African Countries and the Brain Drain: Winners or Losers? Beyond Remittances

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1. Introduction

For at least six decades, consequences of brain drain (BD henceforth) have preoccupied both policymakers and development practitioners. The early view in the mid-1960s stated that BD should not be a worry as the loss in human capital caused by the migrant's departure is compensated by remittances and/or assets left behind (Berry and Soligo, 1969, Grubel and Scott, 1966). A more pessimistic view emerged in the mid-1970s (Bhagwati and Hamada, 1974, Bhagwati and Rodriguez, 1975) emphasizing adverse economic effects and welfare loss for those left behind. Large costs are expected if it induces shortages of labor in key occupations, as when engineers, teachers, or health professionals emigrate in disproportionately large numbers, undermining a country's ability to adopt new technologies, train students, or deal with public health crises such as COVID-19. By contrast, in the Mid-1990s, recent literature on the development impact of BD emphasized the fact that BD need not deplete the stock of human capital in sending countries and can induce economic benefits (Mountford, 1997, Stark et al., 1997). Up to this point, most of this literature has remained theoretical, partly because of strong constraints on data availability. Since the early 2000s, the availability of data has allowed scholars to empirically confirm these positive effects. For instance, Beine et al. (2001) provide evidence that, on average, emigration prospects stimulate human capital formation by creating additional incentives to acquire education. BD can be turned into a gain for the home country under certain circumstances. This study has initiated an extensive empirical literature that has established the possibility of a so-called "beneficial BD" (Batista et al., 2012, Beine et al., 2008, 2010, Cha'ngom et al., 2023, Gibson and McKenzie, 2012, Shrestha, 2017).

Nevertheless, evidencing a positive effect of BD on human capital formation does not imply that emigration significantly stimulates economic development and welfare at the origin. In other words, the analysis should move beyond human capital accumulation and assess how the net human capital responses translate into development outcomes while accounting for additional transmission channels through which BD influences development. To the best of my knowledge, Mishra (2007) is the first study that empirically assesses the economic losses associated with skilled emigration in the Caribbean context. She accounts for direct and indirect losses that high-skilled emigration generates and investigates whether remittances could compensate for them. More recently, relying on a development accounting framework, Docquier (2017), and Docquier and Veljanoska (2020) have considered both negative (human capital flight, technological externality,

and market size effect) and positive (remittances, education incentive, and diaspora externality) feedback effects of emigration. In this literature, little is known about the extent of fiscal costs supported by the source-country governments, or about the way the net effect evolves. Moreover, this literature disregards the migrant's welfare when assessing the development effect of BD which potentially leads to the underestimation of the true real effect (Clemens and Pritchett, 2008).

This issue is critical for Africa, given the continent's remarkable increase in the number of skilled migrants to the OECD over the past three decades. According to OECD statistics,[1] the count of highly skilled African natives aged 25 and above working and residing in the OECD surged to approximately 3.6 million by 2015, compared to 0.7 million in 1990, marking an average increase of 90.3% per decade. While the global skilled emigration rate remained relatively steady between 1990 and 2015 (hovering around 5%), Africa not only experienced a significantly higher emigration rate (13.2%) but also a rising trend (13.2% in 2015 compared to 11.3% in 1990). Notably, while Northern Africa (NAF henceforth) observed a decrease in its skilled emigration rate, Sub-Saharan Africa (SSA henceforth) demonstrated a pronounced upsurge, particularly since 2000. Furthermore, by 2015, Africa accounted for 15% of total immigration into the OECD and received 15.8% of total remittances to developing countries, amounting to $72.5 billion out of $455 billion. While this share might seem proportionate to Africa's representation among OECD immigrants, Egypt ($18.3 billion) and Nigeria ($21.2 billion) alone account for 55% of total remittances to the continent, despite making up only 9.9% of African immigrants in the OECD. In contrast, the remaining 52 African countries, which collectively account for 90.1% of African immigrants in the OECD, received only 45% of total remittances to Africa. Excluding Nigeria and Egypt, Africa's share of remittances to the developing world drops to 7.1%, despite representing 15% of developing-country immigrants in the OECD. Furthermore, while remittances are not exclusively sent by skilled migrants, a well-established body of literature suggests that skilled migrants tend to remit less than their unskilled counterparts (Faini, 2007; Niimi et al., 2010), though Bollard et al. (2010) present a counterargument.

This paper contributes in three distinct ways. Firstly, it conducts a comprehensive assessment of the human capital response to the prospect of

[1] Reported in Docquier and Marfouk. (2006) and in DIOC-Database on Immigrants in OECD countries (2000, 2010, 2015).

emigration from Africa to the OECD, employing the standard beta-convergence model borrowed from Beine et al. (2001, 2008). It utilizes a gravity-based instrumental variable (IV) approach for identification purposes. Secondly, it presents a unified framework for globally evaluating the developmental implications of brain drain. This framework facilitates the assessment of the welfare impact of brain drain on both those left behind and on national workers, irrespective of their geographical location. The framework operates within a nested Constant Elasticity of Substitution (CES) production technology, embedded in a standard development accounting model that endogenizes income per worker, human capital stock, and skilled emigration. Notably, the model encompasses 51 African countries and provides clear mechanisms. It is parameterized to align with African economies, accounting for income per worker, skill-specific emigration rates, the stock of human capital, and the wage gap between skilled and unskilled workers. This approach is innovative as it advances existing literature by quantifying the education subsidy loss, the market size effect, and remittances from skilled emigrants. Furthermore, it includes skilled migrants in the welfare function of sending countries. Thirdly, the paper evaluates how the net economic response to brain drain evolves in Africa. This evaluation spans two periods: one from 1990 to 2015 for those left behind and another from 1990 to 2010 for natural workers. This aspect improves upon existing literature[2].

My analysis indicates that the emigration-driven education incentives, established for developing countries worldwide (Beine et al., 2001, 2008, 2010, Cha'ngom et al., 2023), do not seem to apply in Africa. Low-income countries show no incentives, while Lower Middle and Upper Middle African countries experience a negative incentives effect (-2.8% and -7.9% respectively). This underscores the critical role of basic education as a prerequisite for this incentive effect to be at play. Essentially, regardless of the educational premium associated with emigration prospects, if primary and secondary education levels are low, individuals will not be able to pursue higher education in response to emigration prospects. In other words, the strength of emigration-driven human capital formation hinges on the eligibility for tertiary education. Moreover, the quantitative assessment of the

[2] To the best of my knowledge, all existing studies have predominantly focused on a specific year (Beine et al., 2001; 2008; 2010; Mishra, 2007; Docquier, 2017; Docquier and Veljanoska, 2020), disregarding its temporal dynamics. I acknowledge that while my modeling approach does not explicitly capture the persistence in core variables, it operates as a dynamic discrete model, treating each period *t* as a static model.

developmental impact of BD in Africa demonstrates that, on average, Africa is a net loser, and this loss tends to increase over time. At a regional level, despite an unchanged dynamic pattern, SSA emerges as a net loser, while NAF experiences an ambiguous response. However, the average findings in SSA conceal substantial geographical heterogeneity, with a non-linear net impact across sub-regions. At the country level, more countries exhibit a net income loss (65–75% of African countries) than those that benefit. Interestingly, a different scenario emerges when considering the welfare of skilled emigrants, where Africa becomes a net winner, experiencing a net income gain that increases over time. This dynamic remains consistent at both regional and country levels.

The remainder of the paper is organized as follows. Section 2 presents data and some stylized facts. Section 3 reviews the existing literature. Section 4 assesses the human capital response to emigration prospects. Section 5 presents the development accounting model that links income per worker, human capital, and skill-specific emigration rates. Section 6 presents the parameterization of the model and discusses the benchmark results. Section 7 analyses the robustness of the benchmark results and Section 8 concludes.

2. African Emigration to the OECD: Data and Stylized Facts

Size and structure of African skilled emigration to the OECD

As depicted in Table (A.2), by 2015, Africa stood as the fourth largest source of working-age immigrants for the OECD, accounting for 16.6% of the total stock of immigrants aged 25 and over. This positioned Africa behind Asia (28.9%), Central and Latin America as well as the Caribbean (23.8%), and Non-OECD European countries (22.2%). Regarding skilled emigration, Africa maintained its position (14.7%), following the same sequence of regions. In 2015, Africa held the third-largest share of skilled individuals among migrants (32.9%), trailing behind Asia (51.8%) and the Middle East & Far West (43.7%). This scenario occurs within the context of Africa being the least educated region worldwide, with only 5.1% of individuals aged 25 and over tertiary educated. Notably, there exists substantial heterogeneity across African regions, with NAF (13.4%) relatively more educated compared to SSA (2.9%). SSA is over-represented in global skilled migration to the OECD. The region accounts for 9.6% of global skilled emigration, but 7.8% of global unskilled emigration to the OECD. This contrasts with NAF, which contributes 5.1% to

global skilled emigration against 9.6% to global unskilled emigration to the OECD.

Table (A.3) delineates the trend of skilled individuals of working age born in Africa and living in the OECD from 1990 to 2015. Their numbers surged notably from 0.74 million in 1990 to 3.6 million in 2015, marking an average increase of about 90% per decade. In essence, the population of skilled African-born individuals in the OECD nearly doubled each decade. On average, 61.9% originate from SSA, with 36.9% coming from NAF. The remaining portion includes skilled migrants from Africa whose specific birth countries have not been specified. Significant variation exists within SSA across its sub-regions. Eastern Africa contributed the most significant share of skilled migrants to the OECD during this period, averaging 22.3%, followed by Western Africa (20.4%) and Southern Africa (10.0%). Conversely, Central Africa stands as the smallest contributor of skilled workers to the OECD, averaging merely 8.0% over the period. The combined contribution of Eastern and Western Africa amounts to an average of 42.7% of African skilled migrants, notably higher than Northern Africa's 36.86%. Among Africans with tertiary education residing in the OECD, the majority are represented by six countries, constituting 57.1% of the total. These countries include Algeria, Egypt, Kenya, Morocco, Nigeria, and South Africa, while the remaining 42.9% originate from the other 47 countries.[3]

However, despite the observed increase in the stock of skilled migrants, there has been a structural decline in their growth rate over time, both at the regional and sub-regional levels. Notably, after substantial growth over the decade 1990-2000[4], this growth slightly decreased over the following decade (2000-2010)[5]. The decline in growth rate became significant after 2010, dropping to less than 25% on average. Although it might be argued that the growth from 20102015 represents only mid-decade growth, it's noteworthy that even if this rate doubles in the remaining 5 years, by 2020, the growth rate for 2010-2020 will still stand on average below 50%. This structural pattern also holds at the sub-regional level.

In 2015, at a continental level, it was unsurprising that tertiary-educated Africans in the OECD accounted for 14.7% of the total OECD skilled immigration, while only 5.1% of the African resident labor force held tertiary education. This situation was particularly pronounced for SSA, where skilled immigrants represented 9.6% of OECD skilled immigrants, contrasting with

[3] These statistics exclude Somalia, which is not within our sample.

[4] 115.4% for Sub-Saharan Africa and 148.9% for Northern Africa.

[5] 86.6% in Africa, 96.4% in SSA, and 66.1% in Northern Africa.

the mere 2.9% of the resident labor force with tertiary education. However, these average trends conceal significant heterogeneity across African regions and countries. Panel (a) of Figure (1) illustrates that by 2015, Africa had lost approximately 13.2% of its skilled natives compared to 11.7% in 1990, representing a growth rate of approximately 12.8% over the covered period, or an average growth rate of 4.9% each decade in terms of the native skilled labor force. Regionally, while SSA experienced a significant increase in BD from 11.7% in 1990 to 17.3% in 2015 (as seen in panel (b) of Figure 1), NAF initially increased between 1990 and 2000 (from 10.7% to 14.3%) but underwent a sharp decrease between 2000 and 2015 (from 14.3% to 9.1%).

Moreover, panel (c) indicates that at the sub-regional level, BD displays a similar increasing pattern to SSA, except for Eastern Africa, where the magnitude of brain drain remained relatively stable at around 15% over the period. Despite this common trend over time, the intensity of BD varies significantly across sub-regions. While Middle and Eastern Africa exhibited the largest intensity of brain drain over the period, by 2015, Western and Southern Africa outpaced Eastern Africa, as depicted in panel (c). This dominance of SSA is further supported by panel (d) of Figure (1), showing that, on average, 40% of SSA migrants are highly skilled, as opposed to 20.2% for NAF. Concerning the income group as shown in Table (A.3), low-income countries exhibit the highest skilled emigration rate in Africa. They are followed by lower-middle-income countries. Upper middle-income countries exhibit a relatively smaller brain drain. The case of low-income countries seems relatively contradictory to the existing literature which claims that this income group should exhibit a lower brain drain compared to other income groups especially the middle-income group. This claim is based on the idea that, since migration has a cost, people from low-income countries are less likely to afford migration costs. Overall, as presented in Table (A.3) while LIC and UMIC exhibit a slight increase in brain drain over the period, LMIC have almost kept their skilled emigration rates constant between 1990 and 2010 before the sharp increase between 2010-2015.

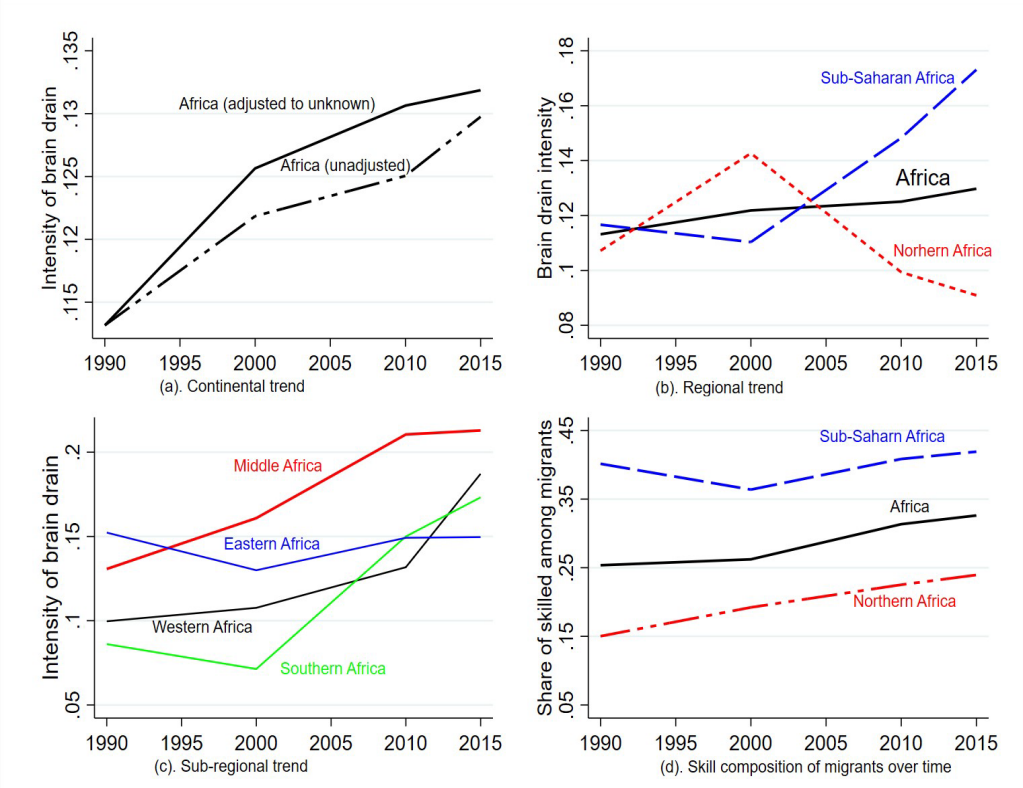
To have a broad view of brain drain at the country level, I present its distribution in 2015 which is the most recent year for which data are available. This is done concerning some economic and demographic characteristics. Figure (2) first provides some key characteristics of brain drain in Africa. Panel (b) and (d) show that BD decreases with the population size as well as resident skilled labor force size. Concerning the total stock of migrants (panel (a)), BD exhibits an inverted U-Shaped; It first increases with an increase in the total stock of migrants up to a certain cut-off level (around 59,800 migrants) and

then decreases. As depicted in panel (c), BD exhibits no clear pattern with the level of development in Africa.

