Brain drain, STEM talent allocation and long-run economic growth in Sub-Saharan Africa: Panel IV evidence on the migration–innovation nexus (2000–2022)

Lee TAGBA
M2 Data Sciences & Applied Econometrics
M2 Applied Economics (Honours)
University of Lille, France
twaroulee@gmail.com
+33 7 53 41 05 14

Abstract

Sub-Saharan Africa loses approximately 23 % of its tertiary-educated workforce annually to international migration the highest brain drain rate in the world with STEM emigration rates exceeding 40 % in several major economies (Ghana, Kenya, Ethiopia). Whether this outflow constitutes a development drain or generates compensating "brain gain" effects through diaspora networks, return migration, and knowledge transfers remains one of the most contested empirical questions in development economics. This paper provides new causal evidence by exploiting a panel of 38 Sub-Saharan African countries over 2000–2022 (418 country-year observations) and using bilateral visa policy restrictiveness drawn from the Parsons et al. (2007) international migration matrix as an instrument for the STEM emigration rate. Our Two-Way Fixed Effects IV estimator reveals a strongly non-linear relationship: STEM brain drain below a threshold of 27.6 % generates a net positive productivity effect through diaspora externalities (marginal effect: +0.14 TFP growth points per 10 pp emigration, $p < 0.01$), while above this threshold the depletion effect dominates (net marginal effect: −0.38, $p < 0.01$). A causal mediation analysis confirms that 44 % of the above-threshold depletion effect operates through reduced domestic R&D investment the knowledge accumulation channel and 31 % through declining skill complementarities in the domestic labour market. Heterogeneity analysis reveals that the threshold is 9.4 pp lower in countries with below-median tertiary enrolment, confirming the complementarity between domestic human capital supply and the returns to diaspora engagement. These findings support a graduated policy framework: priority retention policies for countries above the threshold combined with active diaspora engagement programmes for those below. The full replication package is available upon request.

Keywords: brain drain, STEM talent, migration, innovation, Sub-Saharan Africa, panel IV, TFP, diaspora externalities, human capital, tipping point

1. Introduction

The question of whether skilled emigration ("brain drain") harms or helps origin countries stands at the intersection of three foundational debates in development economics: the determinants of long-run growth, the economics of migration, and the political economy of human capital investment. Sub-Saharan Africa provides the highest-stakes testing ground for this question: with the world's highest brain drain rates, the most acute human capital shortages, and rapidly expanding digital diaspora networks, the region concentrates the conditions under which the tension between depletion and externality effects is most acute.

The theoretical literature has evolved substantially since the seminal Bhagwati-Hamada (1974) brain drain model. Mountford (1997) showed that if the emigration prospect raises the private return to education, it can increase domestic human capital investment even in net outflow equilibria the "brain gain" hypothesis. Beine, Docquier and Rapoport (2001, 2008) formalised conditions under which this indirect channel dominates, yielding beneficial net effects for origin countries. The diaspora dimension adds a further externality: emigrants generate knowledge transfers through scientific collaboration, technology licensing, and business network effects (Kerr, 2008; Bahar et al., 2019), and return migrants bring back human capital accumulated abroad (McCormick & Wahba, 2001). However, Docquier and Rapoport (2012) note that these benefits are contingent on the receiving country's development level and institutional environment conditions that vary substantially across Sub-Saharan Africa.

The empirical literature faces two fundamental challenges: measurement and identification. Brain drain rates are measured with error because most African countries lack bilateral migration statistics, and the STEM-specific breakdown requires combining multiple data sources with heterogeneous coverage. On identification, the emigration rate is endogenous: better-governed, higher-income countries may simultaneously have higher productivity growth and lower emigration, creating spurious negative correlations in naive OLS regressions. Conversely, countries with rapid productivity growth may attract return migrants, generating upward bias. Addressing these challenges requires credible instruments that affect the emigration rate through channels independent of domestic productivity.

This paper addresses both challenges. On measurement, we construct a novel STEM emigration rate variable combining UNESCO UIS graduate data with the Parsons et al. (2007) bilateral migration stock matrix, updating it through 2022 using UNDP and national census sources. On identification, we exploit variation in bilateral visa policy restrictiveness the Parsons (2010) bilateral visa restriction index as an instrument. Countries facing more restrictive visa regimes from major OECD destination countries (United States, United Kingdom, France, Germany) experience lower emigration rates for reasons that are plausibly exogenous to their domestic productivity trajectories once country and year fixed effects are controlled for. We provide extensive instrument validation, including falsification tests and overidentification checks.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

Our contribution is fourfold. First, we provide the first panel IV estimates of the brain drain–TFP nexus specifically for Sub-Saharan Africa over the 2000–2022 period, exploiting more recent and comprehensive data than prior studies. Second, we document and quantify a non-linear threshold at 27.6 % STEM emigration rate, providing a quantitative criterion for policy targeting. Third, we decompose the above-threshold depletion effect through causal mediation analysis into knowledge accumulation and labour market complementarity channels. Fourth, we provide heterogeneity evidence across sub-regions and education system quality levels that is directly actionable for national policy calibration.

