The Legacy of the Transatlantic and Indian Ocean Slave Trades on Contemporary Intent to Migrate in Africa

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Abstract

Using recent individual-level data combined with historical ethnicity-level data on the transatlantic and Indian Ocean slave trades, I find a positive and statistically significant relationship between the slave exports and the intent to migrate observed among Africans today. I investigate using various controls and recent econometrics methods from several angles and conclude that this relationship is causal. Second, the mechanism behind these results is a combination of poverty and mistrust on the one hand, and "survival skills"[1] and place disconnect on the other, all culturally-induced by the slave exports, working in opposite directions to generate the selection into the intended migration through education. This sorting process leads the more productive, educated, and trusting Africans to be more willing to migrate while the less effective, less educated, and less trusting have a higher will to stay behind. These findings imply a brain drain cycle harmful to the development of the origins but beneficial to the destination countries of the intended migration. Moreover, these findings shed light on the cyclical machine behind the poor economic performance among African countries pointed out by Nunn (2008).

[1]The Transatlantic and Indian Ocean slave trades culturally instilled into individuals from the most impacted ethnic groups a higher ability to plan, anticipate, hunt, gather, and process information; and a higher preference for mobile human capital.

1 Introduction

There are a lot of reasons in the literature that explain what drives people to migrate. For example, the search for better economic conditions due to the income gap between the origin and the destination. Kennan and Walker (2011) who finds that expected income is a major driver for migration decision making due both to the geographic differences in mean wages and the search for a better locational match when the income realization in the current location is unfavorable. In the same sense, other works mention education, war, and social instability to explain migration. However, there is evidence that migration decisions can often reverse and that large differences in benefit levels can sometimes provide weak migration incentives (Kennan and Walker, 2010). This finding means that people don't always migrate just because of advantages in the destination place. Other reasons like attachment to place can explain migrants' behaviors. Phan and Coxhead (2019) finds that remittance flows are larger when migrants have higher wages and less attachment to the destination place in Vietnam. This finding means that attachment to place can partly explain migration decision-making when considered in the reverse sense and there is a literature on place attachment and migration as well (Murphy, 2013; McHugh and Mings, 1996; Elder et al., 1996; Rostamalizadeh and Ghasemi-Ardahaee, 2018; Koşar et al., 2021).

In all this, not much attention is given to how historical events like the slave trade can justify the contemporary migrations behaviors of some communities. Moreover, there is evidence that historical facts like the slave trade still profoundly impact some societies today. Nunn (2010) shows that missionaries' intervention has altered the culture of Africans with whom they have first been in contact so deeply that even today, their descendants are more likely to self-identify themselves as Christians. In the same way, Nunn and Wantchekon (2011) shows that the slave trade is the major cause of mistrust among Africans today. On the economic side, Nunn (2008) finds a robust negative relationship between the number of slaves exported and today's poor financial performance of African countries. All this makes it logical to think that one of these long-lasting impacts might be today's migration flows within and out of Africa. Exploring the links between slave trades and migration and how all this is connected to education is a great way to know how much human capital these people acquire before migration decision-making. As a quick recall, slave trades are thought to have started somewhere in the 15th century with Portuguese and Europeans. It began in 1619 in America and was abolished in the United States on 1 January 1808.

