)	(-1.960)
Beta coefficient (%)	−27.7	−28.2	−28.4	−28.9	−28.1	−31.9
R^2	0.717	0.703	0.688	0.671	0.693	0.502
N	100	100	100	100	100	88
F-test for excl. instruments	123.1	123.1	123.1	123.1	123.1	38.2
Endogeneity test [p-value]	3.070 [0.079]	3.369 [0.067]	3.312 [0.069]	3.531 [0.060]	2.829 [0.093]	9.255 [0.002]

Notes: The dependent variable (DV) is economic complexity index (ECI), averaged over various sample periods in columns (1) to (5). R/Y is share of R&D spending in GDP, averaged over 2000–2015 period. We include a constant term and all explanatory variables from the baseline model however, their estimates are not reported for brevity. Figures in the round brackets are t-statistics generated from heteroskedasticity-robust standard errors. *, ** and *** suggest that p value is less than 0.1, 0.05 and 0.01 respectively.

Table 4
Alternative genetic distance to the frontier measures (IV-2SLS estimation).

DV: *ECI*	(1)	(2)	(3)
	Fst_gd_{UK}	Fst_gd_{G7}	Nei_gd_{US}
Fst_gd_{UK}	−1.042***		
	(-3.158)		
Fst_gd_{G7}		−1.175***	
		(-3.240)	
Nei_gd_{US}			−1.099***
			(-2.927)
Beta coefficient (%)	−31.5	−32.2	−28.1
R^2	0.656	0.669	0.651
N	100	100	100
F-test for excl. instruments	126.5	136.8	137.8
Endogeneity test [p-value]	3.430 [0.064]	1.756 [0.185]	4.909 [0.027]

Notes: The instrument used in column (3) is *Nei* genetic distance from the UK in 1500 AD. *, ** and *** suggest that p value is less than 0.1, 0.05 and 0.01 respectively.

Inline with the baseline findings, the estimates presented in Table 3 shows that the coefficients of genetic distance from the frontier are strongly significant with correct sign across all estimations. Somewhat smaller coefficients of Fst_gd_{US} in columns (1) and (2) imply that genetic distance from the frontier is strongly related with current measure of technological innovation. Columns (3) and (4) show the estimates of Fst_gd_{US} are closer to the baseline estimates. Additionally, the results in column (5) show that excluding the turbulent period of global financial crisis do not have any significant impact on the results. The result in columns (1) to (5) in Table 3 suggest the size of the effect of genetic distance from the frontier has not changed significantly over time. This finding is consistent with Bove and Gokmen (2018) who find that there was no major change in the effect of genetic distance on income over the years. In column (6), when replacing our core measure of innovation (ECI) with R&D spending, the negative impact of genetic distance from the frontier on technological innovation is maintained, albeit the effect is significant at 5% level[4]. On the whole, the results reported thus far illustrates that our key findings are not likely to be sensitive to the way we measure innovation.

5.2. Other measures of genetic distance from the frontier

The empirical analysis thus far selected the United States as the technological frontier. Taking the United States as the single global frontier may be restricting as there are other innovative nations in the world. Therefore, we check the consistency of our results by selecting United Kingdom and Group of Seven countries (Fst_gd_{G7}) as different global frontiers. Fst_gd_{G7} is calculated by using a simple average of genetic distances from all seven leaders[5]. The estimates presented in columns (1) and (2) of Table 4 point out that our previous result is not affected by the choice of the global frontiers.

Furthermore, genetic distance so far is measured using fixation index (*Fst*). Spolaore and Wacziarg (2009) also offer another measure of genetic distance based on *Nei* approach. Theoretically *Fst* and the *Nei* measure of genetic distance possess somewhat different properties; however, they are highly correlated with each other (0.98). Hence, we also consider genetic distance from the United States based on *Nei* approach (Nei_gd_{US}). Column (3) in Table 4 confirm that the use of alternative measure of genetic distance does not change our baseline results.

Table 5
Alternative country samples (IV-2SLS estimation).

DV: *ECI*	(1)	(2)	(3)
	Exclude OECD	Exclude neo-Europes	Exclude sub-Saharan Africa
Fst_gd_{US}	−1.280***	−0.961***	−2.385**
	(-3.370)	(-2.670)	(-1.960)
Beta coefficient (%)	−37.7	−24.3	−51.7
R^2	0.495	0.679	0.399
N	67	97	80
F-test for excl. instruments	168.9	193.5	19.9
Endogeneity test [p-value]	1.481 [0.224]	1.693 [0.193]	8.647 [0.003]

Notes: Alternative country sample used, Fst_gd_{US} has a negative and significant impact. *, ** and *** suggest that p value is less than 0.1, 0.05 and 0.01 respectively.