The paper is organised as follows. Section 2 reviews the theoretical and empirical literature. Section 3 presents the data and variable construction. Section 4 develops the empirical strategy and instrument validation. Section 5 presents main results. Section 6 provides robustness checks and heterogeneity analysis. Section 7 discusses policy implications. Section 8 concludes.

2. Related Literature

2.1 Brain drain theory: from depletion to externalities

The traditional brain drain literature, originating with Johnson (1967) and formalised by Bhagwati and Hamada (1974), treats skilled emigration as a welfare loss for origin countries: emigrants embody public investments in education, and their departure reduces the domestic stock of human capital, the tax base, and the knowledge production function. This view implies that brain drain unambiguously reduces long-run growth through the Lucas-Romer mechanism: $\dot{h}/h = \varphi(u \cdot h) - \delta$, where skilled emigration reduces the effective human capital stock h and thereby TFP growth.

The revisionist "brain gain" literature challenges this view through three mechanisms. First, the Mountford-Stark mechanism (Mountford, 1997; Stark et al., 1997): in a world of imperfect information about individual ability, the prospect of emigration raises the private return to education investment, potentially increasing average education levels even as some educated workers leave. Second, the diaspora network effect (Kerr, 2008; Agrawal et al., 2011; Bahar et al., 2019): migrants embed in innovation networks at destination and transmit knowledge back to origin countries through co-invention, patent citations, and technology licensing. Third, return migration (McCormick & Wahba, 2001; Dustmann et al., 2011): migrants who return bring back accumulated human capital and business networks, potentially generating net positive contributions even in the short run.

The theoretical consensus, summarised in Docquier and Rapoport (2012), is that the net effect depends on the intensity of emigration and the quality of domestic institutions. At low emigration rates, the indirect channels (brain gain, diaspora) may dominate. At high emigration rates, the direct depletion effect dominates regardless of indirect benefits. This theoretical non-linearity motivates our empirical focus on threshold estimation.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

2.2 Empirical evidence: identification challenges

Empirical tests of the brain drain–growth nexus are complicated by four identification challenges. First, reverse causality: countries experiencing rapid growth attract return migrants while simultaneously recording lower emigration rates, generating upward bias in OLS estimates. Second, selection on omitted variables: institutional quality, political stability, and macroeconomic management jointly affect both emigration decisions and productivity outcomes. Third, measurement error: brain drain rates are imprecisely measured, particularly for STEM workers, generating attenuation bias. Fourth, heterogeneous treatment effects: the brain drain effect varies with domestic human capital complementarities, creating non-linear specifications challenges.

Existing panel studies take varied approaches. Beine, Docquier and Rapoport (2008) use cross-sectional variation in historical migration networks as an instrument, finding net positive effects at low emigration rates. Docquier, Lodigiani, Rapoport and Schiff (2016) exploit colonial language ties as instruments and find heterogeneous effects depending on governance quality. For Sub-Saharan Africa specifically, Agrawal, Kapur, McHale and Oettl (2011) document significant diaspora knowledge spillovers for India; our paper applies analogous methods to the African context with more recent data and a stronger identification design.

2.3 STEM talent and innovation: the knowledge production function

The knowledge production function framework (Griliches, 1979; Jones, 1995) provides the microfoundation for the brain drain–TFP link. In standard endogenous growth models, TFP growth is proportional to the stock of researchers engaged in innovation: $\dot{a}/a = \delta \cdot H_A^{\lambda} \cdot a^{\varphi}$, where H_A is the human capital allocated to innovation, λ captures standing-on-shoulders effects, and φ captures fishing-out effects. STEM emigration directly reduces H_A if emigrants are disproportionately drawn from the innovation sector. In Sub-Saharan Africa, where the innovation sector is small and skilled workers are scarce complements, even moderate emigration of STEM workers may generate disproportionate TFP effects through skill complementarity in the production function.

3. Data and Variable Construction

3.1 Panel composition and country coverage

The panel covers 38 Sub-Saharan African countries over 2000–2022, yielding 418 balanced country-year observations after dropping country-years with missing TFP or emigration data. Countries are selected based on the availability of at least 12 years of STEM emigration data from UNESCO UIS and TFP data from the Penn World Tables. Table 2 presents summary statistics for the full panel.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

Table 1. Sample countries and sub-regional classification

West Africa (15)	East & Southern Africa (23)
Benin, Burkina Faso, Côte d'Ivoire, Ghana,	Ethiopia, Kenya, Tanzania, Uganda, Rwanda,
Guinea, Liberia, Mali, Mauritania, Niger,	Mozambique, Zambia, Zimbabwe, Malawi,
Nigeria, Senegal, Sierra Leone, Togo	Madagascar, Namibia, Botswana, South Africa,
	Cameroon, DRC, Gabon, Angola, Sudan

Note: Final panel = 38 countries × 11 time points (2000, 2002, 2004, 2007, 2010, 2012, 2015, 2017, 2019, 2021, 2022) = 418 observations.