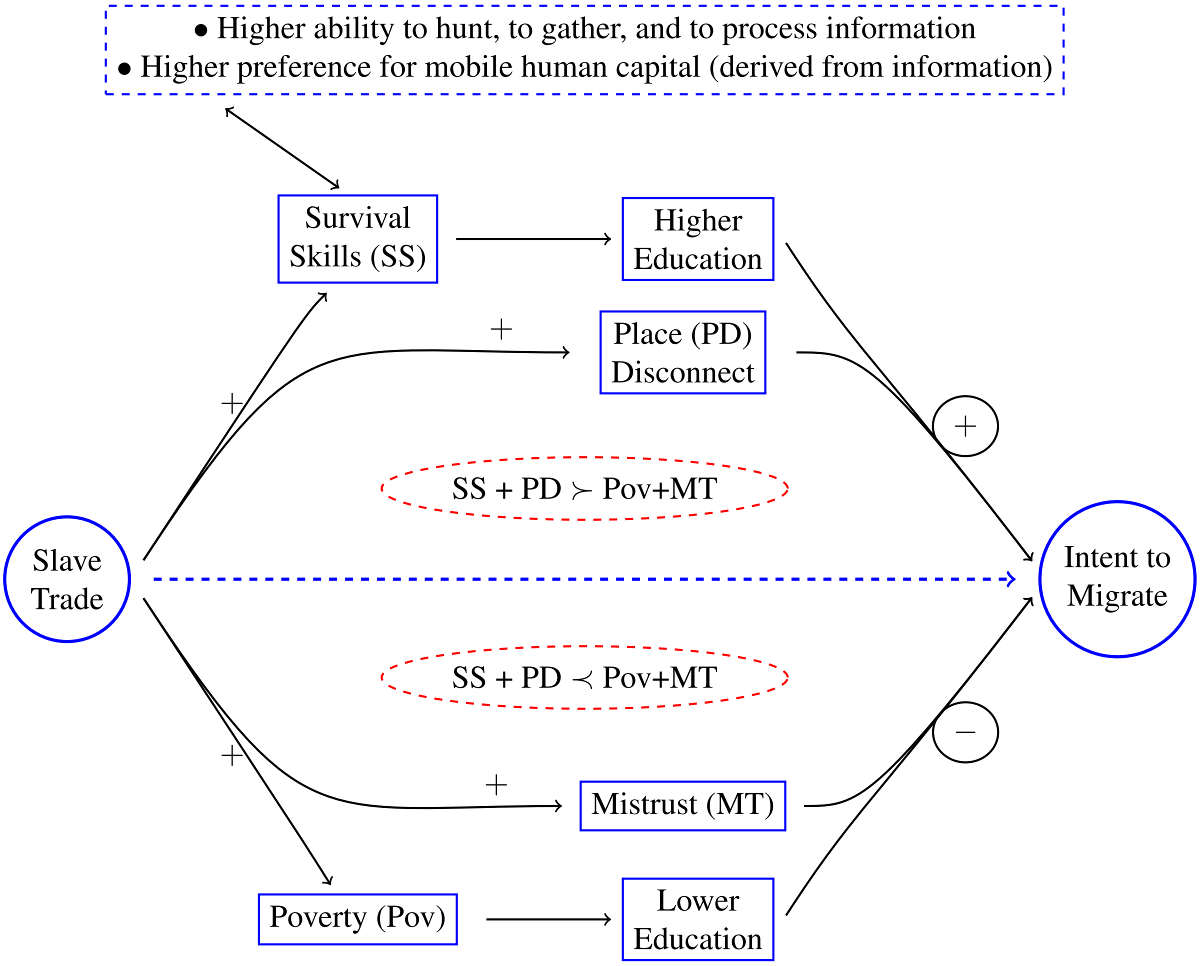
The main challenge in this work is how to extirpate the causal effect of the transatlantic and Indian Ocean slave trades on contemporary intention to migrate and the causal mechanism. The identification is not straightforward because slave trades are a distant past event, and thus trying to connect it to today's outcomes may suffer from spatial autocorrelation in residuals (Kelly, 2019) as well omitted variable bias (Altonji et al., 2005; Oster, 2019). However, the spatial autocorrelation in residuals problem suggested by Kelly (2019) is very unlikely to happen, and even if it does, its implementation in our case is impossible given that the size of the data used in this work is very big.

There is evidence on how long a cultural shock that establishes certain beliefs in people can last before fully dissipating. One such work on the speed of cultural change is Alesina and Fuchs-Schündeln (2007). They study the effects of the division of Germany between 1945 and 1990 on individuals' beliefs about the benefits of redistribution and government intervention. They find that, controlling for observable characteristics, East Germans view government intervention more favorably than West Germans and that the beliefs of East Germans eventually converge to those of West Germans after reunification. Moreover, they find that the differences arising from the shock will take at least 20 to 40 years to fully fall to zero though the division of Germany has lasted for 45 years only. Therefore when naively applied in our case here, this finding means that whatever migration cultural behavior induced by slave trades would take at least from 160 to 320 years before vanishing. The transatlantic and Indian Ocean slave trades have lasted for more than 400 years, and today we are just around 100 years from the shock. This result gives useful insight into why slave trades effects are still persistent in today's data on Africa.

Using individual and macro levels current data combined with historical ethnicity level data on slavery, I find that slave export has a positive and significant effect on today's intent to migrate. The causal mechanism behind this finding is in Figure 1: slave exports induced "survival kills (SS)", which I define as the set of abilities to hunt, to gather, and to process information and higher preference for mobile human capital into the descendants of ethnic groups that suffered the most from the trade. This ability translated into higher learning ability and, therefore, higher schooling. The brutality of the slave trades also induced more place disconnect. Together with the findings in Nunn (2008) and Nunn and Wantchekon (2011), people for whom learning ability plus place disconnect dominate mistrust plus poverty to be more willing to migrate. In contrast, individuals for whom mistrust and poverty dominate survival skills plus place disconnect are less inclined to migrate.