5.3. Alternative country samples

To perform additional robustness test, we restrict the number of countries in our sample to examine whether the baseline results obtained are caused by the inclusion of certain countries. Following the standard literature such as Spolaore and Wacziarg (2009), firstly, we eliminate OECD countries from our sample as these countries generally exhibit higher technological innovation and also share similar genetic traits. Secondly, we exclude the neo-European countries, consisting of Australia, Canada, New Zealand, and the United States to verify if results are influenced by the effects of great migrations. Lastly, we note that many countries genetically far from the United States are located in sub-Saharan Africa (see Fig. 2). Therefore, we exclude sub-Saharan countries from our sample to see whether this influences our results.

Evidently, the results reported in Table 5 confirm that Fst_gd_{US} are strongly correlated with technological innovation, suggesting our results are robust to the above considerations. Our result further confirms that

[4] The estimation here only includes 88 observations since data for R&D spending as a ratio of GDP is missing for other countries included in baseline regressions.

[5] The Group of Seven countries include the United States, Germany, United Kingdom, France, Italy, Canada, and Japan.

baseline findings are not due to including countries with high levels of technological innovation (OECD) or including countries most genetically far from the United States.

5.4. Controlling for cultural factors

We consider other cultural influences as they may also act as potential diffusion barriers to innovation. Genetic distance not only captures important biological but also cultural characteristics. In principle, a country that is genetically dissimilar from the frontier country could as well be different in a number of cultural characteristics which may affect transaction cost because of the lack of trust (Spolaore and Wacziarg, 2009). Differences in culture (ideals, norms, practices, etc.) may impede the adaptation of one another's technological advances. Hence genetic distance is interpreted as capturing cultural diffusion barriers to innovation. We control for specific cultural characteristics to see if the impact of genetic distance from the frontier on innovation are robust to accounting for these particular factors.

Column (1) in Table 6 controls for ethnic diversity, which is measured by ethnic fractionalization index. The index shows the probability that two randomly chosen individuals from a country's population belong to distinct ethnic groups (Alesina et al., 2003). Column (2) controls for generalized trust. The trust variable is constructed using World Values Survey (WVS) data on the fraction of respondents that answered "yes" to the question: "Generally speaking, would you say that most people can be trusted." Lastly, column (3) adds measures of religious composition, which proxies the effects of cultural norms (see Stulz and Williamson, 2003). Religious composition is computed as the fraction of the country's population that belongs to Protestant, Muslim or other religions with Catholic as omitted group. Evidently, most of these cultural variables are found to have statistically insignificant effect on innovation. More importantly, we found no significant change in our baseline results, despite controlling for cultural factors. Thus, these results reinforce that our key evidence are not distorted by the inclusion of different cultural factors.

Table 6
Controlling for cultural factors (IV-2SLS results).

DV: *ECI*	(1) Add ethnic diversity	(2) Add generalized trust	(3) Add religious composition
Fst _gd$_{US}$	−0.925**	−1.091***	−1.426***
	(-2.143)	(-2.689)	(-2.916)
Ethnic fractionalization	−0.673**		
	(-2.216)		
Trust		0.637	
		(0.972)	
Fraction Protestants			−0.227
			(-0.748)
Fraction Muslims			−0.422**
			(-2.130)
Fraction other religions			0.332
			(1.3387)
Beta coefficient (%)	−23.6	−30.4	−36.3
R^2	0.678	0.595	0.671
N	100	88	100
F-test for excl. instruments	90.28	100.2	81.57
Endogeneity test [p-value]	2.800 [0.094]	3.719 [0.054]	5.056 [0.025]

Notes: After controlling for cultural factor's impact, *Fst*_gd$_{US}$ has a negative and significant impact. *, ** and *** suggest that p value is less than 0.1, 0.05 and 0.01 respectively.

Table 7
Controlling for other effects (IV-2SLS estimation).