The five largest source countries for skilled emigrants from Africa in 2015 were Morocco (470,593), Algeria (369,518), Nigeria (367,233), Egypt (256,393), and Kenya (137,745). It appears that the main suppliers of skilled Africans to OECD are large countries dominated by Northern Africa. In terms of emigration rate, the five most affected African countries are Seychelles (77.2%), Zimbabwe (68.0%) Sao Tome and Principe (61.9%), Cape Verde (60.6%), and Mauritius (51.2%). On this side, it appears that the most affected countries are the very small islands countries with populations less than 2.5 million.

Over the years, the number of African countries exhibiting a level of BD that is likely to be detrimental to their economy—i.e., a BD exceeding 15% (Beine et al., 2008; Rapoport, 2018)—has been increasing: 22 countries in 1990 (40.4% of the sample), 27 in 2000 (51.9%), 29 in 2010 (55.1%), and 31 in 2015 (59.6%). These heavily affected countries are dominated by Eastern African countries followed by Western African and Middle African countries. This strongly suggests that since 2000, more than half of the African continent experienced a level of brain drain likely to endanger their economy as a whole. The intensity, as well as the dynamics of skilled emigration from Africa, undoubtedly leads to questioning its consequences for sending countries. But before doing so, it is necessary to review its possible consequences, particularly through the active and potential mechanisms, as described in the existing literature, through which BD affects or is likely to affect source countries.

Figure 1: Brain drain in Africa over time both at regional and sub-regional level



Source: Calculated from DM06 and DIOC

Remittances data: reliability

Official data on remittances collected by the IMF and made available by the World Bank is made by two components: compensation of employees (i) and personal transfers (ii).

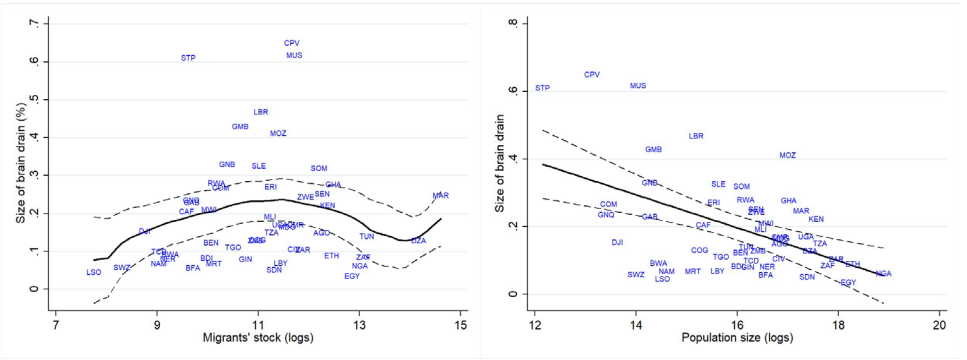
Compensation of employees. It refers to the income of border, seasonal, and other short-term workers who are employed in an economy where they are not residents and of residents employed by nonresident entities (IMF, 2009). This implies that, under the compensation of employees, the total wages of border, seasonal, and other short-term workers, and the salaries of resident staff of nonresident employers such as embassies and international organizations as well as other nonresident companies, are recorded as remittances. The latter may constitute a significant part of the compensation of employees in some countries and therefore overestimate remittances.

Personal transfers. They consist of all current transfers in cash or in kind received by resident households from nonresident households. Personal transfers thus include all current transfers between resident and nonresident individuals (IMF, 2009). Put differently, remittances sent by resident migrants are recorded together with any other personal transfers between residents and non-residents.

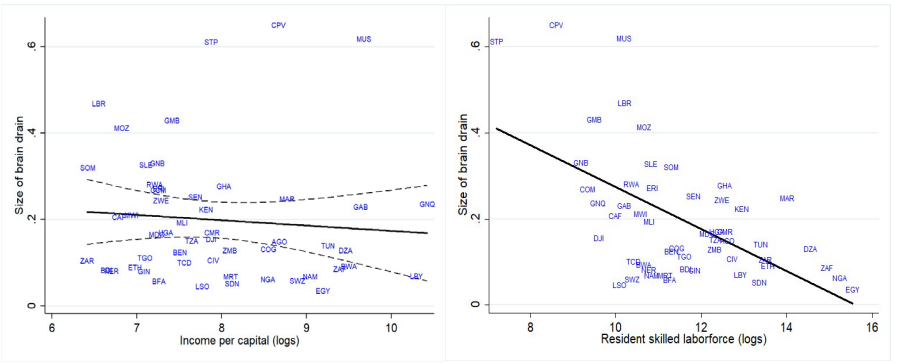
Above the limitations inherent to these two components, different data sources are also likely to report different figures on migrants' remittances as elements included in the two components for each data source (IMF, Central banks) may differ. But, for comparability purposes, rather than considering these different data sources, I rely on the World Bank data as the latter is more suitable for cross-country comparisons.

Figure 2: Distribution of brain drain in 2010 by major characteristics

(a) Income loss structure (b) Income gain structure



(c) Income gain from migrants (%) (d) Net income response to BD



Source: From DM06, DIOC and World Development Indicators (WDI)

3. How Does BD Affect Source Countries? A Literature Review

The literature on the development effect of brain drain in source countries can easily be divided into three strands: the neutralist view of the 1960s, the pessimistic view of the 1970s, and the optimistic view which emerged in the Mid - 1990s known as the new brain drain literature.

Neutralist view of the 1960s

This view claims that the effect of BD on source countries is neutral. Indeed, welfare losses caused by BD are likely to be compensated by remittances and/or assets left behind (Grubel and Scott, 1966; Johnson, 1967; Berry and Soligo, 1969) or simply recovered after a limited amount of time in an adjustment process (Johnson, 1967). It argues that the negative effects of BD should be sought only in the adjustment cost in the short run and in the market failure in the long run. The short-run adjustment cost refers to the time required to train workers who can properly replace those who have emigrated. Welfare loss occurs if direct and indirect gains from emigration are not quantitatively large enough to outweigh the direct and indirect negative externalities. For instance, an individual who might made a scientific discovery or an innovative production process that could substantially increase the productivity of the home country might be diverted to higher paid activity abroad lacking such beneficial externalities. Nevertheless, as explained by Johnson (1967), it is more plausible that in a developing country, migrants might have lacked the sufficient resources and/or socioeconomic climate required for the successful innovation stated above. In some cases, an individual migrates only because the developed destination country can provide the required resources and environment for such a discovery as well as the freedom to experiment the new innovative production processes. Put differently, emigration might well be the only way for an individual to generate a positive externality for their country of origin. In addition, if migrants are from a core profession like scientists, medical doctors, teachers, or engineers, even though their departure might generate large negative externalities for sending countries, this negative effect will hold only for the length of time required to train other new specialists. In summary, the neutralist view concludes that brain drain increases welfare at the world level while the welfare of those left behind is not reduced especially because migrants only take away their marginal product and negative externalities are simply due to short-run adjustment costs which disappear in the long run.

Pessimistic view of the 1970s

Central results of the neutral view stating that BD should not be a worry as skilled migrants will only take away the value of its marginal product which he earns anyway, can be subject to important limitations. Bhagwati and Hamada (1974) highlight three limitations: First, for large rather than infinitesimal shifts of labor due to emigration, there would still be a loss for those left behind. Second, if social return exceeds private return because of important externalities, then again, there is a loss for those left behind. Finally, if the government has subsidized the education that is embodied in the skilled individual who emigrates and if the government would have taxed this skilled individual (realistic with progressive taxation) partially or wholly to recover the return on this investment, then, his emigration does deprive those left behind and thus worsens their welfare. This view explores the welfare effect of BD on those left behind in a more realistic setting. Studies conducted under this strand considered domestic labor market rigidities (Bhagwati and Hamada, 1974; Bhagwati, 1976), informational imperfection Hamada and Bhagwati. (1975) and fiscal losses Bhagwati and Hamada (1974); which have been introduced to emphasize the negative consequences of the BD on source countries. BD is viewed as contributing to the increased inequality between developing and developed countries McCulloch and Yellen (1977) most often through an important reduction in human capital already lacking in such countries Haque and Kim (1995) as well as other negative consequences highlighted earlier.

Labor market rigidities: if wages are higher abroad, emigration prospects will increase the expected wages of educated individuals. This will consequently increase the investment in education and thus the supply of educated labor. If wages are not flexible enough (sticky), the demand for educated labor won't be sufficient to cover its supply when the probability of migrate is less than unity, making some additional educated labor unable to migrate. This process creates educated unemployment. This educated unemployment then leads to the reduction of national income by the amount of the educational subsidy supported by the government. Thus, even in the absence of externality, brain drain can easily lead to unfavorable effects on national income, per capita income, and unemployment of educated labor.[6]

Informational imperfection: Using the "*filtering theory of education"* Hamada and Bhagwati. (1975) shows that BD might serve to identify and filter the

[6] See Bhagwati and Hamada (1974); Fan and Stark (2007a), 2007b for more details.

more efficient worker from the less efficient.[7] So, if the domestic labor market is not able to discriminate as the international labor market does, the economy will tend to lose. This will arise because skilled emigrants are picked up from the category of the more talented individuals. The authors conclude that since the labor market of developing source countries cannot discriminate between highly talented and common labor, BD will cause welfare loss even if wages are flexible. The process described above leads to the concentration of talented individual in developed countries at the expense of developing countries affecting thus their ability to adopt new technologies and consequently ending up increasing the development gap between origin and destination countries.

To sum up, (*i*) brain drain is systematically a negative externality for those left behind. (*ii*) It is a "zero-sum game" with developed countries being more and more developed and developing countries being more and more poor. (*iii*) At the political level, if the international community does not create a mechanism by which international transfers will be done to compensate sending countries for losses caused by BD (an example is the "brain tax" `*a la* Bhagwati (1976)), this phenomenon will keep developing source countries in a poverty trap.

The Optimistic view from the mid 1990s

Under the hypothesis that human capital accumulation is one of the key drivers of economic performance, the pessimistic view has claimed that BD may leave sending countries in a kind of "poverty trap". The rationale of this argument is that the average level of human capital in the origin countries will not grow because destination countries will divert their highly skilled workers. This will increase the productivity of host countries at the expense of sending countries. But in the mid-1990s, a more optimistic strand of the literature emerged. It states that, when emigration is not a certainty, BD will foster human capital accumulation, raise productivity, and consequently enhance economic performance in source countries. So, there is a possibility for a beneficial brain drain with the "brain effect"[8] dominating the "drain effect" (Mountford, 1997; Stark et al., 1997; Beine et al., 2001).[9] An additional condition is that the probability to emigrate should not be too high Beine et al. (2001). From this perspective, brain drain is viewed as a "disguise blessing"

[7] Developed by Arrow (1973) and Spence (1974), it states that education is important not so much because it increases the productivity of workers, but because it allows to filter efficient from common labor.

[8] Migration prospects foster investment in human capital due to higher return abroad.

[9] Actual migration flows reduces the available stock of human capital.

Stark et al. (1997). Using three important considerations such as opportunities, incentives, and information, Stark et al. (1997) showed that brain drain might rather be a disguised blessing as it could result in a brain gain for sending countries. In fact, with the opportunity to migrate and receive higher returns to human capital, some individuals in their home countries invest in human capital and migrate. Some others invest in human capital but do not migrate. Through this process, the newly skilled who have not been able to migrate increase the stock of resident skilled labor force. Consequently, after migration has taken place, the stock of human capital accumulated is larger compared to the pre-migration level.

Empirical literature on the brain drain - development nexus

So far, the existing literature has been exclusively theoretical without any empirical evidence. Empirical studies have emerged with the pioneering study conducted by Beine et al. (2001) which has investigated the impact of migration prospects on human capital accumulation and economic growth in small open developing countries. Using a cross-section of data for 37 countries, their results have been in favour of the optimistic view. They found that there was a possibility for a beneficial BD because migration prospects play a significant role in education decisions.

After the pioneering study of Beine et al. (2001), a wide range of empirical literature has tried to address this issue. These studies have tried to investigate how BD affects human capital formation Beine et al. (2008), economic growth (Beine et al., 2003; Schiff, 2005), welfare of those left behind (Di Giovanni et al., 2015; Schiff, 2018), offsetting capacity of remittances Mishra (2007) and global net effect of brain drain Docquier (2017). Almost all these studies conclude in favor of a beneficial BD under some conditions. Broadly, BD enhances human capital formation and economic growth in source countries with initially low level of human capital and low skilled emigration rate while countries with a high skilled emigration rate (above 15% to 20%) and a proportion of highly educated in the total population above 5% experience a detrimental BD. When residents are better off under migration, it is mainly through remittances in some large recipient countries Di Giovanni et al. (2015), but, on average, remittances do not offset the negative consequences of BD. By including education incentives and diaspora externality to remittances, Docquier (2017) conclude that the developing countries with per capita income below 6000$ are net winners. While macro pieces of evidence have been largely criticized and presented as being unrealistic and based on disputable hypothesis (Clemens, 2016), micro-based studies seem to confirm education incentives (Shrestha, 2017; Gibson and McKenzie, 2012) generated by migration prospect.

So far, the literature has largely disregarded migrants when assessing the consequences of BD in source countries. However, it should be noted that this issue dates back to the 1960s when Grubel and Scott (1966) claimed that a leader's objective function is to maximize the collective welfare (better standard of living for the whole community). In other words, wherever community members are living, the community will be better off if everybody is better off. They stated that emigration will increase the community's standard of living if the migrants improve their income once abroad and if their departure does not reduce the income of those left behind. Place-based measures of economic welfare such as per capita income are usually used to assess the effect of BD; those measures systematically exclude gains to people who emigrate. Gibson and McKenzie (2012) provide another argument justifying the exclusion of migrants. This argument is based on the belief that governments only consider the welfare of current residents rather than the welfare of all the natives. This argument might not be relevant because of "dynamic inconsistency" related to the fact that emigrants were current residents during their schooling and until they emigrated. Clemens and Pritchett (2008) have proposed a systematic way to integrate emigrants into welfare calculations. That is by relying on "income per natural" rather than the traditional "income per capita."

4. Emigration and Human Capital: Gravity-based IV approach

Starting with Mountford (1997), Stark et al. (1997), and Beine et al. (2001), the link between skill-biased emigration rates and pre-migration human capital formation has been theoretically investigated in a two-country setting with a (poor) origin country and a (rich) destination country. Skill-biased emigration prospects are shown to raise the expected return to human capital, thus leading more people to invest (or people to invest more) in education at home before deciding whether to emigrate or not. A growing strand of literature shows empirically that incentives for human capital accumulation in developing countries are based to a significant extent on migration opportunities. Micro-level evidence of a positive impact of emigration on the *net* stock of human capital in the source country has been provided in many studies. They include Chand and Clemens (2008) in Fiji, Gibson and McKenzie (2011) on Tonga and Papua New Guinea, Batista et al. (2012) on Cape Verde, Shrestha (2017) on Nepal among others. To identify causation, these studies exploit survey data on education choices and migration intentions,

microdata on education and exposure to migration by region, or quasi-natural experimental methods. Macro-level evidence of the same relationship can be found in the literature. Using 1990 - 2000 emigration data for 127 developing countries, Beine et al. (2008) estimate that a doubling of a country's emigration rate of highly skilled workers is associated with a 20% increase in the long-run stock of human capital possessed by its nationals, and with a 5% increase in the short run (within a decade). Their findings suggest that under certain conditions the stimulus to skill formation may be strong enough to bring the economy's stock of human capital to a higher level in the post-migration equilibrium. Nevertheless, as far as Africa is concerned, these average effects of emigration prospects on human capital hide regional disparities that might be significant. Indeed, the above-mentioned macro-econometric studies, Africa in general and SSA especially have often been controlled for using regional dummies and findings usually suggest that the region underperforms compared to the remaining developing regions Beine et al. (2008). Consequently, a specific focus on Africa is deserved. In this section, I want to establish the migration-driven incentive specific to Africa using pooled data over two decades for which comparable data exist (1990-2000 and 2000-2010). The idea is to investigate whether skill-biased emigration prospects raise the accumulation of human capital. My starting point is the dynamic β-convergence empirical specification of Beine et al. (2008) written as:

$$\Delta\left(\ln H_{i,t}\right) = \gamma_0 + \gamma_1 \ln\left(H_{i,t}\right) + \gamma_2 \ln\left(m_{i,h,t}\right) + X_{i,t}^{'}\Gamma + \Phi_t + \epsilon_{i,t} \qquad (1)$$

Where $\Delta(\ln H_{i,t}) \equiv \ln(H_{i,t+1}/H_{i,t})$ is the log change in the proportion of skilled workers in the native population of country i between t and t+1, $\ln(H_{i,t})$ is the log of the initial proportion of skilled graduates among natives, $\ln(m_{i,h,t})$ is the log of the skilled emigration rate at the beginning of period t, $X_{i,t}$ is a vector of additional control variables used in Beine et al. (2008) and $\epsilon_{i,t}$ is the error term.