The main contribution of this work to the current literature is unearthing a new causal mechanism behind migration flows among Africans. Therefore this work contributes to the long trand of literature on migration (Kennan and Walker, 2011; Todaro, 1969; Harris and Todaro, 1970; Greenwood and Hunt, 1984; Carrington et al., 1996; Dahl, 2002; Bryan et al., 2014). The causal mechanism has its roots in the most tragic 400-year-long historical trauma that Africans experienced about 200 years ago. In other words, this work contributes to the literature on long-term persitence of historical events (Nunn, 2008; Nunn and Wantchekon, 2011; Whatley and Gillezeau, 2011; Deconinck and Verpoorten, 2013; Levine et al., 2017; Pierce and Snyder, 2018; Athias and Macina, 2020; Levine et al., 2020; Adermon et al., 2021).

Figure 1: Causal Mechanism



2 Data

2.1 Sources and Contents

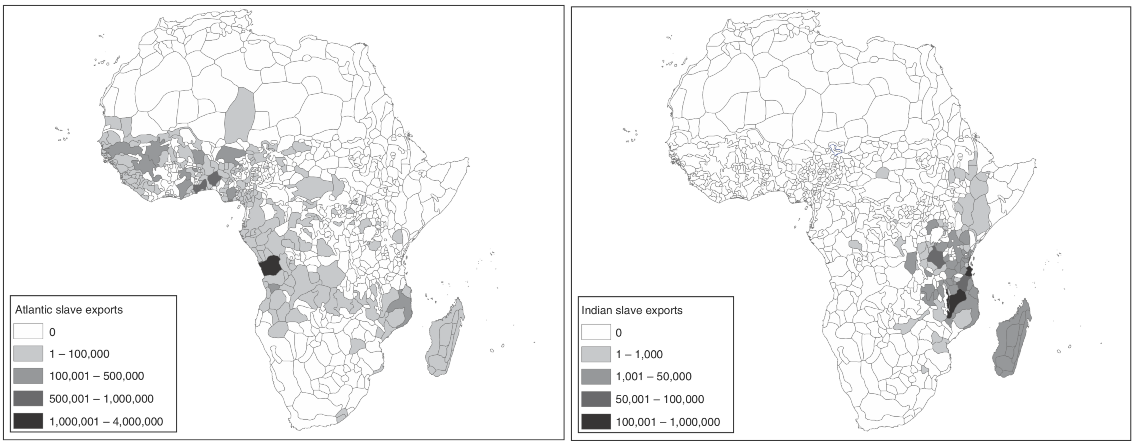
The datasets are from four main sources. The ethnicity-level variables on the Transatlantic and Indian Ocean slave trades mainly the amount of slaves shipped per kilometer squared are from the data used in Nunn and Wantchekon (2011) which it turn used the ethnic data from Nunn (2008). Other variables contained in this dataset is the historic distance of the ethnic centraoide to the coast, ethnic centroide latitude and lomgitude, a variable on if the ethnic group has had contact with the explore or not or if they have contact with railroad, distnace to the sharan slave trade centroid, etc.

The contemporary individual-level variables are from the nationally representative Afrobarometer Round7 released in 2019. This survey ask respondent if in the last 3 years, someone from their household has migrated outside the country for at least 3 months (, someone has migrated, SHM), to which extent they are willing to migrate to another country (intent to migrate, ITM), what would be their destination if they were to migrate (reach of the intended migration, ROM), how much they are planning to migrate (preparation of the intended migration, POM). The survey also contains demographic information on respomdents, gecoded position and a bunch of other questions.

The GDP per capita and population are from World Bank database which is the third source. The fourth source is the UN Internation Migrant Stock which gives information on number of migrants from a given origin to a given destionation.