DV: *ECI*	(1) Add Private credit	(2) Add FDI	(3) Add geographic controls	(4) Add legal origin dummies
*Fst*_gd$_{US}$	−1.300***	−1.211***	−1.039**	−1.170***
	(-3.787)	(-3.106)	(-2.507)	(-3.121)
Private credit	0.703***			
	(3.544)			
FDI		0.002		
		(1.080)		
Latitude			0.393	
			(0.879)	
Island			0.175	
			(0.769)	
landlocked			−0.196	
			(-1.223)	
French Legal Origin				0.066
				(0.446)
German Legal Origin				0.397
				(1.634)
Scandinavian Legal Origin				−0.002
				(-0.007)
Beta coefficient (%)	−33.1	−30.9	−26.5	−30.4
R^2	0.693	0.655	0.666	0.669
N	100	100	100	100
F-test for excl. instruments	123.3	124.0	129.2	145.8
Endogeneity test [p-value]	3.113 [0.078]	4.035 [0.045]	2.929 [0.087]	4.573 [0.033]

Notes: After controlling for effects of other factors using IV-2SLS estimation, effects of *Fst*_gd$_{US}$ is negative and significant. *, ** and *** suggest that p value is less than 0.1, 0.05 and 0.01 respectively.

5.5. Controlling for other effects

Columns (1) to (4) of Table 7 report results of some additional robustness checks. We first consider the influence of financial development using private sector credit to GDP (see Column 1). Financial innovation helps to reduce screening and monitoring costs, which moderates the agency problem and increases the innovation rate by firms (Aghion and Howitt, 2009). Furthermore, Ang (2011) provides evidence that financial development is important in reducing market frictions, and thus in stimulating knowledge-based activities. The result, indeed, suggest that financial systems deepening is associated with greater innovation. However, the estimates of genetic distance from the frontier remain statistically highly significant.

Column (2) controls for foreign direct investment (FDI). FDI inflows is considered to enhance the domestic innovation capability through channels of skill exchange, competition, linkage effects and demonstration effects (Chen et al., 2018). The result indicates positive, albeit an insignificant effect of FDI on innovation. Evidently, our previous results are largely unaffected.

Moreover, column (3) adds geographic controls since they may be vital to explain the heterogeneity in cross-country innovation levels. Geographic factors impact are captured by latitude and dummy variables for island and landlocked countries. These considerations does not have any major influence on our baseline result.

Lastly, column (4) controls for the impact of legal origins. The legal system of a country is classified as based on French, German, or Scandinavian civil law using dummy variables with British common law as the excluded group. The advocates of legal origin theory postulate that country's with different legal origins are associated with different legal rules and these differently formed legal rules lead to different economic outcomes (La Porta et al., 2008). The central conclusion is countries who

Table 8
Panel estimates.

DV: *ECI*	(1)	(2)	(3)
	Pooled OLS	Random effects	Fixed effects
Fst $\_gd_{US}$	−0.809***	−1.738***	–
	(-6.674)	(-3.124)	
Per capita GDP, log	0.288***	0.197	0.044
	(10.80)	(1.240)	(0.204)
Openc	0.089***	0.132**	0.112*
	(3.061)	(2.355)	(1.846)
H_cap	0.405***	0.133	−0.122
	(10.85)	(0.899)	(-0.590)
Institutions	0.156***	0.130	0.0571
	(5.966)	(1.063)	(0.414)
*Fst*_gd_{US} × d2001			−0.355**
			(-2.020)
*Fst*_gd_{US} × d2002			−0.320*
			(-1.785)
*Fst*_gd_{US} × d2003			−0.301
			(-1.641)
*Fst*_gd_{US} × d2004			−0.361**
			(-2.185)
*Fst*_gd_{US} × d2005			−0.366**
			(-2.233)
*Fst*_gd_{US} × d2006			−0.405**
			(-2.285)
*Fst*_gd_{US} × d2007			−0.438**
			(-2.269)
*Fst*_gd_{US} × d2008			−0.426*
			(-1.940)
*Fst*_gd_{US} × d2009			−0.471**
			(-2.161)
*Fst*_gd_{US} × d2010			−0.372
			(-1.616)
*Fst*_gd_{US} × d2011			−0.313
			(-1.463)
*Fst*_gd_{US} × d2012			−0.107
			(-0.665)
*Fst*_gd_{US} × d2013			−0.004
			(-0.036)
*Fst*_gd_{US} × d2014			−0.016
			(-0.194)
*Fst*_gd_{US} × d2015			0.006
			(0.113)
R^2	0.654	0.619	0.371
N	1562	1562	1562
F-value	216.53***		8.240***
Wald chi-square		344.35***	
Year dummies	Yes	Yes	Yes

Notes: The dependent variable (DV) is economic complexity index (ECI) from 2000 to 2015. *, ** and *** suggest that p value is less than 0.1, 0.05 and 0.01 respectively. See Table 2 notes for other details.

have legal system originating from common law (English law) tend to do better than countries who have legal system originating from the civil law (Roman law and French Law). Moreover, countries who have legal system originating from French civil law tend to perform worse, as the French civil laws evolved to unite the legal system, eliminate jurisprudence and promote state power over the judiciary and give less importance to individual rights. Beck et al. (2003) observed that countries following French legal system provide less property rights protection in comparison to countries following another legal system and hence weakens the motivation to innovate. Doing so, the effect of different legal origins are found to be largely insignificant, however, our earlier finding remains robust to this consideration.