To account for heterogeneity, I control for within Africa regions (Northern and Sub-Saharan Africa) as well as income groups (Low, Lower and Upper Middle-income groups) in line with the idea of migration transition curve stating that the development level of sending country nonlinearly matters for the emigration intensity as the latter depicts an inverted U-Shaped Docquier (2017). This leads to the following specification:

$$\begin{aligned}\Delta\left(\ln H_{i,t}\right) =& \gamma_0 + \gamma_1 \ln\left(H_{i,t}\right) + \gamma_2 \ln\left(m_{i,h,t}\right) + \sum_{k=2,3} \gamma_3^k I_i^k + \gamma_4^k NAFD_i + \\ & \sum_{k=2,3} \gamma_5^k \ln\left(m_{i,h,t}\right) \times I_i^k + \gamma_6^k \ln\left(m_{i,h,t}\right) \times NAFD_i + X_{i,t}^{'}\Gamma + \Phi_t + \epsilon_{i,t}\end{aligned} \qquad (2)$$

Where I_i^k is the dummy variable indicating the income group k[10] to which the i^{th} country belongs. NAFD is the dummy which equals 1 if the country is a Northern African country and 0 otherwise. X is the set of explanatory variables including region and income group dummies, country size, population density and urbanization rates. Φ_t captures the time fixed effect.

Identification strategy: Pseudo gravity-based IV approach. I first estimate Equation (2) using pooled OLS, being aware of the fact that such regression raises a number of econometric issues likely to bias the estimates. Indeed, my variable of interest, $ln(m_{i,h,t})$, is likely endogenous due a possible reverse causality problem. In fact, the proportion of educated labor force likely affect the skilled emigration rate. As pointed out by Beine et al. (2008), a larger stock of human capital may reduce the skill premium and then increase emigration incentives through larger wage differentials between origin and potential destination countries. In addition, a larger stock of human capital may increase wages at origin through an increase in worker's productivity resulting from positive externalities that human capital generates (adoption of new technologies, innovation among others). Furthermore, measurement errors constitute another source of endogeneity bias. To control for these endogeneity concerns, my identification strategy relies on Docquier et al. (2016) and is built in four steps: in the first step, I predict skill-specific bilateral migration stocks $\left(\widehat{N}_{ij,st}\right)$ using a pseudo-gravity model with arguably exogenous drivers of international migration. In the second step, I use predicted emigration stocks to predict skill-specific emigration rates $\left(\widehat{m}_{ij,st}\right)$ that I use as instrument for observed skill specific emigration rates$\left(m_{ij,st}\right)$. In the third step, I test the relevance and discuss the exclusion restriction my instrument. Finally, I use it as an instrument to the observed skilled emigration rate to re-estimate Equation (2) with a 2SLS estimation (Further details are presented in Appendix B). I then re-estimate Equation (2) with a Two Stage Least Squares (2SLS).

Empirical findings. Results are summarized in Table (1). The first four columns report the OLS estimates while the remaining columns report gravity-based IV estimates. There are three main parameters of interest: γ_2, γ_5 and γ_6. As shown in Table (1), brain drain rather depletes human capital in Africa albeit non-linearly. Indeed, this effect varies with the level of development while regional disparities are not significant. Doubling the skilled emigration rate in Africa will on average reduce, over a decade, the human stock by 2.7% in Lower middle-income countries and 7.6% in upper-middle-income countries. However, this effect is statistically not significant

[10] k = 1 for LIC, k = 2 for LMIC, k = 3 for UMIC and LIC is the reference group.

in low-income countries. Nevertheless, my findings suggest that there is no statistically significant difference between Northern and Sub-Saharan Africa. These results are robust even when I consider emigration rates differential ($m_{ih} - m_{il}$) in place of high skilled emigration rate as the measure of brain drain.

5. Development Impact of Brain Drain: The Model

Let us consider a small open developing country *i* producing output *Y* using human capital H embodied in workers with two skill groups (high and low skilled) and physical capital *K*. Government provides education to its citizens to maximize the country's GDP through the improvement of labor productivity. Once education is completed, some individuals will migrate to developed country *j* and some will remain on the home country's labor market. When deciding to subsidize education, the government expects to maximize the national GDP net of educational expenditures. Developed destination countries apply selective immigration policies based on skill selectivity such that not all migration expectation will turn into realization. In addition, selective immigration policies applied in destination countries generates a skill-biased emigration from the small developing source country with skilled individuals exhibiting a higher probability of turning their migration expectations into realizations.[11]

We consider an augmented Solow-type production function, following Mankiw et al. (1992), which incorporates human capital. Unlike their approach, which treats human capital stock and labor separately, I assume human capital is embodied in labor. Thus, aggregate human capital is simply the average human capital per worker multiplied by the total labor force. This approach aligns with Caselli (2005), Hsieh and Klenow (2010), Jones and Scrimgeour (2008), and Jones (2014, 2019). I also assume that all changes in total factor productivity (TFP) are captured by human capital, meaning labor efficiency improvements are independent of physical capital. This specification is well-suited for analyzing skill-biased emigration, as it directly impacts a country's human capital stock and allows for a more accurate

[11] i.e. $m^s > m^u$ where m^s is the migration probability for a skilled individual proxied by the skilled emigration rate and m^u is the migration probability for and unskilled individual proxied by the unskilled emigration rate.

estimation of income per worker across countries. The aggregate production function for country *i* at time *t* is given by:

Table 1: Education incentives of emigration prospect: Gravity based IV approach

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Least Squares				Instrumental variable			
ln (H_{it})	-0.132***		-0.130***		-0.173***			
	(0.03)		(0.03)		(0.04)			
ln (h_{it})		-0.096***		-0.094***		-0.123***	-0.118***	-0.115***
		(0.03)		(0.03)		(0.03)	(0.03)	(0.03)
ln ($m_{i,h,t}$)			-0.067***	-0.053**			-0.027	-0.013
			(0.02)	(0.03)			(0.04)	(0.04)
ln (p_{it})	-0.072***	-0.057**			-0.066**	-0.025		
	(0.02)	(0.03)			(0.03)	(0.04)		
NAF × ln ($m_{i,h,t}$)			0.132	0.161			-0.022	-0.011
			(0.14)	(0.14)			(0.09)	(0.09)
LMIC × ln ($m_{i,h,t}$)			0.041	0.044			-0.027*	-0.029*
			(0.04)	(0.03)			(0.02)	(0.02)
UMIC × ln ($m_{i,h,t}$)			-0.082	-0.080			-0.076**	-0.083**
			(0.05)	(0.05)			(0.03)	(0.03)
NAF × ln (p_{it})	0.110	0.145			-0.044	-0.028		
	(0.12)	(0.13)			(0.12)	(0.11)		
LMIC × ln (p_{it})	0.052	0.052			-0.023	-0.027*		
	(0.04)	(0.04)			(0.01)	(0.01)		
UMIC × ln (p_{it})	-0.084	-0.083			-0.070**	-0.079***		
	(0.05)	(0.05)			(0.03)	(0.03)		
Obs	156	156	156	156	156	156	156	156
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F- First Stage					32.73	20.53	53.67	36.42
R2	0.373	0.321	0.370	0.320	0.305	0.305	0.320	0.262

Notes: The dependent variable is the decadal change in the porportion of tertiary educated among natives for each African country. the main explanatory variable is $lnm_{i,h,t}$ with an alternative variant $ln(p_{i,t}) \equiv ln(m_{i,h,t} - m_{i,l,t})$ indicating the intensity of the skilled emigration for the first, and the intensity of positive selection for the second. $ln(p_{i,t})$ takes a log for the African countries only because the condition $m_{i,h,t} > m_{i,l,t}$ is always met. A variant in Cha'ngom et al. (2023) does not admit a log form given instances either of neutral selection ($m_{i,h,t}$' $m_{i,l,t}$) or negative selection ($m_{i,h,t} < m_{i,l,t}$). Because of the endogenous of $ln(m_{i,h,t})$ or $ln(p_{i,t})$, both are instrumented using the gravity based strategy that has consisted in predicting bilateral migration stocks using only arguably exogenous drivers of bilateral migration. The predicted values are then aggregated to African country-decade level, to compute predicted skilled emigration rate $ln(m_{i,h,t})$ and positive selection $ln([p_{i,t})$ intensities. Robust standard errors in parentheses. Standard error are clustered at country level. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

$$Y_{i,t} = F\left(K_{i,t}, H_{i,t}, A_{i,t}\right) \equiv K_{i,t}^{\alpha}\left(A_{i,t}H_{i,t}\right)^{1-\alpha} \tag{3}$$

Where K denotes the stock of physical capital in country i, H_i denotes the total stock of human capital, and A_i is the level of total factor productivity. α and $\beta_{i,t}$ denote respectively the share of capital and human capital the total output.[12] The stock of human capital is equal to the average level of human capital (h) embodied in each worker multiplied by the number of workers (N) (i.e $Hi,t = hi,tNi,t$). The output per worker is derived from Equation (3) as:

$$y_{i,t} = A_{i,t}^{1-\alpha}k^{\alpha}\left(\sum_{a=s,u}\eta_{i,t}^{a}\left(h_{i,t}^{a}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma(1-\alpha)}{\sigma-1}} \tag{4}$$

[12] In the recent migration and growth literature, production technology is modelled without physical capital and assumes that the level of production is proportional to labor in efficiency units (Docquier et al., 2012 ; Djaji´c et al., 2019 ; Docquier (2017); Delogu et al., 22018;Deuster and Docquier, 2018). this formulation has been supporting by the claim that correlation between income per capita and skilled labor force is closed to unity (0.90) justifying the weak role of capital (Docquier, 2017; Delogu et al., 2018). But, I suppose that this rational is likely not to hold in very poor countries like African countries as the correlation between skilled labor force and income per capita is far from unity. It amounted 0.23 in 2015 in Africa. Consequently, I keep physical capital in production technology.

I now consider in line with Jones (2014) that workers are heterogeneous in skill such that the average level of human capital differs across skill groups. In line with Docquier (2017) there are two skill groups namely the high-skilled (h^s) and the low-skilled (h^u). The human capital aggregator decomposing the human capital per worker in two groups allows writing the labor component of output per worker as a Constant Elasticity of Substitution (C.E.S.) function expressed as:

$$h_{i,t} = G\left(h^s_{i,t}, h^u_{i,t}\right) \equiv \left[\eta_{i,t}\left(h^s_{i,t}\right)^{\frac{\sigma-1}{\sigma}} + (1-\eta_{i,t})\left(h^u_{i,t}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \equiv \left(\sum_{a=s,u} \eta^a_{i,t}(h^a_{i,t})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad (5)$$

Where η stands for the relative preference for skilled workers and σ, the elasticity of substitution between skilled and unskilled workers. By replacing h in Equation (4), the output per worker becomes:

$$y_{i,t} = A^{1-\alpha}_{i,t} k^{\alpha} \left(\sum_{a=s,u} \eta^a_{i,t}(h^a_{i,t})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma(1-\alpha)}{\sigma-1}} \quad (6)$$

As skilled emigration mechanically affects the stock of available human capital, h is the first channel through which brain drain enters into the model($h^s_{i,t} = H_{i,t} - \Delta H_{i,t}$) where $\Delta H_{i,t}$ refers to the change in human capital due to skilled emigration.

Brain drain: measurement and counterfactual scenario

Concept of brain drain

Also called “human capital flight”, it refers to the migration of engineers, physicians, scientists, and other very highly skilled professionals with university training (Docquier and Rapoport, 2005); most often from developing to developed countries (Gibson and McKenzie, 2011). Operationally, this concept refers to tertiary educated migrants as a share of all individuals with that education level aged 25 and over, born in that country no matter where they live (Docquier and Rapoport, 2005). It is given by:

$$m^s_{i,t} = \frac{\sum_{j=1}^{J} M^s_{ij,t}}{N^s_{i,t} + \sum_{j=1}^{J} M^s_{ij,t}} \equiv \frac{M^s_{i,t}}{N^s_{i,t} + M^s_{i,t}}$$

Where $M_{ij,t}$ stands for the number of migrants from a given sending country *i* to a destination country *j* and *J* is the number of destination countries.

At the same time, we can also express the rate of low-skilled migration as:

$$m_{i,t}^{u} = \frac{\sum_{j=1}^{J} M_{ij,t}^{u}}{N_{i,t}^{s} + \sum_{j=1}^{J} M_{ij,t}^{u}} \equiv \frac{M_{i,t}^{u}}{N_{i,t}^{u} + M_{i,t}^{u}}$$

Counterfactual scenario

As brain drain mechanically reduces the proportion of skilled workers in the resident labor force (i.e available human capital), it will thus enter the model through *h*. The share of skilled workers in the resident labor force, expressed as $h_i^s = N_i^s/(N_i^s + N_i^u)$, can well be expressed as a function of skill-specific emigration rates (m_i^s, m_i^u), and of the proportion of skilled among natives (H_i). Indeed:

$$h_{i,t}^{s} = \frac{H_{i,t}(1 - m_{i,t}^{s})}{H_{i,t}(1 - m_{i,t}^{s}) + (1 - H_{i,t})(1 - m_{i,t}^{u})} \tag{7}$$

From Equation 7, it is straightforward to simulate a "no skilled emigration" (i.e $m_i^s = 0$) counterfactual or a "neutral selection" (i.e. $\widehat{M}_{i,t}^{s}/M_i \equiv h_{i,t}^{s}$) counterfactual.

Scenario 1: No skilled emigration ($h_{i,t}^{s} = 0$)

This is a hypothetical world in which high-skilled emigration is prohibited so that only unskilled emigration is allowed. Currently, skilled migrants will be part of the resident skilled labor force. Put differently, all skilled natives reside and work in their origin country; consequently, the share of the skilled labor force in the origin country will be greater under this counterfactual scenario in comparison to the observed level in the current world. From equation 7, this counterfactual level of human capital is derived as:

$$h_{i,t(c,1)}^{s} = \frac{H_{i,t}}{1 - m_{i,t}^{u}(1 - H_{i,t})} \tag{8}$$

Scenario 2: No selection in emigration ($\widehat{M}_{i,t}^{s}/M_i \equiv h_{i,t}^{s}$)

Where $\widehat{M}_{i,t}^{s}$ is the stock of highly skilled emigrants compatible with neutral selection. In this scenario, In line with Biavaschi et al. (2020), I consider a situation where migrants are neutrally selected such that all the skill groups

emigrate similarly (see appendix for technical details). The counterfactual level of human capital among natives excluding unskilled migrants is then:

$$h^{s}_{i,t(c,2)} = \frac{H_{i,t}(1-\bar{m}^{s}_{i,t})}{H_{i,t}(1-\bar{m}^{s}_{i,t}) + (1-H_{i,t})(1-\bar{m}^{u}_{i,t})} \tag{9}$$

Where $\bar{m}^{a}_{i,t}\ \forall\ a \in (s,u)$ are neutrally selected skill-specific emigration rates. In summary, the counterfactual level of human capital in the two scenarios is given by:

$$h^{s}_{i,t(c,p)} = \begin{cases} \dfrac{H_{i,t}}{1-m^{u}_{i,t}(1-H_{i,t})} & \longrightarrow p=1 \\ \dfrac{H_{i,t}(1-\bar{m}^{s}_{i,t})}{H_{i,t}(1-\bar{m}^{s}_{i,t}) + (1-H_{i,t})(1-\bar{m}^{u}_{i,t})} & \longrightarrow p=2 \end{cases}$$

Impact of brain drain on sending countries

To investigate how brain drain affects sending countries, I separately evaluate on one side the negative consequences generated by BD and on the other side the positive consequences it generates. Then, the net effect is generated by the combination of the two opposite processes.