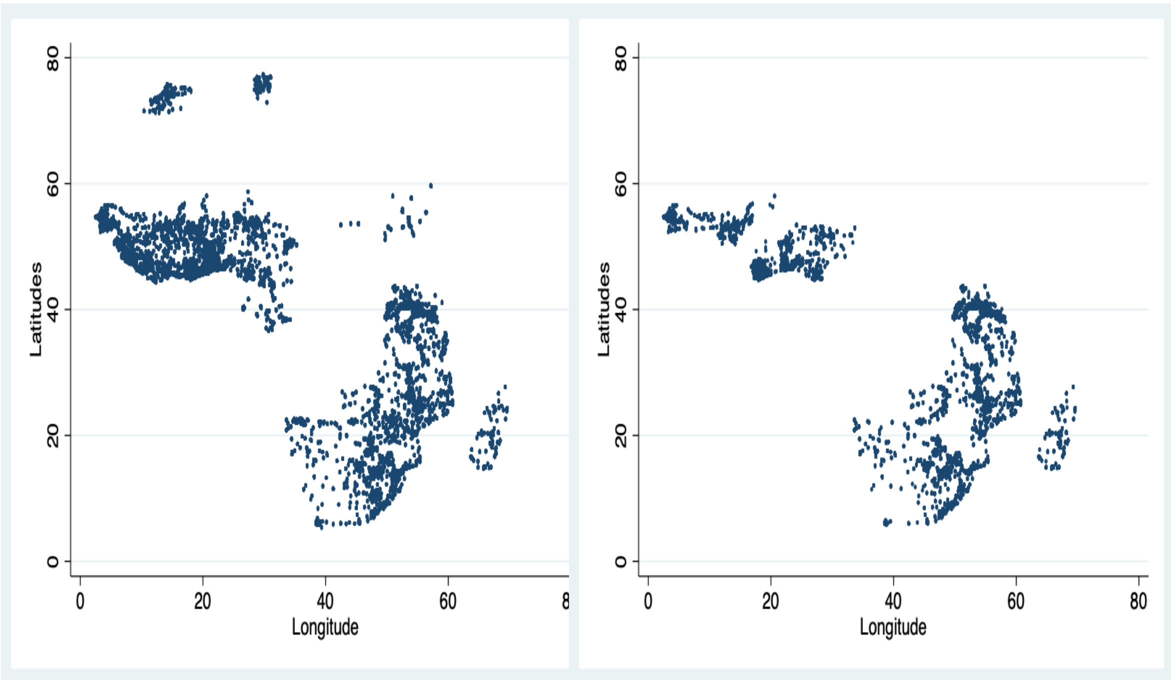
2.2 Coverage areas

The Transatlantic slave trade covers mostly the West (Figure 2a) whereas the Indian Ocean slave trade (Figure 2b) covers mostly the East part of Africa. However, it is common to see on the Figure 2 that some regions suffered from both trades.



(a) Transatlantic slave trade (b) Indian Ocean slave trade

Figure 2: Spacial Distribution of Slaves Taken per Km^2 (Nunn and Wantchekon, 2011)



(a) Afrobarometer Round 7 (b) Sample of this Paper

Figure 3: Spacital Distribution of Respondents

2.3 Descriptive Statistics

The current sample covers 15 countries, instead of 17 like in Nunn and Wantchekon (2011), because of ethnicity names inconsitency between the fourth and seven rounds of Afrobarometer survey. As next step, I am exploring new ethnicity mapping tools like in Müller-Crepon et al. (2021) to enlarge the sample size. The list of countries convered is as follows: Benin(971), Botswana(778), Ghana(1231), Kenya(1320), Madagascar(1057), Mali(898), Mozambique(1688), Malawi(1111), Namibia(346), Nigeria(1364), South-Africa(1189), Senegal(850), Tanzania(1270), Uganda(929), and Zambia(1121). The summary statistics is in Table 1 where variables are grouped by categories. SHM stands for "someone has migrated" and is a measure of the informed-migration as it asked whether or not someone has migrated from the household the last three years. It takes 1 if yes and 0 if no. ITM means "intention to migrate" and is a measure of how willing an individual is to migrate. It takes four modalities: 0 = Not at all, 1 = Little, 2 = Somewhat, and 3 = A lot. ROM means "reach of the intended migration" and is a measure of how far is an individual wishing to reach as destination for his/her potential migration. It takes three values: 0 = Not at all (don't want to migrate at all), 1 = Within Africa (want to migrate but within Africa) and 2 = Outside Africa (want to migrate but outside Africa). The variable LivedPoverty_CAT is the lived poverty index. It is a categorical variable constructed based on 5 items at individual level and takes fours modalities: 0 = Not lived poverty, 1 = Low lived poverty, 2 = Moderate lived poverty, and 3 = High lived poverty (Mattes et al., 2016). The rational behind using this variable is to capture the extent to which poverty can explain intent to migrate, ITM. The variable News_index is a measure of often an individual follows news from a given source. The sources used to build this index are radio, television, newspaper, internet and social media. This index intends to capture the extent to which being informed of oportunities around can drive someone to be willing to migrate. The variable share_district, share_region, and share_country captures both the ethnic fractionalization and ethnic group population share at district, region and country level. The point in including these variables is to capture how much ethnic fractionalisation can influence intent to migrate.