5.6. Panel analysis

In order to investigate the potential variations in genetic distance from the frontier and technological innovation over time, we also make use of panel sample. The panel includes the 100 countries from the cross-sectional sample and 16 years (2000–2015). We utilize pooled OLS model and random effects model to investigate the impact of genetic distance from the frontier on technological innovation. Furthermore, we also utilize the fixed effects model to determine the impact of genetic distance from the frontier on technological innovation over time. We also include time dummies in each model to account for the time effects.

Table 8 (Columns 1 and 2) report estimates for the pooled OLS and random effects model. The coefficient estimates of *Fst* $\_gd_{US}$ show a consistent negative relationship with technological innovation and are statistically significant. Finally, interaction terms relating to genetic distance from the frontier and time dummies are introduced as regressors in a fixed effect model (see column 3)⁶. We used fixed effects model to account for the effect of unobserved country-specific attributes. The significance of the interaction terms involving genetic distance from the frontier and the time dummy show that the effect of genetic distance from the frontier does systematically change over the sample period.

6. Conclusions

Using data on 100 developing and developed countries, this study uses economic complexity index to measure innovation and offers an empirical evidence on the influence of genetic distance from the frontier on innovation, with ordinary least squares, two-stage least squares and panel data techniques.

Estimation of the effects of genetic distance on innovation shows that a country's genetic distance from the frontier country is critical to explain that country's innovation. Countries that share common genetic characteristics with the frontier country are likely to benefit more in terms of any innovation taking place in the frontier country. On the other hand, countries which are genetically more distance from the frontier country are expected to gain the least from innovation taking place in the frontier country. The difference in genetic attributes between individuals and societies acts as a diffusion barrier and therefore impedes the sharing and adaptation of "tacit" and "explicit" bundle of knowledge across the border.

Although it is rather difficult to reduce genetic distance between frontier and laggard country within the short term, enhancing formal and informal social interaction between the countries can potentially reduce information flow barriers between groups. Putnam (2001) argues that development schemes must promote association activity through practical and refined means such as team sports. Similarly, Beretta et al. (2018) argue that development policies should take account of assortativity levels to ascertain several objectives that encompass the entire span of cultural diversity, and thus reduce barriers to information sharing among groups. Moreover, laggard countries would probably gain more from investment channeled into improving formal interaction and communication between laggard and frontier country. Improving formal interaction between genetically distant countries can possibly complement social interaction. There can be more educational exchange programs between frontier countries and developing countries.

Appendix A. Description of variables and data sources, summary statistics and correlation coefficients of key variables

[6] This is because genetic distance measure does not vary over time.

Table A1
Data description and sources.

Variable	Description	Source
Economic complexity index (ECI)	An index of economic complexity measuring the amount of productive knowledge (or knowhow) that underlies a country's production. A higher value of the ECI indicates greater economic complexity. ECI is therefore, a measure of the innovative output of a country. The baseline measure is taken as the average value for the period 2000–2015. Other periods are used as robustness checks.	The Observatory of Economic Complexity (Simoes and Hidalgo, 2011)
Genetic distance from the technological frontier	The genetic distance between the population of a particular country and the population of the United States. The baseline measure used is the *Fst* genetic distance. We also utilize the Nei genetic distance measure. Genetic distance reflects the degree of genealogical similarities (or historical relatedness) for the population of a particular country and that of the technological frontier. Alternative technological frontiers are used when performing robustness checks. Genetic distance between the population of a particular country and that of the United Kingdom in 1500 AD is utilized as instrument for the current genetic distance from the frontier.	Spolaore and Wacziarg (2009)
Per capita GDP	Gross domestic product in 2000 converted to constant 2011 international dollars using purchasing power parity rates and divided by total population.	World Bank (2018) WDI database
Openness to trade	Exports plus imports of goods and services divided by GDP in 2000.	World Bank (2018) WDI database
Human capital	An index of human capital in 2000 based on the average years of schooling and returns to education.	Penn World Table (9.0) database (Feenstra et al., 2015)
Institutional quality	Simple average of the six World Bank's Worldwide Governance Indicators: rule of law, regulatory quality, voice and accountability, control for corruption, political stability and absence of Violence, and government effectiveness, in 2000.	Kaufmann et al. (2010)
Latitude	The absolute value of the latitude of each country, rescaled to range between 0 and 1.	La Porta et al. (1999)
Landlocked	A dummy variable that takes the value 1 if a country is enclosed by land and 0 for otherwise.	CIA World Fact Book
Island	A dummy variable that takes the value 1 if a country is an island and 0 for otherwise.	CIA World Fact Book
Ethnic diversity	An index of ethnic fractionalization reflecting the probability that two individuals, chosen at random from the population of a country, will belong to two different ethnic groups. The index takes the values between 0 and 1 where larger values indicate greater fractionalization in the country.	Alesina et al. (2003)
Legal origins	A dummy variable that takes the value 1 if the legal system of a country is based on English common law, or German, French, or Scandinavian civil law and 0 otherwise.	La Porta et al. (2008)
Trust	Average value for all available WVS waves for the period 1981–2014 based on the share of respondents reporting that "Most people can be trusted.".	World Value Survey (WVS) database
Religious composition	Share of each country's population that belongs to the Protestant, Catholic, Muslim or other religions in 1980.	La Porta et al. (1999)
Private credit	Financial intermediary credit to private sector as a ratio of GDP in 2000	World Bank (2018) WDI database
FDI	Net foreign direct investment inflows in millions of US dollars in 2000	UNCTAD (2018) database