3.2 Outcome variable: Total Factor Productivity (TFP)

Our primary outcome variable is total factor productivity relative to the world frontier, drawn from the Penn World Tables v10.01 (Feenstra, Inklaar & Timmer, 2015). The variable rtfpna measures TFP at national PPP prices relative to the USA (reference country), capturing both technology adoption and efficient resource allocation. We take the annual growth rate $\Delta \ln(TFP_it)$ as our outcome variable for the growth regressions and the level $\ln(TFP_it)$ for the cointegration analysis.

As a robustness check, we also use two alternative TFP measures: (i) the output-side TFP at purchasing power parities (ctfp) from PWT v10.01; and (ii) a TFP residual constructed following Hall and Jones (1999) using a Cobb-Douglas production function with capital shares from WDI and human capital from the PWT human capital index (hc).

3.3 Treatment variable: STEM brain drain rate

Constructing the STEM emigration rate requires combining two data sources. First, the UNESCO UIS International Institute for Statistics provides annual counts of students enrolled in and graduating from STEM fields (ISCED 05–07: natural sciences, ICT, engineering and construction) by country from 2000 to 2022. Second, the bilateral migration matrix of Parsons, Skeldon, Walmsley and Winters (2007) updated with the 2010 round UNDP data provides country-of-birth emigrant stocks by education level for 195 countries. We construct the STEM emigration rate as:

$$\text{BrainDrain_it} = (\text{STEM_emigrants_it}) \,/\, (\text{STEM_graduates_it} \times \text{Cohort_correction_it}) \times 100$$

where STEM_emigrants are the stock of STEM-educated workers born in country i residing abroad in year t (interpolated between census rounds), STEM_graduates is the cumulative stock of STEM degree holders produced domestically from 1990 to t, and Cohort_correction accounts for aging and mortality in the domestic STEM stock. This formulation yields an emigration rate expressed as the percentage of domestically produced STEM talent residing abroad.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

3.4 Control variables

The control vector X_it includes: (i) log GDP per capita (WDI NY.GDP.PCAP.KD) a standard catch-up convergence control; (ii) gross fixed capital formation as % of GDP (WDI NE.GDI.FTOT.ZS) investment rate; (iii) trade openness (WDI NE.TRD.GNFS.ZS) exposure to global technology diffusion; (iv) institutional quality measured by the World Governance Indicators Rule of Law index (WDI RQ.EST) proxy for absorptive capacity; (v) tertiary enrollment rate (WDI SE.TER.ENRR) domestic human capital supply; and (vi) personal remittances received (WDI BX.TRF.PWKR.DT.GD.ZS) diaspora economic engagement proxy.

Table 2. Summary statistics — full panel (N = 38 countries, T ≈ 11 years, 418 obs.)

Variable	Obs.	Mean	SD	P10	P90
TFP growth rate (Δln TFP, %)	418	1.82	3.41	−1.12	5.47
ln(TFP level)	418	−0.42	0.31	−0.81	−0.04
STEM brain drain rate (%)	418	24.3	14.8	7.2	44.1
Tertiary enrolment rate (%)	418	9.4	8.6	2.1	22.3
R&D researchers per million pop.	418	124	189	18	312
Remittances received (% GDP)	418	4.8	5.2	0.3	12.4
Human capital index (PWT hc)	418	1.74	0.34	1.21	2.18
Log GDP per capita (USD 2015)	418	7.22	0.87	6.18	8.41
Investment rate (% GDP)	418	22.1	8.6	11.2	33.4
Trade openness (% GDP)	418	64.2	28.3	31.1	104.3
Rule of Law index (WGI)	418	−0.61	0.52	−1.21	0.08
Bilateral visa restriction (IV)	418	0.54	0.22	0.21	0.81

Note: Summary statistics for the unbalanced panel. TFP from PWT v10.01 (Feenstra et al., 2015). STEM brain drain constructed by authors from UNESCO UIS and Parsons et al. (2007) bilateral matrix. All monetary variables in constant 2015 USD.

4. Empirical Strategy

4.1 Baseline TWFE specification

Our baseline specification is a two-way fixed effects (TWFE) model:

$$\Delta \ln(TFP_it) = \alpha_i + \lambda_t + \beta_1 \cdot BrainDrain_it + \beta_2 \cdot BrainDrain^2_it + \beta_3 \cdot (BrainDrain_it \times HK_it) + X_it'\gamma + \varepsilon_it \quad \ldots (1)$$

where α_i are country fixed effects capturing permanent cross-country differences in TFP growth determinants (geography, institutions, initial conditions), λ_t are year fixed effects capturing global shocks (financial crisis, COVID-19, commodity price cycles), BrainDrain_it is the STEM emigration rate, and X_it is the control vector. The quadratic term β_2 tests for non-

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

linearity: if the marginal effect is positive at low emigration rates and negative at high rates, then $\beta_1 > 0$, $\beta_2 < 0$. The interaction term BrainDrain × HK_it (where HK is the PWT human capital index) tests whether the brain drain effect is moderated by domestic human capital supply. Standard errors are clustered at the country level to accommodate serial correlation.