Table 1: Summary statistics

Variables	Obs.	mean	sd	min	p50	p75	p90	p95	max
				Dummy					
SHM	16,007	0.224	0.417	0	0	0	1	1	1
gender	16,119	0.499	0.500	0	0	1	1	1	1
urban	16,123	0.394	0.489	0	0	1	1	1	1
remittance	15,626	0.187	0.390	0	0	0	1	1	1
				Categorical					
ITM	15,915	0.661	1.095	0	0	1	3	3	3
POM	4,504	0.443	0.651	0	0	1	1	2	2
ROM	15,844	0.494	0.789	0	0	1	2	2	2
LivedPoverty_CAT	15,985	1.503	0.884	0	1	2	3	3	3
Education	16,055	3.406	2.102	0	3	5	6	7	9
				Continuous					
age	16,106	36.57	14.61	18	33	45	58	65	99
age2	16,106	1,551	1,300	324	1,089	2,025	3,364	4,225	9,801
export_area	16,123	2.951	7.513	0	0.120	1.741	6.306	13.98	37.71
ihs_export_area	16,123	0.824	1.197	0	0.119	1.321	2.541	3.332	4.323
Security_idx	14,606	0.0281	1.014	-0.676	-0.676	0.327	1.330	2.333	2.333
News_index	15,849	0.0725	1.651	-1.691	-0.515	1.151	2.763	3.411	4.102
share_district	16,123	0.690	0.329	0.00515	0.821	1	1	1	1
share_region	16,123	0.562	0.335	0.00195	0.591	0.896	0.975	0.987	1
share_country	16,123	0.254	0.249	0.000733	0.187	0.347	0.589	0.976	0.976
total_missions_area	16,123	0.000205	0.000325	0	9.93e-05	0.000247	0.000453	0.000891	0.00276

3 How Close is the ITM to the Real Migration ?

There is strong evidence suggesting that the intent to migrate is much more than just an intention but very close to the reality. First, Figure 4 depicts the average intent to migrate (ITM) among households that have somone who has migrated (Yes) versus the ones which don't (No).

Second, I run the following OLS regression of SHM on ITM:

$$ITM_{i,e,c} = \delta_c + \delta_r + \delta o + \beta_1 SHM_i + \gamma X_i' + \varepsilon_{iec} \quad (1)$$

$ITM_{i,e,c}$ is the intent to migrate of respondent i from ethnic group e in country c;

SHM_i is 1 if someone has migrated from the household of respondent i; δ_c, δ_r, and δ_o are country, religion, and occupation fixed effects respectively; $X =$ is a set of controls: age, age-squared, education, gender, urban, remittance, poverty, news, and recurity indexes, district-level ethinic fractionalization, and number of missionaries per area. Standard Errors are robust and clustered at country-ethnicity level. Table 2 reports the results from Equation 1. There is a strong positive and significant relationship between ITM and the informed-migration (SHM) at household level.

Second, in the afrobarometer, repondents who said they are willing to migrate were asked how much preparation they are doing for the migration. The exact words of the questions are: "Q68B: How much planning or preparation have you done in order to move to another country to live?". This question has the following modalities: " 0 = You are not currently making any specific plans or preparations", "1 = You are planning to move in the next year or two, but not yet making preparations", and "You are currently making preparations to move, like getting a visa". I then run the following OLS of ITN on POM :

$$POM_{i,e,c} = \delta_c + \delta_r + \delta o + \beta_1 ITM_i + \gamma X_i' + \varepsilon_{iec} \tag{2}$$

Table 3 shows how much the intensity of the intent to migate (ITM) explains how much preparation they are putting towards migartion. The controls are age, age squared, gender, urban/rural, lived poverty, news index, security index, and education.

Third, international migrants stock and ITM are positively correlated at country level as shown on Figure 5. Subfigures 5a and 5b contains the real values and subfigures 5c and 5d contain the ranks with and without Namibia, which is an outlier.