Brain loss

Direct loss from skilled emigrant's departure. Due to the migrants' departure, the share of the skilled labor force in the economy mechanically decreases from $\boldsymbol{h^{s}_{i,t(c,p)}}$ to $\boldsymbol{h^{s}_{i,t}}$. Consequently, the direct loss in per worker income is obtained as the percent difference between its current and counterfactual level expressed as:

$$\Delta^{1}_{i,t} = \frac{y\left(h^{s}_{i,t}\right) - y\left(h^{s}_{i,t(c,p)}\right)}{y\left(h^{s}_{i,t(c,p)}\right)} \tag{10}$$

Including external effects to direct loss. Under the hypothesis that social return exceeds private return, skilled migrants do not only take away their direct contribution to national output. Sending countries also lose their indirect contribution through their effect on the productivity of other workers both skilled and unskilled. To account for those external effects, in line with Docquier (2017), we consider two types of externalities: Lucas (1988) type or

total factor productivity externality [13] and Acemoglu (2002) type or skill-biased technical change [14]. Equations (11) and (12) describe respectively those two types of externalities.

$$\check{A_{i,t}} = A_{i,t}\left(\frac{h^s_{i,t}}{h^u_{i,t}}\right)^{\gamma} \tag{11}$$

$$\frac{\check{\eta_{i,t}}}{1-\check{\eta_{i,t}}} = \frac{\eta_{i,t}}{1-\eta_{i,t}}\left(\frac{h^s_{i,t}}{h^u_{i,t}}\right)^{\tau} \tag{12}$$

Where γ materializes the Lucas-type externality and τ materializes the Acemoglu-type externality. Once the new values of A and η are obtained, the new level of counterfactual income per worker is estimated and the brain loss becomes:

$$\Delta^2_{i,t} = \frac{y\left(h^s_{i,t}\right) - y'\left(h^s_{i,t(c,p)}\right)}{y'\left(h^s_{i,t(c,p)}\right)} \tag{13}$$

Including educational subsidy to the above components. The government supports a portion of the cost of education of their citizens in the form of educational subsidy. Such a policy aims to enhance the accumulation of human capital that will allow to foster productivity. When some of those individuals emigrate, it constitutes a fiscal loss for the government which expected to recover its investment through progressive taxation on the income of those skilled individuals.

A tertiary-educated individual who migrates is likely to have benefited from education subsidies during their entire schooling period (primary, secondary, and tertiary). The yearly total public expenditure on education for individuals that move abroad ($\boldsymbol{E^s_{i,t}}$) can be expressed as $\boldsymbol{E^s_{i,t}} = c^s_{i,t}\overline{M}^s_{i,t}$ and $\overline{M}^s_{i,t} = \delta \boldsymbol{M^s_{i,t}}$, where $\overline{M}^s_{i,t}$ is the stock of skilled emigrants who got their education in their home country, $c^s_{i,t}$ the cost of educating each high skilled individual and δ is the share of skilled migrants who got their education at home. Consequently, the educational subsidy loss experienced by each resident's worker is given by:

$$e^s_{i,t} = \frac{\delta\Gamma_{i,t}}{r}\left[\left(\sum_{i=1}^{K} c_k(1+r)^{t_k}\right) - K\right] \tag{14}$$

[13] Skilled workers facilitate innovation and adoption of new and advanced technologies.
[14] Skilled biased technical change affects the relative productivity of skilled workers.

Where Γ is the skilled migrants to resident's labor force ratio (M_i^s/N_i). The new level of brain loss is given by:

$$\Delta_{i,t}^{3} = \frac{\left(y\left(h_{i,t}^{s}\right) - e_{i,t}^{s}\right) - y'\left(h_{i,t(c,p)}^{s}\right)}{y'\left(h_{i,t(c,p)}^{s}\right)} \qquad (15)$$

Including market size externality. Brain drain affects the total demand for goods and services in the origin country as skilled workers earn more and are likely to consume more. Under monopolistic competition, total demand determines whether a firm should enter or exit the market that in turn determines the quantity of goods and services produced (Biavaschi et al., 2020). Put differently, migration in general and brain drain in particular affect the market size. Of course, in a world with total free trade, this should not be a worry, as trade will fully substitute the change in production. However, in practice, trade is costly and the magnitude of the market size effect depends on the trade openness (Docquier and Veljanoska, 2020). Indeed, an increase in the domestic market size leads to the formation of more producers as they can operate on a larger market, leading to higher production and lower price index. So, accounting for monopolistic competition as in Biavaschi et al. (2020); Docquier and Veljanoska (2020), the income loss driven by market size contraction due to emigration is given by:

$$\Delta_{i,t}^{mktsz} = \frac{m_{i,t}}{(\lambda - 1)(1 - m_{i,t})} \qquad (16)$$

Where λ stands for the elasticity of substitution between goods (Feenstra (1994)).

In summary, the total loss from brain drain is given by Equation (15). However, it is still possible to isolate each component of the brain loss by combining Equations (10), (13), (15) and (20) as follow:

$$\Delta_{i,t}^{4} = \frac{\left(y\left(h_{i,t}^{s}\right) - e_{i,t}^{s}\right) - y'\left(h_{i,t(c,p)}^{s}\right)}{y'\left(h_{i,t(c,p)}^{s}\right)} + \Delta_{i,t}^{mktsz} \qquad (17)$$

Adding education incentives. As shown by the new brain drain literature (see the optimistic view of the mid-1990s), the skill-biased migration prospect is likely to create education incentives and then raise investment in education. This mechanism points toward a larger stock of human capital in the post-emigration setting relative to the closed economy. Nevertheless, as shown in Section 4, rather than experiencing emigration-driven human capital formation as shown in (Beine et al., 2001, 2008, 2010), emigration prospects rather seem to deplete human capital formation in Africa. More precisely, the emigration prospects reduce human capital formation in African countries non-linearly conditional on the development level. Although this looks contradictory to the conclusion of the above-mentioned seminal studies, those studies have elements compatible with the present findings. Indeed, Beine et al., (2008; 2010) results suggest that, despite the average positive response of human capital to emigration prospects, SSA were largely under-performing. Put differently, these studies were already suggesting that SSA might be experiencing negative incentive effects. In line with the finding of Section 4, I assume that $\boldsymbol{h^{s}_{i,t(c,p)}}$ depends on skill-biased emigration prospect (m_i^s/m_i^u) and the elasticity of human capital formation to emigration prospect ($\boldsymbol{\beta}$)[15]. Once I account for education incentives, the new counterfactual share of skilled workers in the native population becomes :

$$\ddot{h}^{s}_{i,t(c,p)} = h^{s}_{i,t(c,p)} \left(\frac{m^{s}_{i,t}}{m^{u}_{i,t}} \right)^{-\beta} \tag{18}$$

Once $\boldsymbol{\ddot{h}^{s}_{i,t(c,p)}}$ is obtained, the new counterfactual per worker income is expressed as:

$$y'\left(\ddot{h}^{s}_{i,t(c,p)}\right) = \check{A}^{\beta_{i,t}} k^{\alpha} \left(\sum_{a=s,u} \eta^{a}_{i,t} (\ddot{h}^{a}_{i,t(c,p)})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma(1-\alpha)}{\sigma-1}}$$

The per worker income response to brain drain becomes:

$$\Delta^{5}_{i,t} = \frac{\left[y\left(h^{s}_{i,t}\right) - e^{s}_{i,t} + r^{s}_{i,t,L}\right] - y'\left(\ddot{h}^{s}_{i,t(c,p)}\right)}{y'\left(\ddot{h}^{s}_{i,t(c,p)}\right)} + \Delta^{mktsz}_{i,t} \tag{19}$$

[15] this $\boldsymbol{\beta}$ is income group specific

From brain loss to net effect

Three positive feedback mechanisms are considered here: remittances from skilled migrants, gains from education incentives, and gains from diaspora externalities.

Remittances from skilled migrants: As argued by Grubel and Scott (1966), emigration especially skilled emigration potentially raises the long-term average income of those left behind through remittances. Following this view, emigration gain as remittances ($R_{i,t}$) per worker (N_i) is given by $R_{N,i} = R_{i,t}/N_{i,t}$. Yet, not only skilled migrants remit and this requires disentangling remittances from skilled ($R^{s}_{Ni,t}$) to those from unskilled ($R^{u}_{Ni,t}$) migrants. Gain per resident worker generated by remittances by skilled migrants ($r^{s}_{i,t,N}$) is obtained by combining total remittances per resident worker ($R_{i,t}/N_{i,t}$) and the fraction remitted by skilled migrants ($\Omega^{s}_{i,t}$).

$$r^{s}_{i,t,N} = \Omega^{s}_{i} R_{N,i,t} \equiv \Omega^{s}_{i,t} \frac{R_{i,t}}{N_{i,t}} \tag{20}$$

When accounting for remittances from skilled migrants, the per-worker income response to brain drain becomes:

$$\Delta^{6}_{i,t} = \frac{\left[y\left(h^{s}_{i,t}\right) - e^{s}_{i,t} + r^{s}_{i,t,N}\right] - y'\left(h^{s}_{i,t(c,p)}\right)}{y'\left(h^{s}_{i,t(c,p)}\right)} + \Delta^{mktsz}_{i,t} \tag{21}$$

If $\Delta^{6}_{i,t} > 0$, since $\Delta^{4}_{i,t} < 0$, it would suggest that remittances from skilled migrants fully compensate for losses due to brain drain i.e.

$$\frac{r^{s}_{i,t,N}}{y'\left(h^{s}_{i,t(c,p)}\right)} > \frac{\left[y\left(h^{s}_{i,t}\right) - e^{s}_{i,t}\right] - y'\left(h^{s}_{i,t(c,p)}\right)}{y'\left(h^{s}_{i,t(c,p)}\right)}$$

However, if the reverse holds, then, BD does not generate enough remittances to fully compensate the losses it generates.

Including diaspora externalities to remittances and education incentives. Empirical literature points out the potential of migrant network to stimulate bilateral trade[16], foreign direct investments, and other financial flows (Faini, 2005; Ivlevs and De Melo, 2010). On the other side, trade and FDI drive total factor productivity growth (Anderson et al., 2016; Feyrer, 2019)

[16] Migrants' networks increase the likelihood to add new products in the source country's export basket and consequently shift upward its comparative advantage at international level Bahar and Rapoport (2018).

through the diffusion of knowledge and technology between host and source country. Starting from Equation (11), I modify the total factor productivity technology by including a linearized diaspora externality into the framework as follows:

$$\check{A'_{i,t}} = A_{i,t}\left(\frac{h^s_{i,t}}{h^u_{i,t}}\right)^{\gamma}\left(1+m^s_{i,t}\right)^{\rho} \tag{23}$$

The counterfactual per worker income is then re-estimated as:

$$y''\left(\ddot{h}^s_{i,t(c,p)}\right) = \check{A'_{i,t}}^{1-\alpha}k^{\alpha}\left(\sum_{a=s,u}\check{\eta^a_{i,t}}\left(\ddot{h}^a_{i,t(c,p)}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma(1-\alpha)}{\sigma-1}}$$

The per worker income response to brain drain becomes:

$$\Delta^7_{i,t} = \frac{\left[y\left(h^s_{i,t}\right) - e^s_{i,t} + r^s_{i,t,L}\right] - y''\left(\ddot{h}^s_{i,t(c,p)}\right)}{y''\left(\ddot{h}^s_{i,t(c,p)}\right)} + \Delta^{mktsz}_{i,t} \tag{24}$$

Total brain gain stands out as the difference between Δ^6_i and $\Delta^3_{i,t}$.

Adding gains accruing to migrants in assessing the net effect of BD

The claim that migrants should be integrated when evaluating the costs and benefits of BD dates back in the 1960s when Grubel and Scott (1966) argue that, what should matter is the well-being of natives no matter where they are. Furthermore, migrants are the first to benefit from migration and enjoying better living conditions in the host country compared to what they would have enjoyed in their country is already a gain for the home country as it increases the average well-being of the natives. Relying on the Clemens and Pritchett (2008) approach, I compute the income accruing to all source country's natives irrespective of their living place. Such an income per worker is referred to as *"income per natural worker"*. It stands for the mean annual income of workers born in a given country, regardless of where they currently reside. In other words, it is the annual average income of residents minus that of immigrants plus that of skilled emigrants accounting for the dyadic structure of skilled emigration.

Assuming in line with Djaji´c et al. (2019) that skills are, sometimes, not fully transferable might lead to downgrading in receiving OECD countries. With a given level of skill *h*, a migrant will earn lower $[(1-\zeta)w^{*s}]$ compared to host

country's native (w^{*s})[17], where $\zeta < 1$ is the percentage difference in wages between the OECD native skilled worker and the skilled immigrant's worker. Let consider $\widetilde{w}_i$ as the average income per natural skilled worker for country *i* and w_i^s the income per resident skilled worker in the origin country *i*

$$\tilde{w}_{i,t}^{s} = \frac{w_{i,t}^{s}\left(N_{i,t}^{s} - I_{i,t}^{s}\right) + \sum_{j=1}^{J}(1-\zeta)w_{i,t}^{s*}M_{ij,t}^{s}}{\left(N_{i,t}^{s} - I_{i,t}^{s}\right) + \sum_{j=1}^{J} M_{ij,t}^{s}} \tag{25}$$

Where $I_{i,t}^{s}$ is the stock of skilled immigrants in country *i*; $[(1-\zeta)]w_{i,t}^{s*}$ is average income earn by each skilled migrant from country *i* living in the OECD and $w_{i,t}^{s}$ is the average income for a non migrant skilled worker in the source country *i*.[18] The change in average income of per natural skilled worker of country *i* is then obtain as:

$$\Delta w_{i,t}^{s} = [(1-\zeta)]\tilde{w}_{i,t}^{s} - w_{,t}^{s}$$

From the above expression, it is straightforward to show that the percentage change in per natural worker income directly attributed to what skilled migrants earn abroad is obtained as:

$$\frac{\Delta w_{i,t}}{w_{i,t}} = \frac{\Delta w_{i,t}^{s}[N_{i,t}^{s} - I_{i,t}^{s}]}{w_{i,t}(N_{i,t} - I_{i,t})} \equiv \frac{\Delta w_{i,t}^{s}}{w_{i,t}} h_{i,t}^{s} \tag{26}$$

Starting from Equation (24), I estimate the per natural worker income response to BD by (1) removing remittances in the income response function as they are already part of migrants income and (2) by adding the percentage difference obtained from Equation (26) and the net income response to brain drain becomes:

$$\Delta_{i,t}^{8} = \frac{\left[y\left(h_{i,t}^{s}\right) - e_{i,t}^{s}\right] - y'\left(\ddot{h}_{i,t(c,p)}^{s}\right)}{y'\left(\ddot{h}_{i,t(c,p)}^{s}\right)} + \Delta_{i,t}^{mktsz} + \frac{\Delta w_{i,t}}{w_{i,t}} \tag{27}$$

Because of large differences in income per skilled worker between sending and receiving countries, $\Delta w_{i,t}/w_{i,t}$ is likely to be positive i.e. $\Delta w_{i,t}/w_{i,t} > 0$. But, as

[17] I assume that event though skilled immigrants earn lower wages compared to natives, these wages remain larger than what they would have earned in the sending country i.e. $(1-\zeta)w^{*s} > w^{s}$.