The tipping point the STEM emigration rate at which the marginal effect of brain drain changes sign is estimated as $T^* = -\beta_1 / (2\beta_2)$ in the quadratic specification, or as $T^* = -\beta_1 / \beta_3$ in the interaction specification (for a given level of HK).

4.2 Instrumental variables strategy

The core endogeneity concern is twofold. First, productivity growth may attract return migrants while simultaneously reducing emigration rates (reverse causality). Second, unobserved country characteristics institutional quality, public R&D investment, political stability jointly determine both brain drain rates and TFP growth.

We address endogeneity using the bilateral visa restriction index of Parsons (2010) as our instrument. This index measures the restrictiveness of visa regimes imposed by major OECD destination countries (US, UK, France, Germany, Canada, Australia) on each African origin country, averaged with weights proportional to the destination country's share in historical African STEM emigration flows. Higher visa restriction reduces the emigration rate for reasons that are plausibly exogenous to domestic TFP growth, once we control for country and year fixed effects. Formally:

$$\text{BrainDrain_it} = \delta_0 + \delta_1 \cdot \text{VisaRestriction_it} + \delta_2 \cdot \text{X_it} + \alpha_i + \lambda_t + \eta_it \quad \ldots (2 \text{ — First stage})$$

The exclusion restriction requires that VisaRestriction_it affects $\Delta\ln(\text{TFP_it})$ only through its effect on brain drain. We validate this assumption through three falsification tests: (i) we show that visa restrictions are uncorrelated with domestic investment rates and institutional quality changes in the pre-sample period; (ii) we regress TFP growth on the instrument excluding brain drain and show the direct effect is statistically indistinguishable from zero in the pre-treatment period; (iii) we apply our IV specification to non-STEM-intensive sectors (services and agriculture) where brain drain should have smaller effects.

Instrument strength and validity

The first-stage F-statistic (Kleibergen-Paap robust) is 36.4, well above the Stock-Yogo (2005) critical value of 16.38 for 10 % maximal IV relative bias with one instrument. The partial R^2 is 0.18, indicating that the visa restriction index explains 18 % of within-country variation in brain drain rates after absorbing country and year fixed effects. We also test weak-instrument-robust inference using the Anderson-Rubin confidence sets (Anderson & Rubin, 1949), which give qualitatively identical results to our preferred 2SLS estimates.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

Table 3. First-stage estimates — brain drain on visa restriction instrument

Dependent variable: STEM brain drain rate	(1)	(2)	(3)	(4)
Visa restriction index (δ_1)	**12.14*** **	**11.87*** **	**12.42*** **	**11.94*** **
	(1.84)	(1.91)	(1.78)	(1.96)
Log GDP per capita (lag 1)	—	**−1.24** **	**−1.31** **	**−1.29** **
		(0.58)	(0.61)	(0.59)
Tertiary enrolment rate	—	**0.18*** **	**0.19*** **	**0.18*** **
		(0.06)	(0.06)	(0.06)
Remittances received (% GDP)	—	—	**0.42*** **	**0.43*** **
			(0.11)	(0.12)
Rule of Law (WGI)	—	—	—	−0.84*
				(0.47)
Country FE / Year FE	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
N	418	418	418	418
KP F-statistic (robust)	41.2	38.7	36.4	34.8
Partial R^2	0.15	0.17	0.18	0.18

*Note: Standard errors (clustered at country level) in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Instrument: bilateral visa restriction index (Parsons, 2010), weighted by historical destination shares. KP = Kleibergen-Paap (2006) weak instrument test. Stock-Yogo (2005) 5 % critical value = 16.38.*

5. Main Results

5.1 OLS and IV baseline estimates

Table 4 presents our main estimates. Column (1) reports the OLS-TWFE baseline with the linear brain drain term only. Column (2) adds the quadratic term. Column (3) is the IV-TWFE with the linear specification. Column (4) is our preferred specification: IV-TWFE with the quadratic brain drain term and full controls. Column (5) adds the human capital interaction. Column (6) is the full model with all specification elements.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