4 Slave Exports and the ITM

To examine the effect of slave trade on the intent to migrate, I plot the average slaves taken among each of the four categories of the intent to migrate variable. Figure 6 shows how these two variables are correlated. Low and high slave exports mean below and above median respectively. The amount of slave exported is positively correlated with the intent to migrate on each one of the subfigures 6a and 6b.

Second I turn to using a variety of methods and controls for econometrics regression of the amount of slave taken from every ethnic group per kilometer squared on intent to migrate (ITM). The main OLS specification is as follows:

$$ITM_{i,e,c} = \delta_c + \delta_r + \delta o + \beta_1 IHS\left(SlaveExport\right)_e + \gamma X_i' + \varepsilon_{iec} \tag{3}$$

ITM_i is the intent to migrate of respondent i from the ethnic group e in country c; δ_c, δ_r, and δ_o are country, religion, and occupation fixed effects respectively; $X =$ is a set of controls: age, age-squared, SHM, education, gender, urban, remittance, poverty, news, and recurity indexes, district-level ethinic fractionalization, and number of missionaries per area; $IHS\left(Exports\right)_e$ is the inverse hyperbolic sine of the number of slave per Km^2 taken from ethnic group e. Standard Errors are robust and clustered at country-ethnicity level. The OLS regression results in Table 4 are sigficant and resist all the various controls. Because ITM is a categorical variable, I report the ordered logit with fixed effects results in Table 5. They are also positively significant and stable.

4.1 The IV and its Validity

Third, I instrument the slave trade, with the historical distance from the centroid of the ethnic groups to the coast. In general, it is not a good idea to use distance as an instrument when dealing with migration. However, the very nature of the Transatlantic and

Indian Ocean slave trades makes this particular distance qualify as a perfect instrument, especially when considering migratory behaviors towards overseas. The validity of this instrument, as stated in Nunn and Wantchekon (2011), is that Africans had no overseas knowledge before these two waves of the slave trade. This argument means that there were no migratory behaviors towards overseas induced before the start of slavery. But even if we assume otherwise, whatever overseas migration behaviors, if any, were instilled before the beginning of the Transatlantic and Indian Ocean slave trades should have been reversed after the slave trades. There is a valid justification for why this should be the case. During the exports, which lasted for more than 400 years, running away from the coast to inland was a powerful means to avoid being captured, let alone engaging in overseas activities. You would be an easy catch for enslavement because black people were in high demand overseas wherever they were found. The argument becomes clearer when evidence shows that one event can undo cultural behaviors induced by past events. For example, Nunn (2010) showed that contact with European missionaries altered Africans religious beliefs so much so that they have no problem identifying themselves as Christians today, almost completely forgetting their original religions. The proximity to the sea meant a greater risk of being sold into slavery. Therefore, historical distance to sea should affect intent to migrate only through slave exports. The exclusion restriction also holds because other than the slave exports, the historical distance to the coast is exogenous to anything we can think of in the error terms of our specifications.

The IV specification is as follows:

$$\begin{aligned} \text{First stage: } & IHS\left(Exports\right)_e = \delta_c + \delta_r + \delta o + \beta_1 DistanceToCoast_e + \gamma X_i' + \lambda_{ec} \\ \text{Second stage: } & ITM_{i,e,c} = \delta_c + \delta_r + \delta o + \beta_1 IHS\left(Exports\right)_e + \gamma X_i' + \varepsilon_{iec} \end{aligned} \tag{4}$$

Table 6 reports the results of the IV using the biggest pool of respondents willing to migrate to other parts of Africa, to outside of Africa, and those who want to migrate outside of Africa. The results are significant but weak, probably because the instrument does not fit those who want to migrate to Africa. The fact that these results are weak means sense because Africans may have developed within-Africa migratory attitude before slave exports. In other words, the instrument is best at capturing intent to migrate through "only slave trade" only among respondents who express willingness to migrate outside of Africa. Therefore, I restrict the sample to people who don't want to migrate or want to migrate outside of Africa. I report the results in Table 7. The coefficient in the last column is positively significant and much stronger than the one in Table 6.