[18] $w_{i,t}^{S*}$ stands for the average wage earned by a skilled from country *i* living in an OECD country if skilled immigrant where pay exactly and an OECD skilled native i.e. $w_{i,t}^{S*} = \sum_{j=1}^{P} M_{ij,t}^{S} w_{j,t}^{S*} / \sum_{j=1}^{P} M_{ij,t}^{S}$.

the first component of Equation (27) i.e. $\Delta^{7}_{i,t}$ is either positive or negative, it is not exactly known whether the sign of $\Delta^{7}_{i,t}$ will be positive or negative. The only obvious story here is that $\Delta^{8}_{i,t} > \Delta^{7}_{i,t}$ such that, all sending countries are better off when gains accruing to migrants are taken into account. It will lead either to the reduction of the size of net loss for losers or to the increase in the size of net gains for winners.

6. Calibration and benchmark results

The benchmark model is calibrated for 51 African countries (6 in Northern Africa and 45 in Sub-Saharan Africa) for the years 1990, 2000, 2010, and 2015. Variables are averaged over corresponding periods (1991–2000, 2001–2010, 2011–2015). The model is parameterized to reflect each country's economic characteristics, including labor force structure, income per worker, skill-specific emigration rates, and the skill composition of migrants in the OECD. After calibrating the baseline model, I assess the impact of brain drain by simulating two counterfactual scenarios: (1) no skilled emigration and (2) neutral selection, where the skill distribution of emigrants matches that of the native population in the sending country. This section details the parameterization strategy and presents the benchmark results.

Parameterization

Table (E.1) in the appendix summarizes the calibration outcomes. Using data from Beine et al. (2007) which control for the immigrant's age of entry in the OECD, and provided evidence that 69.1% arrived after the age of 22, I have set the share of skilled migrants educated in the home country at that rate i.e. (δ = 0.691) and identical across countries. For labor share in national income, I use data from Guerriero (2019).The elasticity of substitution between skilled and unskilled workers is taken from Ottaviano and Peri (2012); its value is estimated between 1.3 and 3. Here, I will keep its average i.e. (σ = 2). As far as education subsidies are concerned, I took data on yearly expenditures per student in primary, secondary, and tertiary education that I aggregated to make public subsidy in education per student; its value lies between \$649 and \$33,262 with an average of \$6,448.

To compute the counterfactual per worker income, I calibrate η_i and A_i to match the observed per worker income $y(h^s_i)$; η_i is estimated only after the estimation of the wage ratio that we proxied following the approach of Delogu et al. (2018) as $w_i^s/w_i^u = (1+\mathrm{MR}_i)^{\Delta Y E i}$ Where MR_i is the Mincerian returns to schooling in country i Hendricks (2004) and $\Delta Y E_i$ is the difference in year of

schooling between skilled and unskilled (Barro and Lee, 2013). Docquier (2017) estimates for the year 2010 this wage ratio for a range of 195 countries. In this dataset, all the African countries are considered. As he estimates this ratio from $w_i^s/w_i^u = (1 + MR_i)^{\Delta YEi}$, I consider its estimates for the year 2010 and I use them to extract $(1 + MR_i)$. I then apply the difference in years of schooling between skilled and unskilled from Barro and Lee for each year considered other than 2010 i.e. 1990, 2000, and 2015. This gives value of wage ratio that lies between 1.4 and 11.9 with an average of 3.7. Once the wage ratio is determined, I can calibrate η_i to match wage ratio; it lies between 0.08 and 0.67 with an average of 0.36 and vary across countries and over time. As far as total factor productivity is concerned, once w_i^s/w_i^u and η_i are known, I derive total factor productivity. The calibrated value lies between 263.4 and 217,881.7 with an average of 15,331.6.

I consider two types of productivity externalities: technological externality (γ, see Eq.11) and skill-biased technical change (τ, see Eq.12). I estimate γ as the elasticity of total factor productivity with respect to skilled-unskilled ratio and τ as the elasticity of the ratio of relative preference with respect of $h^s/(1-h^s)$[19]. Results are reported in appendices C and D. The estimated values of γ lie between 0.22 to 0.24. Given the bidirectional link between productivity and education decisions, in line with Docquier (2017), I consider this elasticity as an upper bound for technological externality and I assume that half of the observed value is due to technological externality (i.e. $\gamma = .1$). Values of τ is roughly 0.52. For similar reasons as above, I consider that half of this elasticity is due to skill-biased externality (i.e. $\tau = 0.26$).

As far as diaspora externalities are concerned, a wide range of literature[20] has identified on the one side a causal relationship from migration to trade and foreign direct investment (with respective elasticity of 0.1 and 0.2) and on the other side, a causal relationship from trade and foreign direct investment to total factor productivity (with respective elasticities of 0.3 and 0.01). By combining these findings, Docquier (2017) obtains an elasticity of total factor productivity to emigration of 0.03 which also corresponds to the world total migration rate. I then proxy it by the African emigration rate to the OECD for working age individuals. Using equation (23), in the African context, I set this elasticity at 2.04% (average emigration rate to the OECD over the covered period). This allow us to obtain $\rho = 0.052$. As market size externality is concerned, I considered in line with Feenstra (1994) an elasticity of

[19] Estimated as the slope of: $ln(A_i) = A_0 + \gamma ln\left(h_i^s/h_i^u\right) + \upsilon_i$ and $ln\left(\eta_i^s/\eta_i^u\right) = R_0 + \tau ln\left(h_i^s/h_i^u\right) + \Xi_i$

[20] See Docquier (2017), pp 64 for details

substitutions between good of 4.0 (λ = 4.0). Finally, in order to evaluate remittances from skilled migrants, I assumes that skilled migrants do remit the equivalent of their share in the migrant's population; claims supported both by literature (Faini, 2007; Niimi et al., 2010) and econometric estimation of the propensity to remit of skilled migrants whose results are reported in the appendix E[21].

Benchmark Results

This section describes benchmark results. It provides the average level of losses, gains, and net effect on residents (i) and natural workers[22] (ii). In addition, country profiles are presented followed by regional and sub-regional patterns (iii). This section also presents the pattern of net effect by country size and income group (iv). It finally shows how the net effect has evolved in Africa (v).

As shown in Panel 3a of Figure 3, per-worker income loss increases with the scale of brain drain (BD). The short-dash curve represents direct per-worker income loss relative to the counterfactual "No brain drain" scenario. The long-dash, thin solid, medium-thick, and thick curves illustrate income loss when accounting incrementally for technological externalities, educational subsidies, and education disincentives. The thick solid curve captures the total per-worker income loss due to BD in Africa. While income loss from educational subsidies and market size effects is relatively small, the primary drivers of total income loss are technological externalities—where the departure of skilled workers reduces the productivity of both skilled and unskilled workers left behind (23.8% on average)—and the negative impact on human capital accumulation (47.3%).23 This highlights that BD harms source countries not only by reducing the number of skilled workers but also through the broader negative externalities it generates, which account for over two-thirds of the total estimated income loss.

Countries with a BD rate below 10% experience an average income loss of -3.0%, compared to -5.2% for those with BD between 10% and 30%. For countries where skilled emigration exceeds 40%, income loss surpasses -10%.

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[21] To have a clear idea of such behaviour in our sample, we will estimate the following econometric models. $ln\left(R_i/M_i\right) = \alpha_0 + \alpha_1 m_i + \alpha_2 \psi_i^s + \Gamma' X_i + \epsilon_i$ and $ln(R_i) = \varphi_0 + \varphi_1 M_i + \varphi_2 \psi_i^s + \Lambda^0 X_i + \theta_i$ Where $X$is the vector of control variables. If $\alpha_2 < 0$ or $\varphi_2 < 0$, then skilled migrants remit less. If $\alpha_2 > 0$ or $\varphi_2 > 0$, then skilled migrants remit more. If α_2 or φ_2 are statistically insignificant, then migrants remit more or less the same amount whatever their skill profile.

[22] In this setting, natural workers include resident workers and skilled emigrants

[23] Appendix G.1 provides a full description of the contribution of each transmission channel to the size of either income loss or income gain.

While these results clearly show that higher BD leads to greater income losses, the key question now is whether these losses might be offset by positive feedback mechanisms.

Panel 3b of Figure 3 depicts the average income gain experienced by Africa for different levels of BD. Contrary to income loss that is positively correlated to the size of BD, income gain looks non-linear across different sizes of BD. The total income gain depicts an inverted U-shaped as it increases with BD when the latter is lower than 40% and decreases for larger values. In terms of its size, income gain on average ranges between +0.40% and +3.81%. From this perspective, compared to income loss, it is worth noticing that many African countries are experiencing net decline in the income of their resident labor-force.

As depicted in Panel 3c, accounting for gains accruing to skilled migrants themselves completely reshapes both the size and pattern of brain gain. While income gain for those left behind reaches its highest average level at +3.8%, the latter exit +20% for some countries when natural workers are accounted for (i.e. those left behind + skilled emigrants). However, the pattern of income gain remains unchanged. Natural worker's income gain increases for countries with BD below 60% and decreases in the upper tail of the BD distribution, especially for countries experiencing a BD larger than 60%. Thus, it is straightforward to expect that sending countries' natural workers would always be better off in presence of BD than workers left behind as far as income at destination is larger than income at origin.

Combining Panels 3a, 3b, and 3c of Figure 3 gives the net effect of BD depicted on Panel 4d. It comes out that, for those left behind, countries experiencing an average brain drain lower than 10% are net winners while the remaining tend to be net losers. Nevertheless, the net per natural income response to BD deeply increases compared to the net per resident worker income response. Only countries with BD larger than 60.0% experience a net income loss under the latter setting. These findings are purely driven by the wage gap between African countries and the OECD.

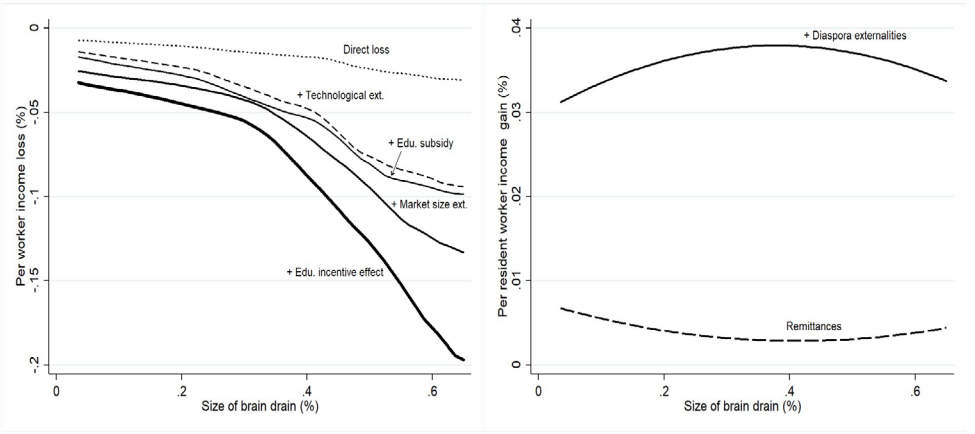
The findings described so far depict the average picture and consequently hide substantial heterogeneity across countries. In 2010, out of the 51 countries included in this study, only 15 exhibited a net income gain while the remaining 36 were net losers i.e. nearly 1 winner for 2 to 3 corresponding losers. Once skilled emigrants are integrated into the analysis, the net effect significantly improves. Out of the 51 African countries considered, 43 exhibit a net income gain while only 8 remain net losers i.e. there are more winners than losers. While there are more losers than winners for resident workers,

there are more winners than losers for natural workers (i.e. when skilled migrants are taken into account). Net per natural worker income gain exceeds +20.0% for countries like Liberia (+63.9%)[24] Eritrea (+25.2%), Somalia (+24.5%), Sao Tome and Principe (24.1%), Gambia (+22.5%), Comores (+22.2%), Zimbabwe (+20.7%).

To illustrate the claim that "*including skilled emigrants improves the net income response of sending countries,*" I present a map of Africa for 2010 (Figure 5). The first map shows the net income response to brain drain (BD) considering only resident workers, while the second includes skilled emigrants, highlighting the distinction between winners and losers. Countries with a red cross are those without data; colored countries are those experiencing a net brain gain and different colors simply materialize differences in the size of net gains. The darker the color, the higher is the net income gain. The left map materializes the winners presented earlier when only resident workers matter. Moving from the left map to the right one, the number of colored countries significantly increases. As I pointed it out earlier, this observed improvement is driven by the wage gap between source and destination countries controlling for downgrading.

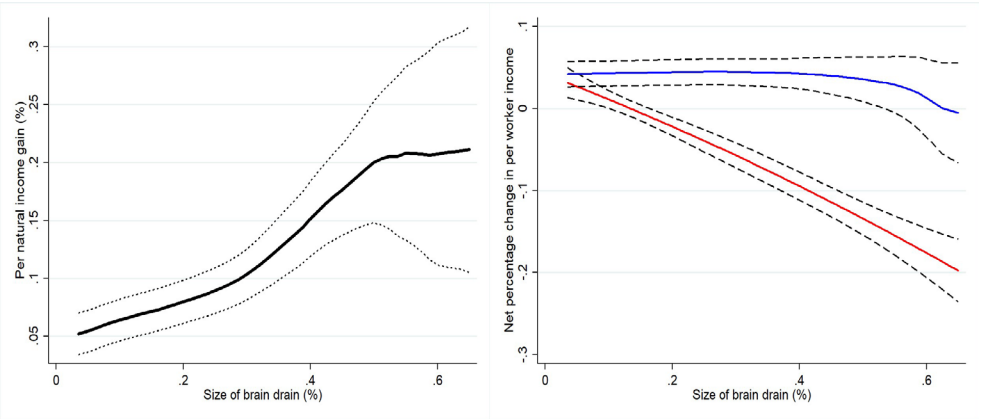
Figure 3: Average income loss, gain and net effect.

(a) Income loss structure (b) Income gain structure



(c) Income gain from migrants (%) (d) Net income response to BD

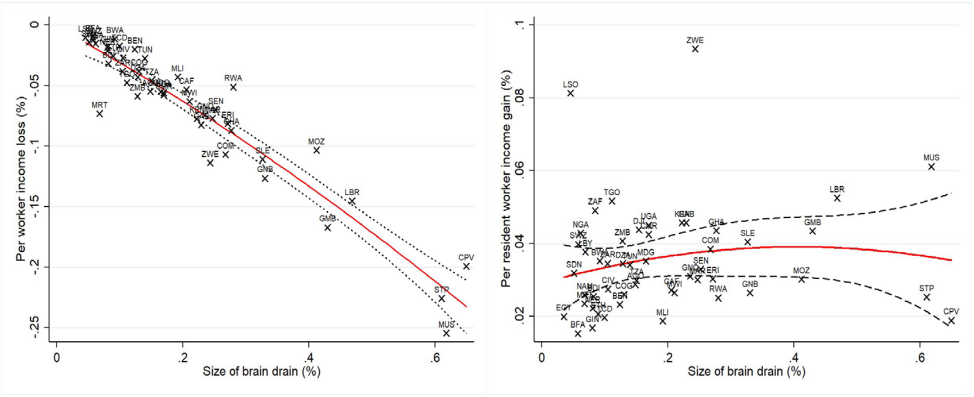
[24] For graphical presentation purposes, Liberia has not been plotted on the figure 4d



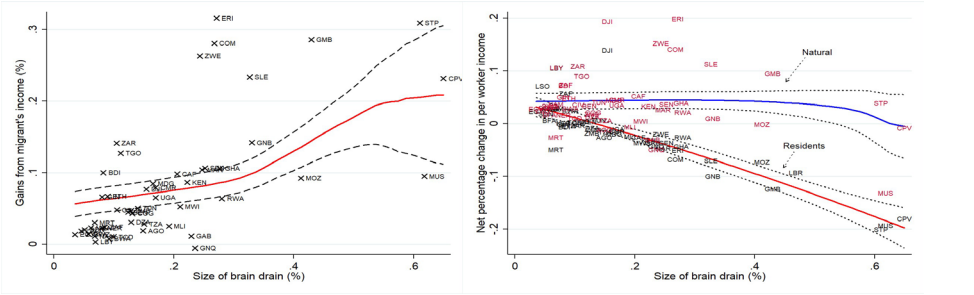
So far, I have focused on 2010 to analyze the structure of losses and gains from BD and its net effect in Africa. However, the evolution of BD's net impact over time has been largely overlooked in the literature. As shown in Table G.2, net income loss from BD—particularly for resident workers—has increased over the decades, reflecting the rising trend of skilled emigration from Africa. SSA primarily drives this increase, while North Africa follows a non-linear pattern. At the sub-regional level, Middle and Eastern Africa have experienced the most significant net income losses. Smaller countries have been disproportionately affected, with the highest negative impacts, while low- and lower-middle-income countries have also faced substantial losses. Upper-middle-income countries, though also experiencing significant losses, are likely affected by a compositional effect, as many (e.g., Botswana, Gabon, Equatorial Guinea, Mauritius, Namibia) are small, and most small countries are low-income (e.g., Burundi, Central African Republic, Eritrea, Liberia, Sierra Leone, Togo). When accounting for migrants' welfare at their destinations, Africa as a whole becomes a net winner, with gains increasing over time. In 2010, the net gain was approximately +5%, indicating that allowing skilled migration to the OECD increased native workers' income by 5% compared to a hypothetical scenario where skilled emigration was prohibited. At the regional level, a representative worker in SSA experienced greater gains (up to +4.8%) than their North African counterpart (up to +3.3%).