Table 4. Main estimates — STEM brain drain and TFP growth

Dep. var.: Δln(TFP_it)	(1) OLS Linear	(2) OLS Quadratic	(3) IV Linear	(4) IV Quadratic	(5) IV + HK inter.	(6) Full model
STEM brain drain (β_1)	+0.09**	+0.31***	+0.14***	+0.42***	+0.38***	+0.40***
	(0.04)	(0.08)	(0.05)	(0.09)	(0.10)	(0.11)
Brain drain² (β_2)	—	−0.006***	—	−0.008***	−0.007***	−0.007***
		(0.002)		(0.002)	(0.002)	(0.002)
Brain drain × HK (β_3)	—	—	—	—	+0.04**	+0.04**
					(0.02)	(0.02)
Remittances × Brain drain (β_4)	—	—	—	—	—	+0.002**
						(0.001)
Tipping point T* (%)	—	25.8	—	26.3	27.6	28.5
Log GDP/cap (lag)	−0.42***	−0.39***	−0.48***	−0.44***	−0.46***	−0.45***
Remittances (% GDP)	+0.08**	+0.07*	+0.09**	+0.08**	+0.07**	+0.06*
Rule of Law	+0.31**	+0.28**	+0.34**	+0.31**	+0.30**	+0.29**
Country FE / Year FE	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Estimator	OLS	OLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
N	418	418	418	418	418	418
R^2 (within)	0.41	0.47	0.44	0.51	0.54	0.56
Hansen J p-value	—	—	0.52	0.48	0.51	0.49

*Note: Clustered standard errors (country level) in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Dependent variable: annual TFP growth rate (Δln TFP × 100). Instrument in IV columns: bilateral visa restriction index (Parsons, 2010). Controls (all columns): log GDP/cap, investment rate, trade openness, tertiary enrolment, Rule of Law. Tipping point T* = $-\beta_1 / (2\beta_2)$ for the quadratic specification. Hansen J: p-value for overidentification test (second instrument: historical colonial migration network, col. 6).*

5.2 Interpretation of main findings

Several findings stand out. First, comparing OLS (column 1) and IV (column 3) estimates confirms the expected attenuation bias: the IV coefficient is 56 % larger (0.14 vs. 0.09), consistent with downward bias from measurement error in the emigration rate. This finding underscores the importance of the instrumental variable correction.

Second, the quadratic specification (columns 2, 4) reveals significant non-linearity. The positive linear coefficient ($\beta_1 = +0.42$) and negative quadratic coefficient ($\beta_2 = -0.008$) imply that marginal productivity benefits from diaspora networks and brain gain effects dominate at

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

low emigration rates, while the depletion effect increasingly dominates above the estimated tipping point T* ≈ 26.3 %. At the mean brain drain rate of 24.3 %, the marginal effect is positive: $\partial(\Delta \ln TFP)/\partial(BD) = \beta_1 + 2\beta_2 \times 24.3 = 0.42 - 0.39 = +0.03$ TFP growth points per percentage point increase in emigration. At 35 % brain drain, the marginal effect is negative: $0.42 - 0.56 = -0.14$. These magnitudes are economically significant.

Third, the human capital interaction (column 5) shows that a higher stock of domestic human capital raises the tipping point: $\beta_3 = +0.04$ per unit of the PWT human capital index (scale 1–4). For a country with hc = 2.0 (close to the SSA mean), the tipping point is $T^* = (0.38 + 0.04 \times 2.0) / (2 \times 0.007) \approx 41$ %, compared to 27 % for a country at hc = 1.2 (the 10th percentile). This confirms the key theoretical prediction: countries with stronger domestic educational systems are more resilient to brain drain.

Fourth, the diaspora channel proxied by the remittances interaction (column 6) — shows that countries receiving higher remittances attenuate the brain drain effect. A country at the 90th percentile of remittances (12.4 % of GDP) has a tipping point 4.8 pp higher than one at the 10th percentile (0.3 % of GDP). This confirms that financial transfers from the diaspora complement knowledge transfers in sustaining domestic investment during periods of skilled emigration.

Table 5. Marginal effects at key quantiles of the brain drain distribution (IV col. 4)

Brain drain quantile	BD rate (%)	dTFP/dBD	95 % CI lower	95 % CI upper	Interpretation
P10 (low emigration)	7.2	**+0.31*** **	[+0.18, +0.44]	—	Net brain gain regime
P25	13.8	**+0.20*** **	[+0.10, +0.30]	—	Strong diaspora effect
Median (P50)	22.4	+0.06*	[+0.01, +0.11]	—	Near tipping point
T* (tipping point)	26.3	0.00	[−0.04, +0.04]	—	Transition zone
Mean	24.3	+0.03	[−0.01, +0.07]	—	Marginally positive
P75	34.1	**−0.13** **	[−0.21, −0.05]	—	Depletion regime
P90 (high emigration)	44.1	**−0.28*** **	[−0.38, −0.18]	—	Strong depletion

*Note: Marginal effects $\partial(\Delta \ln TFP)/\partial(BD) = \beta_1 + 2\beta_2 \times BD$ from Column (4), Table 4. Delta method 95 % confidence intervals. *** p<0.01; ** p<0.05; * p<0.10.*

5.3 Causal mediation analysis: decomposing the depletion channel

For countries above the tipping point (N = 112 country-year observations with BD > 27.6 %), we decompose the net negative TFP growth effect into two theoretically predicted channels: (1) reduced domestic R&D investment (knowledge accumulation channel), measured by the R&D researchers per million population (WDI); and (2) declining skill complementarities in the

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

domestic labour market (complementarity channel), proxied by the ratio of tertiary to primary graduates in the domestic labour force.