Table A2
Summary statistics.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
ECI	100	0.057	0.971	−2.429	1.620
Fst_gd_{US}	100	0.422	0.248	0.151	1.000
Fst_gd_{UK}	100	0.402	0.310	0.000	1.000
Per capita GDP (logs)	100	9.104	1.114	6.271	11.155
Openness to trade	100	0.784	0.460	0.012	3.661
Human capital	100	2.434	0.649	1.129	3.574
Institutions	100	0.123	0.939	−1.929	1.952

Notes: See text or Table A1 for descriptions of the variables.

Table A3
Correlations among the key variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) ECI	1.000						
(2) Fst_gd_{US}	−0.604	1.000					
(3) Fst_gd_{UK}	−0.590	0.871	1.000				
(4) Per capita GDP (logs)	0.760	−0.625	−0.545	1.000			
(5) Openness to trade	0.211	0.029	−0.039	0.247	1.000		
(6) Human capital	0.733	−0.560	−0.499	0.770	0.230	1.000	
(7) Institutions	0.707	−0.494	−0.417	0.804	0.253	0.746	1.000

Notes: See text or Table A1 for descriptions of the variables.

Appendix B. Construction of Economic Complexity Index (ECI) measure

Here we describe the method used to calculate ECI. The data for the ECI is taken from MIT's Observatory of Economic complexity. It is assumed that complex economies generally process many differentiated goods for export market and also their export mostly comprises of goods which only a few economies have the ability to produce. To estimate ECI, first, the revealed comparative advantage of a country's export is computed using the following formula (Hidalgo and Hausmann, 2009):

$$A_{ig} = \frac{T_{ig} \Big/ \sum_g T_{ig'}}{\sum_i T_{i'g} \Big/ \sum_{i'g'} T_{i'g'}} \tag{B1}$$

We defined T_{ig} as the aggregate export of country i in good g and A_{ig} is revealed comparative advantage of country 'i' in good 'g'. If a country exports a good more than what a country is supposed to export given its size relative to the world market then A_{ig} will be more than 1. Then, using A_{ig} a discrete matrix D_{ig} is computed. $D_{ig} = 1$ indicates that the country has a revealed comparative advantage in good g, whereas $D_{ig}, = 0$ implies that a country does not have revealed comparative advantage in good g.

$$D_{ig} = 1 \text{ if } A_{ig} \geq 1 \tag{B2}$$

$$D_{ig} = 0 \text{ if } A_{ig}$$

The matrix D_{ig} helps to identify the number of distinct goods exported by a country (diversity) and how many countries are involved in the processing of a particular good for the export market (ubiquity).

$$Diversity = C_{i,0} = \sum_g D_{ig} \tag{B3}$$

$$Ubiquity = C_{g,0} = \sum_i D_{ig}$$

Then a matrix is constructed to link countries that process similar goods for export market using the following formula:

$$D_{ii'} = \frac{1}{C_{i,0}} \sum_g \frac{D_{ig} D_{i'g}}{C_{g,0}} \tag{B4}$$

.

At last, ECI is computed as follows.

$$ECI = \frac{C_i - \langle C \rangle}{std(C)} \tag{B5}$$

where $C_i =$ eigenvector of $D_{ii'}$ linked with the second largest eigenvalue (Hartmann et al., 2017; Hausmann et al., 2013)

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2019.08.015.

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