Figure 4: Income loss, income gain and Net income response by country 2010

(a) Total income loss (percentage)(b) Total income gain (percentage)



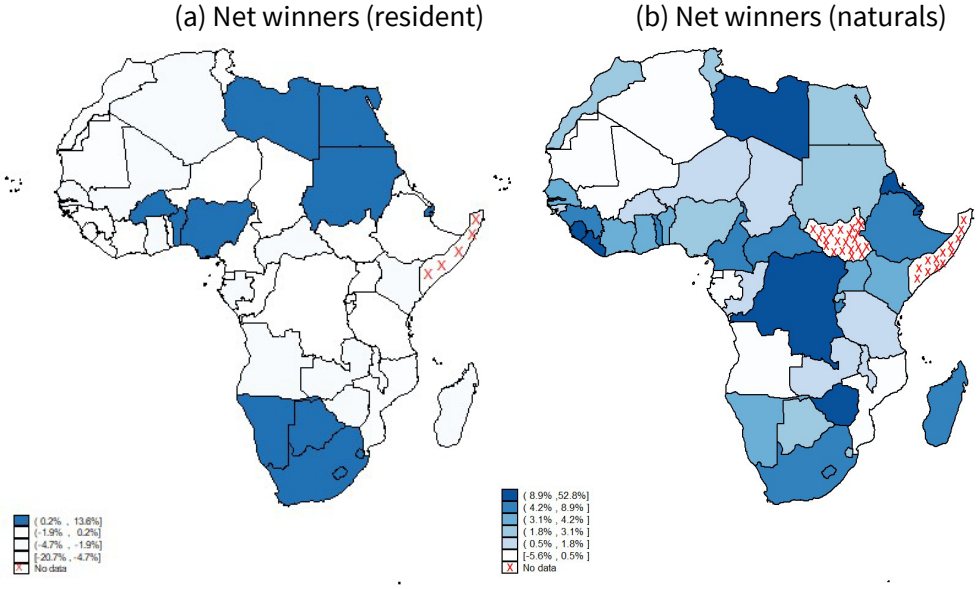
(c) Total income gain from migrants (%) (d) Net income response to BD



At the sub-regional level, Western, Middle, and Eastern Africa are better off with Western Africa experiencing the largest net income gain. Nevertheless, Southern Africa rather experiences a decline in the net income response to BD (at least for the decades 1990-2000 and 2000-2010). The explanation is straightforward: Southern African countries are Upper-middle-income countries characterized by a relatively low level of skilled emigration rates, higher wages, and low wage differential from OECD countries. Because of downgrading (that its immigrants have lower wages compared to natives for a given level of qualification in the host country), what skilled migrants from Southern Africa earn is finally lower than what they would have earned if they did not emigrate to the OECD. Since roughly 50% of Southern Africans in the OECD are tertiary educated, this results in a slight decline in the per-natural worker income. As far as country size and income groups are concerned, while small countries as well as Low-income countries exhibit the largest net income gain (+9.7% and +8.2% respectively largely explained by the composition effect described earlier), net gains are insignificant in Upper

middle-income countries (negative for some decades). This is due, on the one hand, to a smaller income gap between these countries and the OECD, and on the other, to the relatively lower scale of skilled emigration (as a share of the native labor force). As a result, the pool of skilled workers earning higher wages abroad is not large enough to increase the average income of a representative native worker.

Figure 5: From net resident to net natural per worker income response 2010



What are the most important channels? As summarized in Table G.1, at continental level, while technological externalities and depletion in human capital account for more than 2/3 of total income loss caused by BD, diaspora externalities and migrants' welfare in the OECD account for no less than 92% of the total income gain established in this study. This structure holds at a sub-regional level as well, although Southern Africa depicts a slightly different structure with a direct effect contributing to more than 25% of the total income loss against only 11.1% for SSA. Furthermore, while migrants' welfare in the OECD accounts for nearly 50% of the total income gain, it represents only one-third in Northern Africa. At the sub-regional level, Southern Africa fares worse when migrants' welfare is considered, with its net income response contracting by 12.7%. However, this decline is partially offset by the region's strong diaspora. The other sub-regions depict the same picture as SSA. In addition, the structure of income loss is independent to the level of development. But the latter is not true on the gain side as income gain is dominated by migrants' welfare (more than 2/3) in low-income countries

and diaspora externalities in lower and upper-middle-income countries (45.6% and 75.3% respectively).

7. Sensitivity Analysis and Robustness Checks

The framework I use estimates the baseline impact of brain drain (BD) in Africa by weighing its costs and benefits. Benchmark findings reveal that when emigrants are excluded, Africa as a whole is a net loser, with losses increasing over time in line with rising skilled emigration. At the country level, the majority (about 71%) of African nations experience net losses. However, when skilled emigrants are included, the proportion of losing countries drops significantly to an average of 16%. That said, these results may be sensitive to parameter choices, counterfactual assumptions, or the structural formulation of the model.

Table (6) depicts the sensitivity of the benchmark result to the form of production technology, counterfactual scenario, and parameter variants. Columns (1) to (4) report the net income response for resident workers while Columns (5) to (8) report the net income response for natural workers. Each of the two cases shows under each variant the number of African countries experiencing a net loss, their share, the correlation with the benchmark, and the average intensity of the net effect. I choose the year 2010 rather than 2015 for comparability purposes. Indeed, the DIOC database does not allow to building of a bilateral skilled emigration matrix for 2015, migrants are accounted into the model only till 2010. I first allow the structural formulation of the production technology to change such as considering only human capital in the long run as being conducive to income per worker[25]. Changing the structural formulation (see Panel 6c) has a slightly important effect on the size of net impact as it multiplies the net effect by a factor of 1.9 (-5.2% against -2.7% in the benchmark) as well as on the number of losers (80% against 70% in the benchmark). Furthermore, as depicted in Panel 6b, allowing the removal of positive selection in African skilled emigration increases the bad effect of BD (-3.9% against -2.7% in the benchmark). In other work, positive selection offsets to some extent the negative impact of emigration. To understand why African countries are on average worse off under neutral selection, think about the composition of gains and losses. On the gain side for instance, since diaspora externalities are much more related to the number of emigrants rather than to their education structure, this effect

[25] (Docquier (2017), Djaji´c et al. (2019), Delogu et al. (2018))

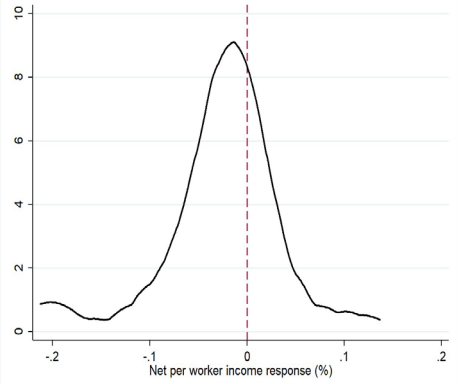
almost cancels out as the migrant population remains unchanged. The same logic applies to remittances.

I then assess how my benchmark findings react to changes in the parameters values (+/- 25%). For that purpose, I first increase the value of all the parameters by 25% (upper bound) and then decrease them by 25% (lower bound). As shown on Panel 6d of Figure 6, the departure from my benchmark is negligible. This strongly suggests that my findings are robust to important changes in parameter values. Globally, my findings resist a change in the production technology, to the choice of counterfactual scenario as well as to a change in parameter values.

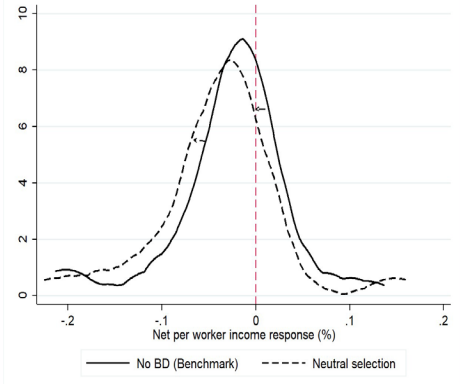
So far, my findings strongly indicate that BD is harmful for those left behind in Africa. They are robust to model specification, different counterfactual scenarios, and parameter variants. They indeed show that, in Africa, there are more losers than winners, and the number of losers as well as the intensity of net income loss increase over the decades following the pattern of skilled emigration. In 2015, 75.0% of African countries were experiencing a net income loss ranging between -18.7% and -0.02%. In addition, among the losers, more than 35% of the sample experienced a net income loss larger than -5%. These findings, at least for Africa, do not support the claim of the new BD literature stating that BD turns into brain gain when positive feedback mechanisms are taken into account. For example, Docquier (2017) shows at world level that when positive feedback mechanisms are accounted for (remittances, education incentives, and diaspora externalities), virtually all the countries are on average net winners while countries with income per capita of around $600 experience the largest net income gains around +3%. More interestingly, he finds that even middle-income countries (around $6,000) with the largest emigration rate are net winners albeit they experience the lowest net gain around +1.5%. These results have been further confirmed by a recent study conducted by Docquier and Veljanoska (2020) for the year 2010 covering 195 sending countries. Their findings suggest that skill-biased emigration is not harmful to those left behind for at least 75% of their sample. But, if more attention is paid to these findings, it is not that much contradictory to what the present study has found.

Figure 6: Sensitivity analysis

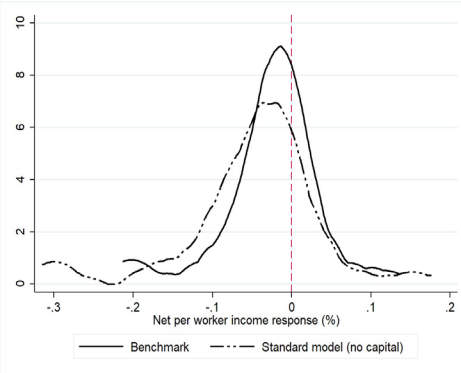
(a) Benchmark results



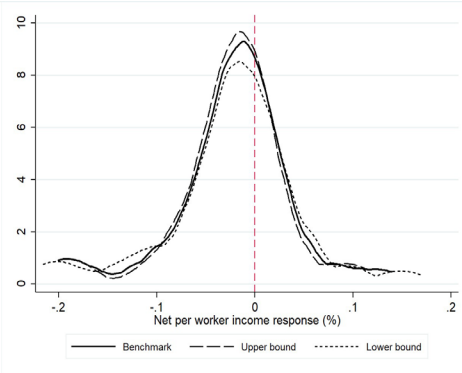
(b) Sensitivity to selection



(c) Sensitivity to technology



(d) Sensitivity to parameters



First, both Docquier (2017) and Docquier and Veljanoska (2020) do not account for neither educational subsidies nor remittances from skilled migrants. Furthermore, education incentives established at the global level do not hold for Africa and I rather find a disincentive effect that depends upon the development level of the country. Consequently, the net effect is likely overestimated in the above-mentioned studies. While there would be a consensus on the necessity to account for educational subsidies, remittances from skilled emigrants would not be that clear for their respective studies as they also controlled for unskilled emigration. Second, global average picture would hide important disparities. Indeed, the average picture presented in Docquier (2017) does not mean that all the countries are close to the mean and there are sufficient reasons to believe that African countries even in that setting are worse off and experience a net income loss for many of them.

This result challenges to some extent the claim that BD turns into brain gain, especially through the human capital channel. Although there is no proof that education incentives do exist in Africa, even if it was the case, its transformation into economic outcomes in the short and medium run is not guaranteed. Income per worker in Africa is not that sensitive to changes in human capital as expected by the new BD literature. Consequently, emigration prospects even when rising human capital ex ante would not necessarily turn it into economic benefit. Although economists like the idea that education buys growth, facts seem to contradict this view and there are two possible coherent explanations. First, as highlighted by Fan and Stark (2007a), the emigration prospect, by increasing the incentive to acquire additional education can at least in the short and/or medium run lead either to educated unemployment or to over-education. This is especially the case in the context of a sticky wage rate and an increase in the labor supply with the demand remaining more or less unchanged. The second reason that can explain why additional human capital would not necessarily turn into an increase in wages is the issue of the quality of the newly educated workers left behind. As argued by Schiff (2005), abilities are heterogeneous, and high-ability individuals (those who would have acquired education even if emigration was not an option despite the returns on education being lower) will emigrate, resulting in a lower ability level for the educated individuals remaining in the home country. Put differently, BD deprives Africa of their most talented, young, and productive workers such that even if the newly educated workers that could not emigrate were employed, they could not just be as productive as those who have flee the country are; thanks to selective immigration policies at destination.

Nevertheless, these findings also strongly and robustly suggest that natural African workers are better off under BD compared to a counterfactual world in which skilled emigration is prohibited. The question here is whether one should only care about those left behind or about natives no matter where they live. One should keep in mind that in the absence of BD, skilled emigrants would have been resident workers and their welfare would have been a source of concern for policymakers. Put differently, how BD affects skilled migrants themselves is also important to consider such that the most suitable way to assess costs and benefits from skilled emigration should be to account for the situation of both resident and skilled emigrants. By doing so, BD rather leads to the general improvement of natural workers' conditions in Africa. These findings remain robust even when accounting for a 20% wage downgrade, meaning that skilled immigrants from Africa earn 20% less than OECD natives with comparable skills. The net effect on native

workers is driven mainly by the wage gap between sending and receiving countries and is equally influenced by the distribution of skilled emigrants across destinations.

8. Concluding Remarks and Policy Options

Brain drain (BD) is often perceived as detrimental to low- and middle-income source countries, where skilled individuals emigrate in disproportionately large numbers. While recent literature suggests that positive feedback effects from BD can sometimes offset its negative consequences, the net impact remains complex. Many African countries likely experience net losses due to the exceptionally high emigration of highly skilled individuals. To assess BD's impact on African economies, I take three steps. First, I test the brain gain hypothesis using an improved IV approach to determine whether skilled emigration prospects incentivize education, accounting for regional and developmental differences. Second, applying a structural model for 51 African countries within a development accounting framework, I find that BD harms resident workers, with losses intensifying over time—reflecting the rising trend of skilled emigration from Africa. Finally, extending the analysis to include emigrants—i.e., considering natives rather than only residents—reveals net gains for Africa overall, driven by substantial income disparities between Africa and OECD countries.