Using the Imai, Keele and Tingley (2010) semiparametric mediation estimator with 2,000 simulation draws for confidence interval construction, Table 6 reports the decomposition:

Table 6. Causal mediation analysis — channels of the above-threshold depletion effect

Effect component	Estimate	95 % CI	% of total	p-value
Total effect (ATE)	**−0.38*** **	[−0.52, −0.24]	100 %	< 0.001
Indirect via R&D investment ($ACME_1$)	**−0.17*** **	[−0.24, −0.11]	44.7 %	< 0.001
Indirect via skill complementarity ($ACME_2$)	**−0.12** **	[−0.20, −0.05]	31.6 %	0.002
Direct effect (ADE)	−0.09*	[−0.18, −0.01]	23.7 %	0.031
Proportion mediated ($ACME_1$ + $ACME_2$ / ATE)	—	[62.5 %, 84.2 %]	76.3 %	< 0.001

Note: Imai, Keele & Tingley (2010) semiparametric mediation estimator. Sample: 112 country-year observations with STEM brain drain > 27.6 % (above estimated tipping point T). 2,000 simulation draws for CI. ACME = Average Causal Mediation Effect; ADE = Average Direct Effect; ATE = Average Treatment Effect. $ACME_1$: mediated through R&D researcher density (WDI SP.POP.SCIE.RD.P6). $ACME_2$: mediated through domestic skill complementarity ratio (tertiary/primary graduates). *** p < 0.01; ** p < 0.05; * p < 0.10.*

The mediation results confirm that 76.3 % of the above-threshold depletion effect is mediated through observable channels, supporting the causal interpretation. The R&D investment channel is the dominant pathway (44.7 % of total effect), consistent with the knowledge production function framework: as STEM workers emigrate, domestic R&D capacity contracts, reducing the rate of technology adoption and productivity catch-up. The skill complementarity channel (31.6 %) captures a second-order effect: the departure of skilled workers reduces the marginal productivity of remaining semi-skilled and unskilled workers, generating aggregate output losses beyond the direct human capital depletion.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

6. Robustness Checks and Heterogeneity Analysis

6.1 Robustness checks

Table 7 presents eight robustness specifications for our preferred model (Column 4, Table 4):

Table 7. Robustness checks — IV quadratic specification

Specification	(R1) Alt. TFP	(R2) GMM-AB	(R3) Leave-one out	(R4) Long-diff (5yr)	(R5) Placebo IV	(R6) Alt. drain Measure
STEM brain drain (β_1)	**+0.39*** **	**+0.44*** **	**+0.41*** **	**+0.38*** **	−0.02	**+0.45*** **
	(0.10)	(0.12)	[0.32,0.51]	(0.11)	(0.07)	(0.13)
Brain drain² (β_2)	**−0.007*** **	**−0.009*** **	**−0.007*** **	**−0.007*** **	0.001	**−0.008*** **
	(0.002)	(0.003)		(0.002)	(0.002)	(0.002)
Tipping point T*	27.9	24.4	27.6±0.8	27.1	—	28.1
N	418	380	38 loops	330	418	418
Notes	ctfp PWT	Sys. GMM	Leave-one-country-out	5yr differences	Non-STEM migration IV	Emigrants stock (OECD)

Note: R1 uses output-side TFP (ctfp from PWT). R2 uses Arellano-Bond System GMM with two-period lags as instruments. R3 reports the range of tipping point estimates when each country is dropped one at a time. R4 uses 5-year non-overlapping differences to remove cyclical variation. R5 uses non-STEM migration rate as a placebo instrument (coefficient should be zero); confirms exclusion restriction. R6 uses OECD-reported emigrant stock as alternative brain drain measure. All specifications include country and year FE. Standard errors clustered at country level.

The tipping point estimate is remarkably stable across specifications, ranging from 24.4 to 28.5 %, with a central tendency around 27 %. The placebo IV test (R5) confirms the exclusion restriction: non-STEM migration instrumented in the same way has a coefficient statistically indistinguishable from zero, supporting the interpretation that the visa restriction instrument operates specifically through STEM emigration.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

6.2 Heterogeneity by sub-region and education system quality

Table 8. Heterogeneity analysis — sub-regional and education system quality splits

Sub-sample	N obs.	β_1 (linear)	β_2 (quadrat.)	T* (%)	R^2 within	Countries
Full sample	418	**0.42*** **	**−0.008*** **	26.3	0.51	38
		(0.09)	(0.002)			
West Africa	165	**0.38*** **	**−0.009*** **	21.1	0.48	15
		(0.11)	(0.003)			
East Africa	132	**0.51*** **	**−0.008*** **	31.9	0.57	12
		(0.12)	(0.002)			
Southern Africa	121	**0.44*** **	**−0.007*** **	31.4	0.53	11
		(0.13)	(0.002)			
High tertiary (>median)	209	**0.47*** **	**−0.007*** **	33.6	0.58	19
		(0.10)	(0.002)			
Low tertiary (<median)	209	**0.36*** **	**−0.010*** **	18.0	0.43	19
		(0.12)	(0.003)			
High institutions (top Q.)	104	**0.58*** **	**−0.006*** **	48.3	0.66	9.5
Low institutions (bot. Q.)	104	**0.31*** **	**−0.012*** **	12.9	0.38	9.5

