Barriers to the Diffusion of Technology Across Countries: Assessing the Impact of Genetic Distance on Firm Productivity

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Introduction

- What accounts the large differences in economic development across countries?
- A large and growing literature demonstrates that:
  - Human capital accounts 10-30% of the cross country income differences
  - Physical capital accounts 20% of the income differences
  - TFP (efficiency in production) accounts 50-70% of the income differences (Hsieh and Klenow, 2010)
- Why does productivity differ so much across countries and firms?
- Macro factors: differences in institutions, government policies, geography, integration & differences in technological adoption.
- Micro factors: Managerial talent, quality of inputs, IT, R&D, experience, innovation, competition, & Knowledge transfers.
- Does genetic distance affect the diffusion of technology?

Introduction

- Genetic distance is the time elapsed since two populations have shared common ancestors (Spolaore and Wacziarg, 2009)
- Genetic distance between populations captures the degree of genealogical relatedness between populations over time.
  - Therefore, it can be interpreted as a general metric for average differences in traits (beliefs, customs, habits, values, etc) transmitted with variation across generations
- Recent literature shows that genetic distance explains cross-country differences in
  - trust (Guiso et al. 2009)
  - financial development (Ang and Kumar, 2014)
  - well-being (Burger et al. 2015)
  - new firm entry (Guedes et al, 2019)
  - per capita income (Spolaore and Wacziarg, 2009)

Introduction

In this paper, we

- investigate the effect of genetic distance on firm productivity

  $\Rightarrow$ *the first micro-level evidence*

- employ novel group quantile instrumental variable (GQIV) estimation technique using the data of more than 32000 firms in 84 countries.

Introduction

Hypothesis: Higher genetic distance from the world technology leader (the US) acts as a barrier to technology adoption in laggard countries,

$\Rightarrow$ *thus, depresses the TFP of firms in the latter*

Difficult to test empirically this hypothesis for two reasons

1. The treatment variable (genetic distance) is measured at the country-level while firm productivity is available at the firm-level.

   $\Rightarrow$ *thus, we cannot apply standard panel data approaches*

2. Substantial heterogeneity in firm productivity (Syverson, 2011) invalidating mean-type regression

   $\Rightarrow$ *calls for using distributional-type approach such as quantile regression*

   $\rightsquigarrow$*But, due to the presence of country fixed effects, classical quantile regression method will not identify the true effect of genetic distance.*

Introduction

To address these issues,

- we employ a novel Instrumental Variable (IV) quantile regression for group level treatment proposed by Chetverikov et al. (2016).

Summary of findings

Main result,

- Genetic distance has a negative effect on firm productivity.

Specific results,

- firms in countries that are more genetically distant from the US have lower productivity on average.
- the intensity of this effect varies across the distribution of firms' total factor productivity.
- an increase in genetic distance tends to hurt high productive firms more than low productive firms.
- our findings are robust to several sensitivity checks.

Contribution

Contribution 1:

We provide a micro channel evidence through which genealogical distance reduces the diffusion of technology from the technology frontier to the adopter countries

Contribution 2:

We investigate the distributional impact of genetic distance on the productivity of firms.

Data

Data

Micro data

- World Bank enterprise survey (WBES) of more than 32,000 firms in 84 countries is used in the analysis.
- The survey questionnaire contains identical questions for all countries
- Key variables used: TFP, ownership type, firms' commencement year, exporting status, and firm size etc.

Macro data

- Genetic distance (GD), religion distance, and language distance to the US are collected from Spolaore and Wacziarg (2018)
  - ✓ GD is between 0 and 1. $0 \equiv$ identical populations. $1 \equiv$ completely different populations.
- Legal origin, landlockedness, tropical land area, absolute latitude, and physical distance are collected from CEPII.
- Average real GDP, per capita GDP, trade openness are from WDI
- Institutional quality, government systems, colonial ties, wars dummies are found from Samuel Standaert's website

Measuring Total Factor Productivity (TFP)

Productivity is the measure of efficiency in production, i.e. how much output is obtained from a given set of inputs (Syverson, 2011)