I highlight a policy option that, to my knowledge, remains underexplored: leveraging migrants' strong attachment to their home countries as a source of development finance. International migration is often perceived as permanent, but evidence suggests otherwise. Dustmann and Goerlach (2016) and OECD (2008) show that 20% to 50% of migrants in the OECD return within 5 to 10 years. This reflects their deep-rooted preference for their home country. Even those who do not return often hesitate due to uncertainty about their post-return prospects. A viable incentive for their return would be facilitating migrant contributions to a capitalization-based pension system in their home country. This system could, in turn, serve as a crucial development finance mechanism, either replacing or complementing foreign debt, which home countries currently secure at international market rates. Such a policy has two key advantages: (i) it creates domestic debt in foreign currency, improving the home country's current account balance, and (ii) it ensures debt service is repaid in local currency, stimulating local demand and production. In the medium to long term, if implemented effectively, this

approach could enhance African economies and, when combined with other policies, reduce migration pressures on OECD countries, ultimately leading to a significant decline in BD.

Future research is needed to determine the relevance of such a policy and to identify the necessary conditions for its implementation in Africa. This involves evaluating its potential effectiveness and identifying the specific circumstances under which it would yield the desired impact.

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Supplementary Appendix

A Sample description

A.1 Country list

Angola (AGO), Burundi (BDI), Benin (BEN), Burkina Faso (BFA), Botswana (BWA), Central African Republic (CAF), Cote d'Ivoire (CIV), Cameroon (CMR), Congo Democratic Rep. (COD), Congo Rep. (COG), Comoros (COM), Cape Verde (CPV), Djibouti (DJI), Algeria (DZA), Egypt (EGY), Eritrea (ERI), Ethiopia (ETH), Gabon (GAB), Ghana (GHA), Guinea (GIN), Gambia (GMB), Guinea-Bissau (GNB), Equatorial Guinea (GNQ), Kenya (KEN), Liberia (LBR), Libya (LBY), Lesotho (LSO), Morroco (MAR), Madagascar (MDG), Mali (MLI), Mozambique (MOZ), Mauritania (MRT), Mauritius (MUS), Malawi (MWI), Namibia (NAM), Niger (NER), Nigeria (NGA), Rwanda (RWA), Sudan (SDN), Senegal (SEN), Sierra Leone (SLE), Sao Tome and Principe (STP), Swaziland (SWZ), Seychelles (SYC), Chad(TCD), Togo (TGO), Tunisia (TUN), Tanzania (TZA), Uganda (UGA), South Africa (ZAF), Zambia (ZMB), Zimbabwe (ZWE).

A.2 Regions

Sub-Saharan Africa (SSA): AGO, BDI, BEN, BFA, BWA, CAF, CIV, CMR, COD, COG, COM, CPV, ERI, ETH, GAB, GHA, GIN, GMB, GNB, GNQ, KEN, LBR, LSO, MDG, MLI, MOZ, MRT, MUS, MWI, NAM, NER, NGA, RWA, SEN, SLE, STP, SWZ, SYC, TCD, TGO, TZA, UGA, ZAF, ZMB, ZWE.

Northern Africa: DJI, DZA, EGY, LBY, MAR, SDN, TUN.

A.3 SSA sub-regions

Western Africa: BEN, BFA, CIV, COM, CPV, GHA, GIN, GMB, GNB, LBR, MLI, MRT, NER, NGA, SEN, SLE, TGO.

Southern Africa: BWA, LSO, NAM, SWZ, ZAF.

Middle Africa: AGO, CAF, CMR, COD, COG, GAB, GNQ, STP, TCD.

Eastern Africa: BDI, COM, ERI, ETH, KEN, LBR, MDG, MOZ, MUS, MWI, RWA, SYC, TZA, UGA, ZMB, ZWE.

A.4 Country size

Large countries: COD, DZA, EGY, ETH, GHA, KEN, MAR, NGA, SDN, TZA, UGA, ZAF. **Medium countries**: AGO, BDI, BEN, BFA, CIV, CMR, GIN, MDG, MLI, MOZ, MWI, NER, RWA, SEN, TCD, TUN, ZMB, ZWE.

Small countries: CAF, COG, ERI, LBR, LBY, MRT, SLE, TGO.

Very small countries: BWA, COM, CPV, DJI, GAB, GMB, GNQ, LSO, MUS, NAM, STP, SWZ, SYC.

Income groups

Low-income countries (LIC): BDI, BEN, BFA, CAF, COD, COM, ERI, ETH, GIN, GMB, GNB, LBR, MDG, MLI, MOZ, MWI, NER, RWA, SEN, SLE, TCD, TGO, TZA, UGA, ZWE.

Lower middle-income countries (LMIC): AGO, CIV, CMR, COG, CPV, DJI, EGY, GHA, KEN, LSO, MRT, MAR, NGA, SDN, SWZ, STP, TUN, ZMB.

Upper middle-income countries (UMIC)**:** DZA, NAM, BWA, GAB, GNQ, LBY, MUS, SYC, ZAF.

A.5 Data

Data on emigration stocks from Africa to the OECD are from two sources: Docquier and Marfouk. (2006) for the year 1990 and Database on Immigrants in OECD Countries (DIOC) for the years 2000, 2010 and 2015. The methodology followed by these two dataset are identical as the second used the methodology developped by the first. The dataset by Docquier and Marfouk. (2006), that we will refer to as DM06 in the remaining document, compiled data on stock of immigrants in OECD countries for the years 1990 for 174 origin countries and 2000 for 195 countries. They considered 30 OECD destination countries for both 1990 and 2000 albeit in 1990, Czeck Republic, Hungaria, Korea and Mexico were not yet members of OECD countries (They joined OECD between 1994 and 1996). We consider DM06 dataset only for the year 1990. We take data on African countries already aggregated by DM06 at each level of education for individuals aged 25 and over. The DIOC dataset provides for each country of destination and each country of origin the number of immigrants at different level of education and age. DIOC considers 34 OECD destination countries and 195 origin countries (While the OECD has 36 countries, Lativia and Lithuania has joined OECD only in 2016 and 2018 respectively i.e. only out of the period covered by the dataset). The little difference on stock of African emigrants in OECD countries for 2000 between DIOC and Docquier and Marfouk. (2006) datasets are to some extent explained by the difference in numbers of destination countries (34 for DIOC and 30 for Docquier and Marfouk. (2006) as Chile, Estonia, Israel and Slovenia joined OECD only in 2010). These datasets were built using information on emigration obtained by aggregating consistent immigration data collected in OECD countries. Information about origin, skill and age of immigrants are available from national population censuses and registers (Docquier and Marfouk. (2006).

The dataset considers all working age individuals age 25 and over, born in Africa and living in the OECD. Skilled migrants, as defined by Docquier and

Marfouk. (2006)) are those who have at least tertiary educated no matter where they completed their education. In the first step, using DIOC dataset, I compute emigration stock from African countries by educational attainment for the years 2000, 2010 and 2015. In the second step, I merge stocks from DM06 to stocks computed in step one making a coherent global dataset over the period 1990 to 2015. I then evaluate the migratory pressure by expressing these numbers in percentage of the total labor force born in the origin country (residents + emigrants) belon. I consider two skill groups i.e. skilled and unskilled.

Estimation of emigration rate by skill group requires data on the size and skill structure of adult population in source countries. Data on population size by age group are from United Nations. Population is then split accross skill groups using data on human capital stock in sending countries. As in DM06, these data are from Barro and Lee (2013) for 1990, 2000 and 2010 and Barro and Lee (2015) for 2015. As Barro and Lee data are available only for 36 African countries (i.e. 18 countries without data), we apply for those countries with missing data the educational proportion of neighboring countries having the closest enrolment rate in the secondary education. In some of these countries, as secondary enrolment rate were not available, we apply the educational proportion of the country with the closest human development index.

In summary, I obtain the total stock of African migrants in the OECD by country of

birth *i*, by skill group *a* through the following expression for a giving year *t*:

$$M_{i,t}^{a} = \sum_{j=1, j\neq i}^{J} M_{ij,t}^{a} \quad (28)$$

Where $a \in \{s, u\}$ and J stands for the total number of OECD destination countries.

Emigration intensity is obtained as:

J

$$m_{i,t}^{a} = \frac{\sum_{j=1,\ j\neq i}^{J} M_{ij,t}^{a}}{N_{i,t}^{a} + \sum_{j=1,\ j\neq i}^{J} M_{ij,t}^{a}} \equiv \frac{M_{i,t}^{a}}{N_{i,t}^{a} + M_{i,t}^{a}} \quad (29)$$

Where N^{a} stands for the resident labor force in the origin country belonging to the age and skill group of interest. i.e. $m_{i,t}^{s} = M_{i,t}^{s}/(M_{i,t}^{s} + M_{i,t}^{u})$, and $m_{i,t}^{u} = M_{i,t}^{u}/(M_{i,t}^{s} + M_{i,t}^{u})$.

Our focus on the OECD destination only, is explained by two core motives: (i) Data availability constraints; except for datasets mentioned above,

other existing datasets on emigration do not split emigration with respect to education attainment. (ii) While total emigration is largely intra African, skilled emigration is strongly positively biased toward OECD destination. In other words, data from extended DIOC (E-DIOC) suggest that in 2000 and 2010, OECD destination accounted for 90.4% and 92.0% of skilled emigration respectively. Nevertheless, I am aware that by disregarding non-OECD destinations, I underestimate the magnitude of African brain drain especially for countries like Egypt and Sudan in the neighbordhood of the Gulf States; Estwani, Namibia, Lesotho, Malawi, Botswana and Zimbabwe in the Neighbordhood of South Africa; Cote d'Ivoire and Burkina Faso which swap a lot of skilled workers. Indeed, Intra African BD accounted for more than 30% of skilled emigration stock in nine countries (Burkina Faso, Botswana, Lesotho, Malawi, Namibia, Niger, Estwani and Zimbabwe). Except for Burkina Faso, Cote d'Ivoire and Niger, South Africa was the main destination of 98.7% of them. Consequently, incorporating Gulf States and South Africa will refine the dataset; But as such data are available for only 2000 and 2010 (E-DIOC), we have decided not to incorporate them in order to make data comparable over time.

Building an aggregate measure of emigration stock and emigration rates for African countries by educational attainment has encountered two major problems: (i) African migrants whose country of origin is unknown, related to as" Africa" in the place of their country of birth. (ii) African migrants whose level of education is unknown. DM06 have suggested two approaches which can be used in order to deal with this second issue: either split them into skilled and unskilled using relative weight of the two components; or assimilate them to unskilled. In the present study, I assimilate them to unskilled.

Table A.1: World migration toward OECD in 2015 for individuals aged 25 and over

	Skilled	Unskilled	Total migration	Share of skilled
Africa	14.7%	17.8%	16.6%	32.9%
Northern Africa	5.1%	9.5%	7.9%	24.0%
Subsaharan Africa	9.6%	8.2%	8.7%	42.0%
East Asian and Pacific	23.9%	14.7%	17.8%	49.8%
Europe and Central Asia	18.3%	24.7%	22.6%	30.0%
Latin America and Caribbean	18.4%	27.2%	23.7%	28.8%
Middle East	6.0%	4.3%	5.2%	43.1%
South Asia	16.9%	8.0%	11.3%	55.5%
Unknown	1.8%	3.4%	2.8%	23.7%
Total (in thousands)	24,643	43,838	66,281	37.2%

Source: Author's compilation using DIOC (2015)

These computations include 52 African countries (i.e. 6 from NA and 47 from SSA), 35 East Asian and Pacific countries, 29 European and Central Asian countries, 38 Latin American and Caribbean countries, 14 Middle Eastern countries and 8 South Asian countries. African computations include Somalia.

Table A.2: Dynamic of skilled migrants from Africa 1990-2015

(In thousand)	1990	2000	2010	2015
Africa	729.5	1,571.7	2,932.4	3,557.0
Northern Africa	254.3	632.9	1,051.3	1,291.0
	34.9%	40.3%	35.9%	36.3%
Sub-Saharan Africa	475.2	884.7	1,737.8	2,200.2
	65.1%	56.3%	59.3%	61.9%

Western Africa	143.6	288.3	606.4	814.6
	19.7%	18.3%	20.7%	22.9%
Southern Africa	79.1	149.6	295.6	341.8
	10.8%	9.5%	10.1%	9.6%
Eastern Africa	200.4	315.8	603.0	745.4
	27.1%	20.1%	20.6%	21.0%
Middle Africa	52.1	131.0	232.7	298.3
	7.1%	8.3%	7.9%	8.4%
Unknown	-	54.1	143.3	65.4
	-	3.4%	4.9%	1.8%
06 Largest suppliers	412.5	899.8	1,592.8	1,929.1
	56.5%	59.3%	57.1%	55.3%

Source: Authors' calculation from DM06 and DIOC.

The 06 largest suppliers are Algeria, Egypt, Kenya, Morocco, Nigeria and South Africa.

Table A.3: Distribution of brain drain in Africa

	Skilled migrants stocks				size of brain drain			
	1990	2000	2010	2015	1990	2000	2010	2015
	At continental level							
Africa	729,551	1,517,519	2,789,025	3,490,986	11.3%	12.2%	12.5%	13.0%
Africa adj.	729,551	1,571,664	2,932,359	3,556,411	11.3%	12.6%	13.1%	13.2%
	By region							
NAF	254,310	632,859	1,051,263	1,290,832	10.7%	14.3%	9.9%	9.1%
SSA	475,241	884,660	1,737,762	2,200,154	11.7%	11.0%	14.8%	17.3%
	By Sub Saharan African Sub region							
Western	143,598	288,258	606,445	814,643	10.0%	10.8%	13.2%	18.7%
Southern	79,138	149,594	295,642	341,800	8.6%	7.1%	15.0%	17.3%
Middle	52,129	131,003	232,672	298,316	13.1%	16.1%	21.1%	21.3%
Eastern	200,376	315,805	603,003	745,395	15.2%	13.0%	14.9%	15.0%
	By country size							
LC	554,523	1,115,683	2,014,224	2,455,413	12.2%	10.5%	12.8%	14.7%
MC	63,795	183,805	381,167	485,767	12.3%	18.1%	20.9%	21.7%
SC	79,016	170,198	289,498	428,227	22.3%	22.2%	21.1%	23.6%
VSC	32,218	47,833	104,136	121,579	20.3%	23.9%	25.2%	24.6%
	By income group							
LIC	161,362	260,716	498,177	650,561	14.7%	15.0%	19.6%	19.9%
LMIC	430,141	855,079	1,597,899	2,024,053	12.0%	11.5%	12.1%	15.1%
UMIC	138,049	401,724	692,949	816,372	10.0%	12.9%	14.3%	14.6%

Note: Africa Adjusted referred to the size of brain drain computed when accounting for skilled migrants from Africa with unknown countries of birth. Western (16 countries), Southern(6 countries), Middle (9 countries) and Eastern Africa (16 countries) are Sub-Saharan African sub regions. By income group, we use the latest World Bank classification based on GNI per capita at current $; LIC are countries with GNI per capita below $1,025; LMIC have a per capita income between $ 1,025 and $3,995; UMIC belongs to the range $3,995 and $12,375 and HIC with per capita income above $12,375. As only Seychelles belongs to the group of high income countries in Africa, we have integrated it in the group of UMIC. With respect to the population size, Large Countries (LC) are countries with population larger than 25 million; Medium Countries (MC) are those with population between 10 million and 25 million; Small Countries (SC) are those with population between 2.5 million and 10 million and Very Small Countries (VSC) are those with population lower than 2.5 million. NAF refers to Northern Africa and SSA refers to Sub-Saharan Africa

B Gravity based IV

The gravity-based prediction of skill specific bilateral migration stocks $\hat{N}_{ij,s,t}$ is obtained using the following pseudo-gravity model:

$$\ln N_{ij,s} = \beta_0 + \beta_1 \ln pop_i + \beta_2 \ln dist_{ij} + \beta_3 \ln w_j + \beta_4 \ln Network_{ij,t-10} + \beta_5 Guest_{ij} + \beta_6 Lang_{ij} + \beta_7 Col_{ij} + \beta_8 Cont_{ij} + \mu_j + \epsilon_{ij} \quad (30)$$

$$\ln N_{ij,t,s} = \beta_0 + \beta_1 \ln pop_{i,t} + \beta_2 \ln dist_{ij} + \beta_3 \ln w_{j,t} + \beta_4 \ln Network_{ij,t-10} + \beta_5 Guest_{ij} + \beta_6 Lang_{ij} + \beta_7 Col_{ij} + \beta_8 Cont_{ij} + \sum_{t=00,10} \beta_9 \delta_t + \sum_{t=00,10} \beta_{10} \delta_t \times \ln dist_{ij} + \mu_j + \epsilon_{ij,t} \quad (31)$$

Where ln$pop_{i,t}$ is the log of total population at origin at time *t*, ln$dist_{ij}$ is the log of weighted distance between *i* and *j* based on bilateral distances between the biggest cities of the two countries weighted by the share of the city in the total population of the country. ln$w_{j,t}$ is the log wage in the OECD destination country j. ln$Network_{ij,t-10}$ is the log of network size in the destination country *j* proxied by the total stock of migrants from *i* to *j* tens years earlier no matter their age and level of education. $Guest_{ij}$ is a dummy variable taking the value 1 if a Guest Worker program between *i* and *j* were observed during the decade prior to the census and 0 otherwise. $Lang_{ij}$ is a dummy variable equal to 1 if the same language is spoken by at least 9% of the population in both countries and 0 otherwise. Col_{ij} and $Cont_{ij}$ are dummy variables that equal 1 if countries *i* and *j* have colonial link and share common borders respectively and 0 otherwise. μ_j and δ_t are destination and time fixed effects. We do not include the origin-country fixed effects as they are likely to be endogenous while we would like to rely on truly exogenous factors of bilateral migration stocks.