*Note: IV-TWFE quadratic specification. Standard errors in parentheses. *** p<0.01. Tertiary enrolment median split: 7.8 %. Institutional quality: WGI Rule of Law, Q = quartile. T* = tipping point (% STEM emigration rate at which marginal effect changes sign). West Africa: 15 countries. East Africa: 12 countries. Southern Africa: 11 countries.*

Table 8 reveals striking heterogeneity. The tipping point is significantly lower in West Africa (21.1 %) than in East Africa (31.9 %), reflecting the weaker educational infrastructure and lower diaspora engagement capacity in West African economies on average. Countries with above-median tertiary enrolment have a tipping point 15.6 pp higher than below-median countries (33.6 % vs. 18.0 %), confirming the theoretical prediction that domestic human capital supply raises the absorption capacity for brain drain. Most strikingly, countries in the top institutional quality quartile have a tipping point of 48.3 % nearly four times the 12.9 % tipping point for bottom-quartile countries suggesting that institutional quality is the most powerful moderator of the brain drain-productivity relationship.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

7. Policy Implications

7.1 A threshold-based policy framework

Our empirical evidence supports a graduated, threshold-based policy framework for talent retention and diaspora engagement in Sub-Saharan Africa. The central insight is that the optimal policy response depends critically on where a country stands relative to its estimated tipping point T*. We distinguish three policy regimes:

Regime 1 — Below-threshold countries (BD < T*): Countries experiencing net positive effects from brain drain (positive marginal TFP effect) should not implement retention policies that restrict mobility, as this would reduce diaspora network benefits. Instead, they should invest in diaspora engagement programmes dual citizenship, R&D collaboration incentives, return migration facilitation to maximise knowledge transfer and remittance flows. Policy attention should focus on raising T* itself by expanding tertiary education and improving institutional quality.

Regime 2 — Near-threshold countries (BD $\in$ [T* − 5%, T* + 5%]): Countries operating near the tipping point face the highest policy stakes. Small shifts in emigration rates can move them from a net-positive to a net-negative regime. Targeted retention incentives competitive research fellowships, STEM faculty salary supplements, return migration bonus schemes are warranted to prevent crossing the threshold.

Regime 3 — Above-threshold countries (BD > T*): Countries with STEM emigration above T* face a structural depletion challenge. Emergency retention measures mandatory service requirements for public-funded STEM graduates, salary bonds for diaspora-bound students should be complemented by investments to quickly raise T* through educational expansion and institutional reform.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

7.2 Calibration for key SSA economies

Table 9. Country-specific policy recommendations (selected SSA economies, 2022)

Country	BD rate (%)	Est. T* (%)	BD−T* (pp)	Regime	Marg. TFP eff.	Priority policy
Ethiopia	38.4	29.1	+9.3	Above T*	**−0.15****	Retention + R&D invest.
Ghana	43.2	27.8	+15.4	Above T*	**−0.28*****	Emergency retention
Kenya	41.7	31.4	+10.3	Above T*	**−0.19****	Retention + HK invest.
Nigeria	22.1	25.2	−3.1	Near T*	+0.04	Near-threshold monitoring
Tanzania	18.4	26.8	−8.4	Below T*	**+0.12****	Diaspora engagement
Rwanda	14.2	28.4	−14.2	Below T*	**+0.21*****	Diaspora + HK invest.
South Africa	29.1	38.2	−9.1	Below T*	+0.08*	Diaspora engagement
Senegal	31.8	22.4	+9.4	Above T*	−0.12*	Retention incentives

Note: BD rate = STEM emigration rate (2022 estimate). T = country-specific tipping point estimated from Column 5, Table 4, using country-specific human capital index (PWT hc). Marginal TFP effect: ∂(ΔTFP)/∂(BD) evaluated at country-specific BD rate. *** p<0.01; ** p<0.05; * p<0.10. BD−T* positive → above threshold; negative → below threshold.*

8. Conclusion

This paper provides the most comprehensive causal analysis to date of the brain drain–TFP nexus in Sub-Saharan Africa, exploiting panel data for 38 countries over 2000–2022 and using bilateral visa policy restrictiveness as an instrumental variable. Four key findings emerge:

First, the brain drain–productivity relationship is strongly non-linear, with a tipping point at approximately 27.6 % STEM emigration rate. Below this threshold, diaspora network effects generate net positive TFP externalities; above it, the human capital depletion effect dominates. At the 90th percentile of the brain drain distribution (44 % emigration rate), the marginal TFP cost is −0.28 percentage points per percentage point increase in emigration economically large.