TFP is a widely used measure of productivity

The World Bank Enterprise Surveys (WBES) revenue based TFP is calculated as follows:

$$\begin{aligned} \ln(Y_{i\tau g}) &= \alpha_1 \ln(K_{i\tau g}) + \alpha_2 \ln(L_{i\tau g}) + \alpha_3 \ln(M_{i\tau g}) + \alpha_4 \ln(K_{i\tau g}) \times I_g \\ &\quad + \alpha_5 \ln(L_{i\tau g}) \times I_g + \alpha_6 \ln(M_{i\tau g}) \times I_g + \nu_{i\tau g} \qquad (1) \\ \nu_{i\tau g} &= \omega_g + \omega_t + \lambda_\tau + \zeta_{i\tau g}, \end{aligned}$$

Where, $Y_{i\tau g}$, $K_{i\tau g}$, $L_{i\tau g}$, and $M_{i\tau g}$ are total sales, capital, labour intermediate materials in firm i, industry τ and country g.

Measuring Total Factor Productivity (TFP)

- I_g is a dummy variable indicating whether country g is high or low income country

- ω_g, ω_t and λ_τ capture country, year and industry fixed effects, and $\zeta_{i\tau g}$ are idiosyncratic shocks.

- The revenue based TFP is then obtained as the residual of the regression (1) plus the fixed effect terms, i.e.

$$\widehat{TFP}_{i\tau g} = \widehat{\nu}_{i\tau g} \quad = \quad \widehat{\omega}_g + \widehat{\omega}_t + \widehat{\lambda}_\tau + \widehat{\zeta}_{i\tau g}. \tag{2}$$

Methodology

Empirical Specification

A standard quantile model to investigate the distributional impact of genetic distance on TFP (Koenker and Bassett, 1978):

$$Q_{TFP_{i\tau g}|GD_g,X_{i\tau g},\omega_\tau,\varepsilon_g}(u) = GD_g\beta(u) + X'_{i\tau g}\gamma(u) + \omega_\tau(u) + \varepsilon_g(u) \qquad (3)$$

Where,

- GD_g is the measure of genetic distance of country g from the US
- $X_{i\tau g}$ denotes micro covariates
- $Q_{TFP_{i\tau g}|GD_g,X_{i\tau g},\omega_\tau,\varepsilon_g}(u)$ is the uth conditional quantile of $TFP_{i\tau g}$
- $\omega_\tau(u)$ are the unobserved industry-level fixed effects

$\beta(u)$ is the parameter of interest, and measures the effect of genetic distance on the uth quantile of firms' TFP.

Empirical Specification

$\beta(u)$ in Eq. 3 does not identify the impact GD for two reasons:

1. It does not control for unobserved country fixed effects
2. Endogeneity (i.e. GD can be measured with error and/or reverse causality)

To address these issues, we use the group quantile instrumental variable (GQIV) estimation technique of Chetverikov et al. (2016).

Following Spolaore and Wacziarg (2009), Ang and Kumar (2014) and Kumar and Singh (2019), we instrument Genetic distance from the US (GD_g) with Genetic distance from the UK in 1500 AD (i.e. $GD^{1500}_{g,UK}$).

Empirical Specification

As such, we can employ Chetverikov et al. (2016) to consistently estimate $\beta(u)$.

This can be implemented by the following two-step approach.

- *Step* 1: For each country, estimate the uth quantile of $TFP_{i\tau g}$ with $X_{i\tau g}$ & a constant by by the classical quantile approach:

$$\widehat{\varphi}(u) \quad = \quad \arg\min_{\gamma} \sum_{i=1}^{N_g} \rho_u\big(TFP_{i\tau g} - \widetilde{X}'_{i\tau g}\varphi\big), \tag{4}$$

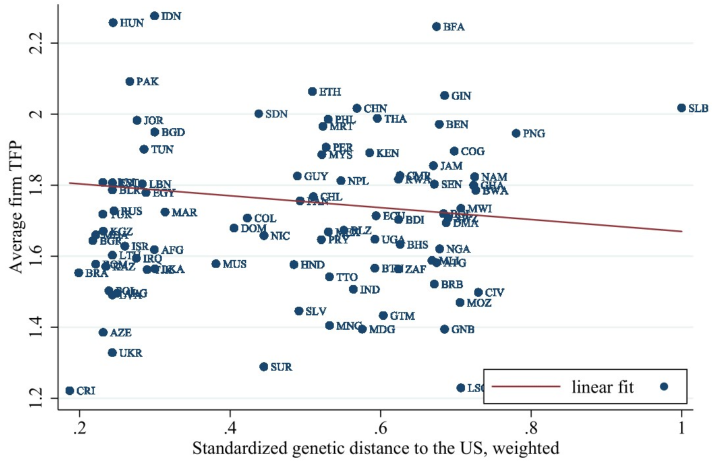
- *Step* 2: Estimate $\widehat{\beta}(u)$ using a 2SLS regression of $\widehat{\varphi}_(u) = [\widehat{\varphi}_1(u), \ldots, \widehat{\varphi}_G(u)]'$ on GD, macro covariates, GD^{1500}_{UK} as an IV for GD and a set of industry dummies.