We first estimate equation (30) for each year (1990, 2000 and 2010). However, since most of our determinants of skill-specific emigration rate are time invariant, we follow Feyrer (2009), Docquier et al. (2016) and move to a panel setting in which we add time fixed effects and interaction between time fixed effects and weighted distance between *i* and *j* as stated in equation (31). As pointed out in Docquier et al. (2016), identification comes from the time-varying effect of distance between country pairs on skill specific migration, reflecting gradual changes in migration costs[30]. As far as these changes are common to all countries, they will be exogenous with respect to any particular country. Secondly, the predicted skill-

specific emigration rates are then obtained by aggregating skill specific emigration stocks over destinations, $\sum_j \widehat{N}^s_{ij,t}$ for each t and by dividing the obtained sum by the skill specific native labor-force for each corresponding year. Thirdly, we use gravity based predicted high skilled emigration rate and emigration rates differential to instrument the observed skilled emigration rates on the one hand and gap in emigration rates on the other hand in our first stage regression.

$$(m_{i,h,t} - m_{i,l,t}) = \alpha_0^{gr} + \alpha_1^{gr} \ln(\hat{m}_{i,h,t} - \hat{m}_{i,l,t}) + \alpha_2^{gr}(H_{i,h,t}) + \sum_{k=2,3,4} \alpha_3^{k,gr} I_i^k + \sum_{k=2,3,4} \alpha_4^{k,gr} (\hat{m}_{i,h,t} - \hat{m}_{i,l,t}) \times I_i^k + X'_{i,t}\beta^{gr} + \Phi_t + \epsilon_{i,t} \quad (32)$$

Where $X_{i,t}$ is the set of controls used in the second stage regression.

B.1 Zero stage estimation

As expected, it appears that Distance between country pairs, population size at origin, income at destination, network, common language and colonial link play a key role in explaining bilateral migration stocks especially high skilled migration stocks. While distance from origin to destination negatively impact bilateral migration stocks, they are favored by population size, network, language and colonial links. Moreover, the influence of distance decreases over the decades reflecting the decrease in migration cost over time.

Table B.1: Pseudo-Gravity model - predict bilateral migration stocks (Stage zero)

	(1) M_{ijh}	(2) M_{ijl}	(3) M_{ijh}	(4) M_{ijl}	(5) M_{ijh}	(6) M_{ijl}	(7) M_{ijh}	(8) M_{ijl}
$\ln(Dist_{ij})$	-0.198**	-0.549***			-0.200**	-0.478***		
	(0.09)	(0.08)			(0.08)	(0.07)		
$\ln(Dist_{ij})\times$ 2000			-0.125*	-0.369***			0.016	-0.210**
			(0.08)	(0.07)			(0.07)	(0.08)
$\ln(Dist_{ij})\times$ 2010			-0.488***	-0.383***			-0.537***	-0.326***
			(0.10)	(0.11)			(0.08)	(0.08)
$\ln(Pop_i)$	0.386***	0.108***	0.388***	0.092**	0.405***	0.090*	0.395***	0.082
	(0.03)	(0.04)	(0.03)	(0.04)	(0.06)	(0.05)	(0.06)	(0.05)
$\ln(Net_{i,j}-20)$	0.482***	0.546***	0.480***	0.593***				
	(0.05)	(0.05)	(0.05)	(0.04)				
$\ln(Net_{i,j}-10)$					0.488***	0.621***	0.498***	0.668***
					(0.10)	(0.08)	(0.10)	(0.07)
$\ln(wageHS_{dest})$	0.158		0.187		0.183		0.198*	
	(0.13)		(0.13)		(0.11)		(0.12)	
$\ln(wageLS_{dest})$		0.239		0.201		0.184		0.145
		(0.18)		(0.17)		(0.15)		(0.14)
Guest pr.i,j	0.024	0.157	-0.187	0.254	-0.069	0.030	-0.285	0.139
	(0.19)	(0.27)	(0.24)	(0.22)	(0.16)	(0.20)	(0.22)	(0.18)
Com. lang.	0.509***	0.464**	0.533***	0.431**	0.459***	0.291	0.468***	0.239
	(0.11)	(0.23)	(0.11)	(0.20)	(0.16)	(0.28)	(0.16)	(0.24)
Col. link	0.645**	0.441**	0.706***	0.375**	0.959***	0.567***	1.003***	0.477**
	(0.25)	(0.20)	(0.25)	(0.15)	(0.17)	(0.21)	(0.17)	(0.19)
Contiguity	-0.854***	-1.810***	-1.057***	-1.247***	-0.657***	-1.458***	-0.912***	-0.913***
	(0.17)	(0.13)	(0.14)	(0.14)	(0.15)	(0.13)	(0.14)	(0.14)
Obs	5,304	5,304	5,304	5,304	5,304	5,304	5,304	5,304
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dest. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	No	No	No	No	No	No	No	No
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.827	0.920	0.896	0.938	0.801	0.905	0.881	0.920

Note: Robust standard errors in parentheses. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1.

First stage estimation

First stage estimates strongly suggests that predicted skilled emigration rate is a very good predictor of *their observed counterpart with* the R^2 of the first stage is around 0.89.

Table B.2: Relevance of the instruments

	(1) $\ln(p_{i,t})$	(2) $\ln(p_{i,t})$	(3) $\ln(m_{i,h,t})$	(4) $\ln(m_{i,h,t})$
$\ln(\widehat{m_{i,h,t} - m_{i,l,t}}) \equiv \ln(\widehat{p_{i,t}})$	0.935***	1.093***		
	(0.09)	(0.11)		
$\ln(\widehat{m_{i,h,t}})$			1.009***	1.165***
			(0.09)	(0.10)
Northern Africa × $\ln(\widehat{p_{i,t}})$		-0.269		
		(0.18)		
Northern Africa × $\ln(\widehat{m_{i,h,t}})$				-0.152
				(0.14)
Northern Africa		-0.971*		-0.476
		(0.54)		(0.35)
$\ln(H_{i,t})$		0.272**		0.307***
		(0.11)		(0.10)
Population density		0.001		0.001**
		(0.00)		(0.00)
Small Countries		-0.199		-0.174
		(0.15)		(0.15)
Medium Countries		0.053		0.070
		(0.16)		(0.15)
Large Countries		-0.506**		-0.406**
		(0.20)		(0.19)
Obs	156	156	156	156
Time FE	Yes	Yes	Yes	Yes
Outliers	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
R^2	0.595	0.668	0.624	0.701

Note: Robust standard errors in parentheses.
Standard error are clustered at country level Significant coefficients are denoted with stars as follows:
*** p<0.01, ** p<0.05, and * p<0.1.

C Technological externalities

Table C.1: Technological externality and skill-biased technical change

	(1) $\ln(A_{i,t})$	(2) $\ln(A_{i,t})$	(3) $\ln(\eta_{i,t}/(1-\eta_{i,t}))$	(4) $\ln(\eta_{i,t}/(1-\eta_{i,t}))$
$\ln(A_{i,t-1})$	0.790***	0.664***		
	(0.04)	(0.07)		
$\ln(\eta_{i,t-1}/(1-\eta_{i,t-1}))$			0.522***	0.521***
			(0.10)	(0.11)
$\ln(h_{i,t}/(1-h_{i,t}))$	0.053	0.095**	0.226***	0.237***
	(0.05)	(0.05)	(0.05)	(0.06)
Obs	153	153	156	156
Years FE	Yes	Yes	Yes	Yes
Country size FE	No	Yes	No	Yes
Regional FE	No	Yes	No	Yes
Income group FE	No	Yes	No	Yes
Intercept	Yes	Yes	Yes	Yes
R^2	0.730	0.762	0.808	0.814

Note: Robust standard errors in parentheses.
Standard error are clustered at country level. Significant coefficients are denoted with stars as follows:
*** p<0.01, ** p<0.05, and * p<0.1.

D Remittances and the brain drain: Who remit more?

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	R_i/L_i(logs)	R_i(logs)	R_i (logs)	R_i/L_i (logs)	R_i (logs)	R_i (logs)
m_i (log)	0.446***	0.339***		0.499*	0.396*	
	(0.150)	(0.122)		(0.290)	(0.225)	
M_i (log)			0.410***			0.191
			(0.151)			(0.382)
M_i^s/M_i^u (log)	-0.104	-0.137	-0.116	-0.037	-0.043	-0.384
	(0.278)	(0.287)	(0.291)	(0.475)	(0.429)	(0.549)
Inc. per worker (log)	0.658***			0.645**		
	(0.200)			(0.253)		
GDP (log)		0.896***	0.556***		0.875***	0.732**
		(0.094)	(0.151)		(0.096)	(0.348)
Constant	-0.711	-1.724	0.528	-0.333	-0.914	-1.630
	173	173	173	159	159	159
	0.22	0.39	0.40	0.23	0.39	0.38
F first stage				19.2	35.8	29.3

Values into parenthesis are robust standard errors. R_i/L_i= remittances per worker, R_i= total remittances, m_i= emigration rate, M_i= migrants' stock, M_i^s/M_i^u= Share of skilled in the migrant's population. Instrumental variable approach use as instruments for migration the following variables: landlock dummy, english dummy, Dual citizenship dummy, Island dummy and public expenditure on education.

E Parameters

Table E.1: Common and country specific parameters

Para.	Description	Mean	St. Dev.	Min	Max	Source
δ	prop. home edu.	0.691	-	-	-	Beine et al. (2007)
α	Capital share	0.32	0.097	0.17	0.71	Calibrated
$1-\alpha$	Labor share	0.68	0.097	0.29	0.83	Guerriero (2019)
σ	Elast. of subst.	2	-	-	-	Ottaviano & Peri (2012)
w^s/w^u	Wage ratio	3.7	1.6	1.4	11.9	Calibrated
η	Rel. preference	0.36	0.13	0.08	0.67	Calibrated
A	TFP	15,132	24,462	263	217,881	Calibrated
γ	Techno. ext.	0.24	0.09	-	-	Estimated
τ	Skill bias ext.	0.22	0.04	-	-	Estimated
ρ	Diaspo. ext.	0.052	-	-	-	Calibrated
ψ^s	Rem. from Skilled	0.36	0.15	0.05	0.75	DM06 and DIOC
λ	Elas. of subs. b/w goods	4.0	-	-	-	Feenstra(1994)
β_{LIC}	Edu. incentives LIC	0	-	-	-	Estimated
β_{LMIC}	Edu. incentives LMIC	-0.028	-	-	-	Estimated
β_{UMIC}	Edu. incentives UMIC	-0.079	-	-	-	Estimated

F Sensitivity and robustness checks

Table F.1: Results sensitivity to model and parameter variants

	Net per resident worker				Net per natural worker			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	Losers	Share	Corr.	Average	Losers	Share	Corr.	Average
Benchmark	36	0.706	1.000	-2.7%	8	0.157	1.000	4.6%
Neutr. selection	39	0.765	0.960	-3.9%	12	0.235	0.978	3.3%
Std. Model	41	0.804	0.991	-5.2%	18	0.353	0.952	2.0%
param. × 1.25	35	0.686	0.996	-2.6%	10	0.196	0.994	4.6%
param. / 1.25	37	0.725	0.994	-2.9%	8	0.157	0.997	4.3%
$\sigma\times$ 1.25	36	0.706	0.999	-2.6%	8	0.157	1.000	4.6%
$\sigma/1.25$	37	0.725	0.998	-2.9%	8	0.157	0.999	4.4%
$\gamma\times$ 1.25	38	0.745	1.000	-3.0%	10	0.196	0.999	4.3%
$\gamma/1.25$	36	0.706	1.000	-2.4%	7	0.137	0.999	4.8%
$\tau\times$ 1.25	40	0.784	0.999	-3.3%	11	0.216	0.997	3.9%
$\tau/1.25$	35	0.686	0.999	-2.1%	7	0.137	0.998	5.1%
$\lambda\times$ 1.25	35	0.686	0.999	-2.4%	7	0.137	0.999	4.8%
$\lambda/1.25$	37	0.725	0.999	-3.0%	9	0.176	0.999	4.3%
$\beta\times$ 1.25	35	0.686	0.999	-2.5%	8	0.157	1.000	4.7%
$\beta/1.25$	36	0.706	1.000	-2.8%	9	0.176	1.000	4.5%
$\rho\times$ 1.25	33	0.647	0.997	-2.2%	7	0.137	0.998	5.0%
$\rho/1.25$	40	0.784	0.998	-3.6%	12	0.235	0.998	3.6%

G. Channels

Table G.1: Decomposition of channels by size

	Direct	Techn. Ext.	Edu. subs.	Mkt. size	Edu. desinc.	Remit.	Diasp. ext.	Migrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Africa	12.8%	23.8%	9.4%	6.6%	47.3%	7.5%	43.5%	49.0%
By region								
SSA	11.1%	24.1%	10.5%	6.4%	47.9%	7.6%	42.0%	50.3%
NAF	25.9%	21.4%	1.7%	8.4%	42.6%	6.5%	54.3%	39.2%
By sub-region								
Western	16.6%	31.8%	9.0%	10.8%	31.8%	5.7%	31.7%	62.7%
Southern	15.9%	28.4%	12.7%	30.4%	12.6%	38.9%	73.8%	-12.7%
Middle	18.0%	30.5%	9.9%	10.6%	31.0%	0.3%	54.7%	45.0%
Eastern	18.0%	29.5%	13.7%	6.8%	32.0%	3.7%	34.8%	61.4%
By country size								
Large	8.5%	12.8%	10.0%	0.2%	68.7%	6.4%	45.7%	47.9%
Medium	17.3%	31.9%	9.9%	7.4%	33.4%	4.1%	44.8%	51.1%
Small	17.4%	31.7%	9.3%	11.3%	30.3%	2.7%	33.4%	63.9%
V. Small	8.4%	19.4%	8.5%	8.2%	55.5%	16.5%	50.1%	33.4%
By income group								
LIC	16.4%	28.4%	12.5%	6.7%	36.0%	2.9%	29.7%	67.4%
LMIC	20.1%	31.2%	9.1%	8.4%	31.2%	11.8%	45.6%	42.7%
UMIC	15.9%	28.4%	11.9%	10.3%	33.5%	2.3%	75.3%	22.4%

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