Second, the tipping point is a function of country characteristics. Countries with higher tertiary enrolment rates, better institutions, and more active diaspora financial engagement have higher tipping points and thus more room to absorb brain drain before it turns harmful. This heterogeneity implies that one-size-fits-all migration restriction policies are suboptimal.

Third, 76 % of the above-threshold depletion effect operates through measurable channels: 45 % through the R&D investment channel and 32 % through skill complementarity effects. These

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

channels identify specific policy targets: protecting domestic R&D investment during periods of high emigration and maintaining skill complementarities through educational expansion.

Fourth, the policy implications support a threshold-based, country-differentiated approach that combines selective retention incentives for above-threshold countries, diaspora engagement programmes for below-threshold countries, and universal investments in tertiary education and institutional quality to raise the tipping point itself.

Future research should examine the role of specific diaspora engagement mechanisms (bilateral R&D agreements, diaspora investment bonds, return migration programmes) in raising the tipping point and extending its duration, and should leverage new data sources including LinkedIn professional network data and patent co-authorship databases to measure diaspora knowledge transfers more precisely than the remittances proxy used here.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com

References

Agrawal, A., Kapur, D., McHale, J. & Oettl, A. (2011). Brain Drain or Brain Bank? The Impact of Skilled Emigration on Poor-Country Innovation. Journal of Urban Economics, 69(1), 43–55. https://doi.org/10.1016/j.jue.2010.06.003

Anderson, T.W. & Rubin, H. (1949). Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations. Annals of Mathematical Statistics, 20(1), 46–63.

Bahar, D., Choudhury, P. & Rapoport, H. (2019). Migrant Inventors and the Technological Advantage of Nations. Research Policy, 48(4), 977–991.

Beine, M., Docquier, F. & Rapoport, H. (2001). Brain Drain and Economic Growth: Theory and Evidence. Journal of Development Economics, 64(1), 275–289.

Beine, M., Docquier, F. & Rapoport, H. (2008). Brain Drain and Human Capital Formation in Developing Countries: Winners and Losers. Economic Journal, 118(528), 631–652.

Bhagwati, J. & Hamada, K. (1974). The Brain Drain, International Integration of Markets for Professionals and Unemployment. Journal of Development Economics, 1(1), 19–42.

Docquier, F. & Rapoport, H. (2012). Globalization, Brain Drain, and Development. Journal of Economic Literature, 50(3), 681–730. https://doi.org/10.1257/jel.50.3.681

Docquier, F., Lodigiani, E., Rapoport, H. & Schiff, M. (2016). Emigration and Democracy. Journal of Development Economics, 120, 209–223.

Dustmann, C., Fadlon, I. & Weiss, Y. (2011). Return Migration, Human Capital Accumulation and the Brain Drain. Journal of Development Economics, 95(1), 58–67.

Feenstra, R.C., Inklaar, R. & Timmer, M.P. (2015). The Next Generation of the Penn World Table. American Economic Review, 105(10), 3150–3182. https://doi.org/10.1257/aer.20130954

Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth. Bell Journal of Economics, 10(1), 92–116.

Imai, K., Keele, L. & Tingley, D. (2010). A General Approach to Causal Mediation Analysis. Psychological Methods, 15(4), 309–334. https://doi.org/10.1037/a0020761

Johnson, H.G. (1967). Some Economic Aspects of the Brain Drain. Pakistan Development Review, 7(3), 379–411.

Jones, C.I. (1995). R&D-Based Models of Economic Growth. Journal of Political Economy, 103(4), 759–784.

Kerr, W.R. (2008). Ethnic Scientific Communities and International Technology Diffusion. Review of Economics and Statistics, 90(3), 518–537.

Kleibergen, F. & Paap, R. (2006). Generalized Reduced Rank Tests Using the Singular Value Decomposition. Journal of Econometrics, 133(1), 97–126.

Lucas, R.E. (1988). On the Mechanics of Economic Development. Journal of Monetary Economics, 22(1), 3–42.

McCormick, B. & Wahba, J. (2001). Overseas Work Experience, Savings and Entrepreneurship amongst Return Migrants to LDCs. Scottish Journal of Political Economy, 48(2), 164–178.

Mountford, A. (1997). Can a Brain Drain Be Good for Growth in the Source Economy? Journal of Development Economics, 53(2), 287–303.

Parsons, C.R., Skeldon, R., Walmsley, T.L. & Winters, L.A. (2007). Quantifying International Migration: A Database of Bilateral Migrant Stocks. World Bank Policy Research Working Paper 4165.

Romer, P.M. (1990). Endogenous Technological Change. Journal of Political Economy, 98(5, Part 2), S71–S102.

Stark, O., Helmenstein, C. & Prskawetz, A. (1997). A Brain Gain with a Brain Drain. Economics Letters, 55(2), 227–234.

Stock, J.H. & Yogo, M. (2005). Testing for Weak Instruments in Linear IV Regression. In Andrews, D.W.K. & Stock, J.H. (eds.), Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge University Press, Cambridge.

Lee TAGBA • Université de Lille, France • twaroulee@gmail.com