5 Education and Slave Trade

In this section, I use OLS, Ordered-logit, and IV-2sls with a wide set of controls to explore the impacts of the slave trade on education. The main estimation equation is as follows:

$$YS_{iec} = \delta_c + \delta_r + \delta o + \beta_1 IHS\left(SlaveExports\right)_e + \gamma X_i' + \varepsilon_{iec} \tag{5}$$

YS_{iec} is the years of schooling of respondent i from the ethnic group e in country c; δ_c, δ_r, and δ_o are country, religion, and occupation fixed effects respectively; $X =$ is a set of controls: age, age-squared, SHM, whether there is a school in the survey geographic location of the respondent, gender, urban, remittance, poverty, news, and recurity indexes, and district-level ethinic fractionalization; $IHS\left(SlaveExports\right)_e$ is the inverse hyperbolic sine of the number of slave per Km^2 taken from ethnic group e. Standard Errors are robust and clustered at country-ethnicity level. The fourth column to the right in Tables 8 through 11 are my main results (This applies to all the Tables throughout this paper). These results, especially Table 10, suggest that slave trades have a positive and significant impact on education.

There are two causal mechanisms to these results. First, there is evidence that people from a community that experiences persecution and expropriation adopt the behavior of investing in mobile capitals, which can be proxied by education and not related to any particular geographical location, rather than physical capitals. One such work is Becker et al. (2020) in which the authors show that the descendants of Polish who were forced into migration after World War II have one extra year of schooling than the descendants of those Polish who stayed at home. In the context of this work, the slave trades is the biggest human persecution and expropriation event ever in human history. Blacks were mere assets, let alone their properties as lands, houses, etc. Living in the slave trades is constantly subject to fear of being the next to be captured. If they catch you, you become an asset and then lose all your physical properties. In case you manage to escape, you still lose all your physical properties. Therefore, it means sense to develop more preference for investing in mobile capitals that you can run away with in case of danger, which leads to a more place disconnect attitude. This ability to have less attachment to place is explored in depth using the reach of the intent to migrate (ROM) later in this work.

Second, the ability to anticipate, gather, and process information was a critical habit during the slave trades because people's lives depended on it. At that time, gathering information on the tactics of your neighbors who may turn on you at any time, knowing when the slave buyers or catchers will be in the village, learning the languages of your enemies, etc., are all very critical to surviving. Therefore, this ability to value information gathering and processing transmits across generations, especially those whose ethnic groups have suffered the most from the slave exports. I refer to the set of these abilities as "Survival Skills" and define it on Figure 1

Another takeaway is that the relation between slave exports and education is positive at micro-level (Fourth column to the right in Tables 10 and 12) but negative at macro level (Subfigures 7a and 7a). This finding is a shred of evidence that people who get the highest education are the ones migrating. On the other hand, the relationship between poverty (GDP per capita) and intent to migrate is unclear. See Figure 9. Without the group of outliers (Nigeria, South Africa, Namibia, Botswana), it seems there is evidence that the higher the GDP, the higher the intent to migrate (Subfigures 9b and 9d).

6 Evidence of Place Disconnect (ROM)

This section aims to explore place disconnect behavior induced by slavery into the descendants of ethnic groups heavily impacted by these two slave trades. Figure 8 showcases this impact graphically. I run the following regression

$$ROM_{i,e,c} = \delta_c + \delta_r + \delta o + \beta_1 IHS\left(SlaveExports\right)_e + \gamma X_i' + \varepsilon_{iec} \tag{6}$$

ROM_i is the reach of the intent to migrate of respondent i from the ethnic group e in country c; δ_c, δ_r, and δ_o are country, religion, and occupation fixed effects respectively; $X =$ is a set of controls: age, age-squared, SHM, education, gender (1 = male, 0 = female), urban, remittance, poverty, news, and recurity indexes, district-level ethinic fractionalization, and number of missionaries per area; $IHS\left(SlaveExports\right)_e$ is the inverse hyperbolic sine of the number of slave per Km^2 taken from ethnic group e. Standard Errors are robust and clustered at country-ethnicity level. Tables 13 and 15 report the OLS and IV-2sls results respectively. The results are significantly positive and resist all the controls and fixed effects. The IV identification is the same as in Equation 4.

We learn from Nunn (2008) that slave exports have positive impacts on poverty, and Nunn and Wantchekon (2011) demonstrates that mistrust is one of the channels through which the trades have created poverty among descendants of ethnic groups which suffered the most from the exports. In addition, we learn from previous sections of this work that the people more willing to migrate are those who get more education and that slave trades also positively impact education. These findings put together imply that one additional slave exported from a given ethnicity increases the degree of place disconnect.