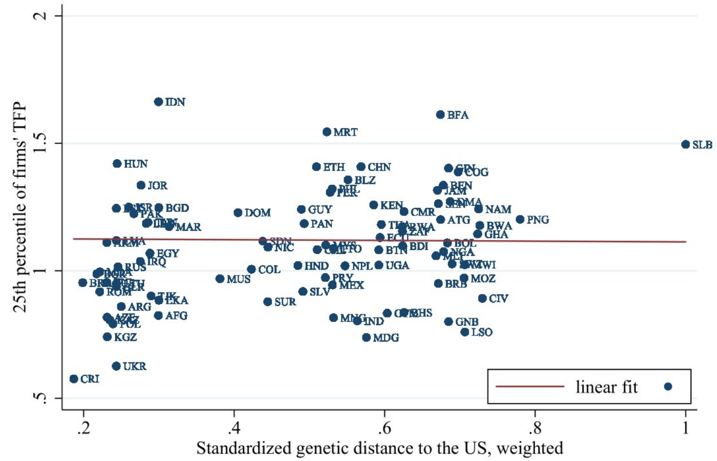
Descriptive Statistics #1

Table 1: Number of Firms by Sector

Sector	Number of Firms	Percentage
Textiles	2,722	8.39%
Leather	171	0.53%
Garments	4,356	13.42%
Food	6,382	19.67%
Metals and machinery	4,677	14.41%
Electronics	825	2.54%
Chemicals and pharmaceuticals	2,837	8.74%
Wood and furniture	1,201	3.70%
Non-metallic and plastic materials	3,419	10.54%
Auto and auto components	488	1.50%
Other manufacturing	3,713	11.44%
Retail and wholesale trade	179	0.55%
Hotels and restaurants	355	1.09%
Other services	632	1.95%
Construction & Transportation	487	1.51%
Total number of firms	32,444	100%

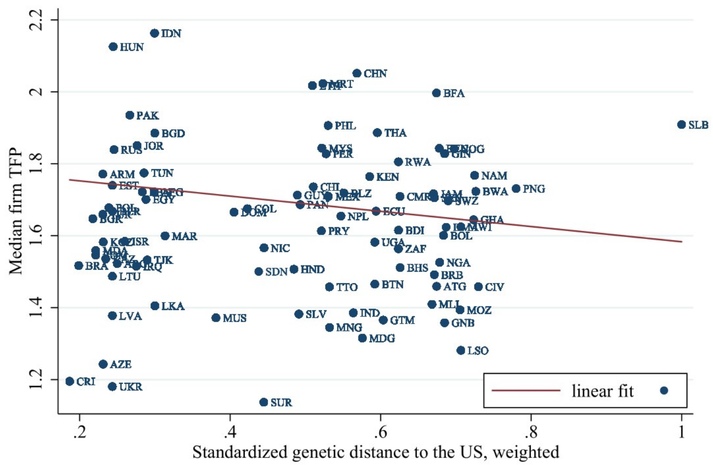
Figure 1: Partial scatter plots of genetic distance (GD) against country TFP

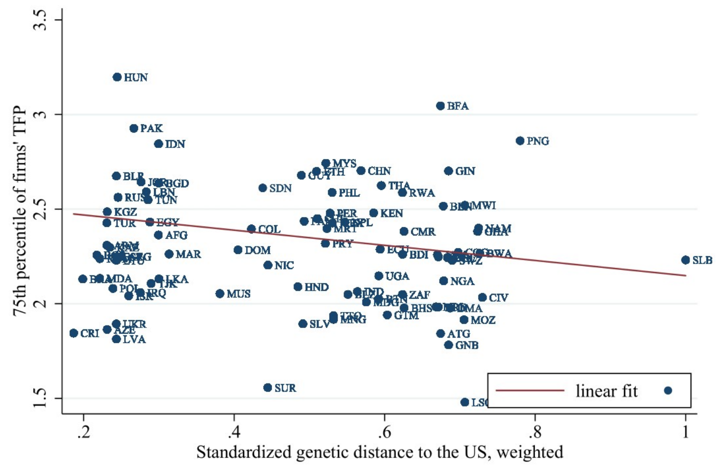




(a) Average TFP & GD

(b) 25th quantile TFP & GD





Results

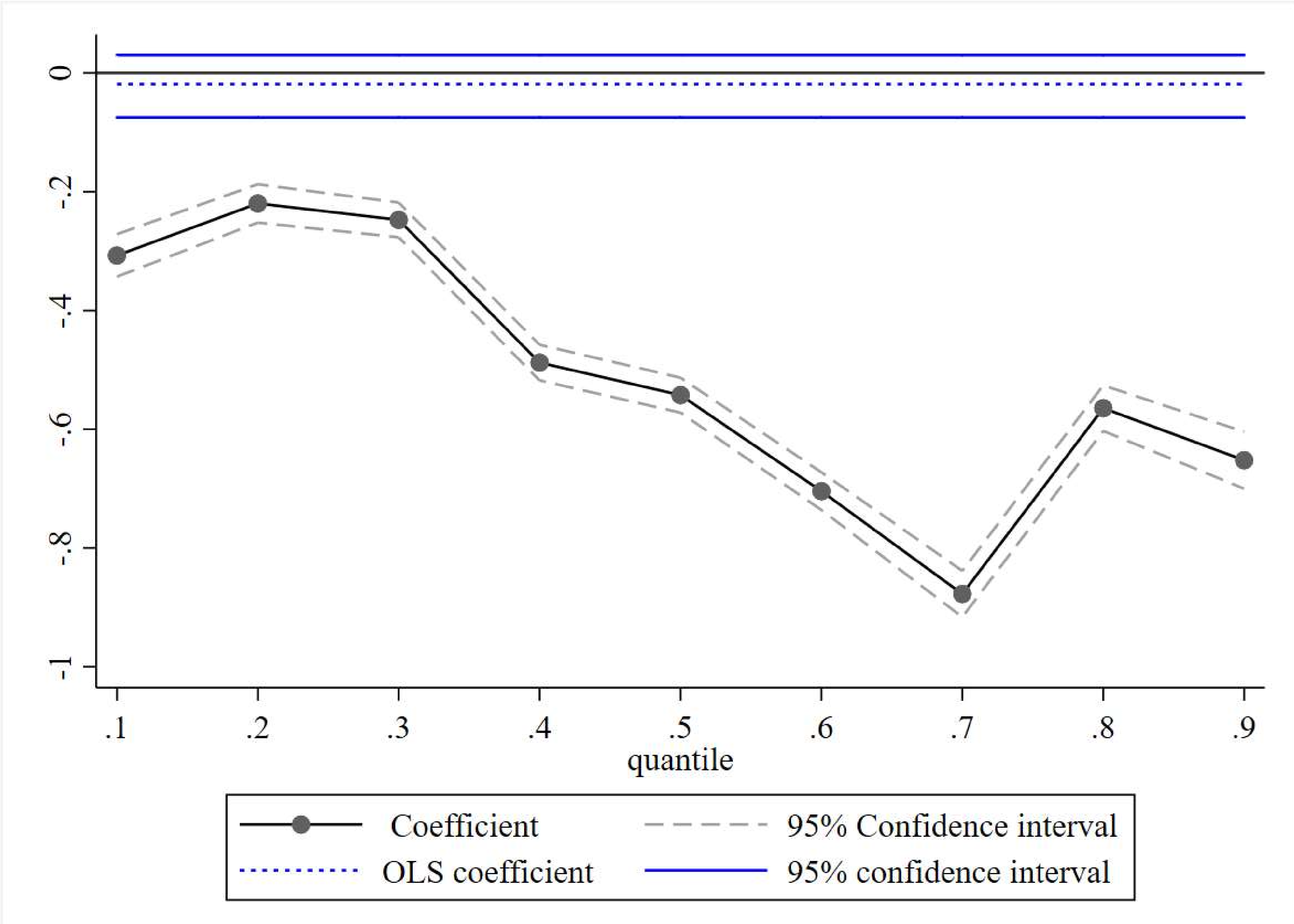
Baseline Results: without IV

Table 2: Impact of genetic distance on firm productivity– Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
		Quantiles				
	2SLS	0.10	0.30	0.50	0.70	0.90
Genetic distance to the US (weighted)	-0.02	-0.30***	-0.24***	-0.54***	-0.87***	-0.65***
	(0.0397)	(0.0285)	(0.0149)	(0.0150)	(0.0198)	(0.0244)
Real GDP Per Capita (log)	0.03***	0.13***	0.129***	0.15***	0.29***	0.19***
	(0.0050)	(0.0036)	(0.0029)	(0.0027)	(0.0040)	(0.0052)
Openness (log)	0.25***	0.56***	0.53***	0.67***	1.07***	0.66***
	(0.0191)	(0.0145)	(0.0112)	(0.0108)	(0.0183)	(0.0204)
Institutional Quality	-0.01	0.04***	0.02***	0.02***	.0010	-0.03***
	(0.0016)	(0.0008)	(0.0005)	(0.0006)	(0.0012)	(0.0013)
War Dummy	0.09***	-0.36***	-0.16***	-0.089***	0.04**	0.07***
	(0.0125)	(0.0075)	(0.0054)	(0.0062)	(0.0104)	(0.0111)
Parliament Dummy	0.07***	-0.46***	-0.38***	-0.26***	0.475**	0.56***
	(0.0257)	(0.0220)	(0.0180)	(0.0176)	(0.0197)	(0.0280)
Presidential Dummy	0.04*	-0.49***	-0.47***	-0.34***	-0.31***	0.17***
	(0.0237)	(0.0216)	(0.0194)	(0.0169)	(0.0182)	(0.0296)
Firm-level covariates	Yes	Yes	Yes	Yes	Yes	Yes
Other macroeconomic covariates	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No
Number of Countries	84	84	84	84	84	84
Number of Firms	30,042	30,786	30,786	30,786	30,786	30,786

Baseline Results: without IV

Figure 3: Baseline– Impact of genetic distance on firm productivity



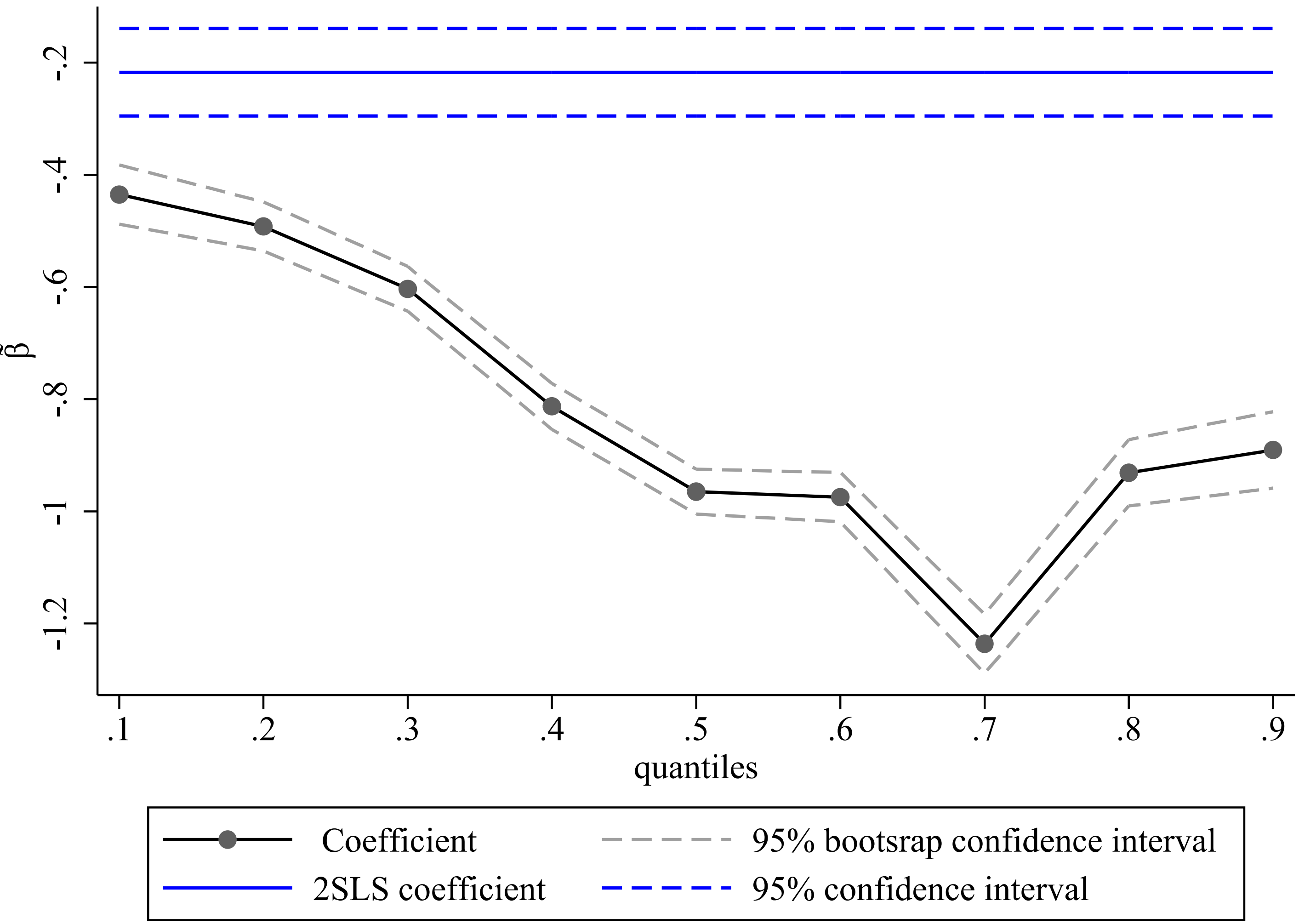
Baseline Results: with IV

Table 3: Impact of genetic distance on firm productivity– IV estimates

	(1)	(2)	(3)	(4)	(5)	(6)
		Quantiles				
	OLS	0.10	0.30	0.50	0.70	0.90
Genetic distance to the US (weighted)	-0.21***	-0.43***	-0.60***	-0.96***	-1.24***	-0.89***
	0.0397	(0.0269)	(0.0204)	(0.0204)	(0.0269)	(0.0348)
Real GDP (log)	0.03***	0.14***	0.14***	0.17***	0.31***	0.20***
	(0.0050)	(0.0037)	(0.0029)	(0.0028)	(0.0042)	(0.0052)
Openness (log)	0.25***	0.59***	0.60***	0.74***	1.15***	0.71***
	(0.0191)	(0.0148)	(0.0113)	(0.0111)	(0.0191)	(0.0229)
Institutional Quality	-0.0048	0.04***	0.02***	0.02***	.0012	-0.03***
	(0.0016)	(0.0008)	(0.0005)	(0.0006)	(0.0012)	(0.0013)
War Dummy	0.0858***	-0.37***	-0.18***	-0.09***	0.02**	0.05***
	(0.0125)	(0.0075)	(0.0056)	(0.0063)	(0.0105)	(0.0111)
Parliament Dummy	0.04	-0.48***	-0.45***	-0.33***	-0.02	0.51***
	(0.0257)	(0.0226)	(0.0183)	(0.0176)	(0.0197)	(0.0278)
Presidential Dummy	0.03	-0.49***	-0.49***	-0.35***	-0.32***	0.15***
	(0.0237)	(0.0216)	(0.0189)	(0.0169)	(0.0185)	(0.0288)
Firm-level covariates	Yes	Yes	Yes	Yes	Yes	Yes
Other macroeconomic covariates	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	84	84	84	84	84	84
Number of Firms	30,042	30,786	30,786	30,786	30,786	30,786

Baseline Results: with IV

Figure 4: Baseline– Impact of genetic distance on firm productivity



Robustness Checks

- Use alternative measure of genetic distance.

  $\Rightarrow$ *genetic distance with the UK (Ang and Kumar, 2014)*

- Excluding European countries from the sample.
- Controlling for technology adoption in 1500AD.
- Use alternative TFP measure.

  $\Rightarrow TFP_{kl}$

Conclusion

Conclusion

We investigate the effect of genetic distance on firm productivity for a large set of countries.

We estimate the effect at different distribution of TFP using firm level data on 84 countries.

Larger genetic distance from the technology frontier reduces firms' productivity. The negative effect is also higher for more productive firms than low productive firms.

The difference in genetic attributes between populations acts as a diffusion barrier, and therefore impedes the imitation, learning and adoption of technology across firms.

Enhancing formal and informal social interaction between firms in laggard and frontier countries can potentially reduce technology flow barriers between firms in the medium and long-run.