The causal channel of this result cannot be only through poverty, and here is the why. First of all, it takes a non-negligible level of trust to migrate. Whether legal or illegal, migrating means going into the unknown and therefore involves trusting people and institutions at the destination. One can even ask why you would be willing to relocate if you cannot trust people. Meaning that the willingness to migrate cannot be fully attributed to only mistrust. Second, those willing more to migrate are the ones who have the highest education. Third, there is abundant evidence that poverty negatively impacts years of schooling (Lee and Barro, 2001; Hanushek and Kimko, 2000; Self and Grabowski, 2004; Thapa, 2013) and that evidence shows up in this work as well in Table 19. Thus, people with more willingness to migrate cannot be the poorest because migration is through education, and the poorest people don't have the highest education. Put together, these findings imply that an increase in the reach of the intent to migrate induced by slave trade is likely to be through the channel of place disconnect and not through poverty or mistrust.

7 Further Robustness Checks

7.1 More controls and Various estimation methods

The first step in my coefficient stability analysis endeavor is to control everything I can put my hands on, which I did in all the regressions. The second is to use different methods like Ordered-logit and historical distance of the ethnic centroid to the coast instrumental variable. All the estimates resist these techniques.

7.2 Selection into the observables variables

In this section, I give an alternative argument for why the above estimates are unlikely to suffer from omitted variable bias. To do that, use the approach developed by Altonji et al. (2005) (referred to as AET) and later improved by Oster (2019). According to these two papers, we can compute the coefficient $Delta$, which stands for how bigger the selection on unobservables will have to be to completely explain away the effect of slave trades on intent to migrate, reach of the intent-to-migrate, and education. If the absolute value of *Delta* is greater than 1, it is very likely that our estimate is causal and not driven by omitted variable bias. Also, comparing the *Delta*s gives an idea of their relative power to explain our variables of interest. The *Delta* of slave export equals 1.84352, 5.39437, and 1.84352 on intent to migrate, education, and the reach of intent-to-migrate, respectively. These delta values suggest that the estimated coefficient of slave exports on intent to migrate, education, and reach of intent-to-migrate are robust and very unlikely to suffer from omitted variable bias. A similar technic is in many papers, including Nunn and Wantchekon (2011)

Another way to justify the robustness of these estimates is in Tables 18 and 20. The coefficients move away from zero when including more controls. This evidence suggests that these estimates are robust and unlikely to suffer from omitted variable bias still based on the insights from AET and Oster (2019). Similar argument has been used in other works like Bellows and Miguel (2009) and Voors et al. (2012).

Note: Tables 18, 19 and 20 in appendix contain the full controls and their coefficients.

8 Discussion

People living in the same family in Africa are likely from the same ethnic group. The two possible sources of ethnicity diversity comes from “the wives” and in-law family related members or strangers. However, there is evidence that women do not migrate as much as men do. Therefore, the “someone who has migrated” may be from the same ethnic group as the respondent of the survey of Afrobormeter. Consequently, we should expect the slave trades to affect the informed migration the same way it affects ITM. This argument means that SHM may be endogenous. However, including SHM in the regressions does not hinder the estimates at all. Even better, the coefficients improve, including the effect of slave export on ITM (Fifth column of all the regression Tables).

The results of SHM as an outcome variable are in Tables 16 and 17. These two tables report the OLS and IV-2sls results of slave export on SHM. The first two columns are positive and significant. But these results broke apart when controlling for country fixed effects, probability because I could not properly include observables like the age, the gender, the education, and the occupation of the "someone who has migrated" as I don't have them.

9 Conclusions

The Transatlantic and Indian Ocean slave trades, which lasted for more than 400 years and were abolished around 200 years ago, have a positive and statistically significant impact on the intent to migrate today among Africans. I investigate the relationship using various controls and methods and conclude that it is causal. Poverty and mistrust on one hand and survival skills and place disconnect on the other together constitute the selection machine into the intended migration.

First, the slave exports enrooted mistrust into the descendants of ethnic groups heavily raided during the trades (Nunn and Wantchekon, 2011) which is one of the causes of low economic performance among Africans today (Nunn, 2008). At the same time, to stay one step ahead of their enemies, including slave catchers who may well be their neighbors, and to avoid or win the atrocities and wars related to enslavement, people developed a higher ability to hunt, gather, and process information. I denote the set of these abilities as "survival skills". These information loving capabilities lead their descendants to have more schooling today.

Moreover, the systematic expropriations that characterized the enslavement instilled into people a higher preference for mobile human capital (Becker et al., 2020) which leads to a higher place disconnect attitude. These findings, taken together, lead people for whom place disconnect and survival skills dominate mistrust and poverty to be more willing to migrate. In contrast, those for whom mistrust plus poverty dominate place-disconnect and survival skills, on the other hand, have less appetite for migration. This argument is clearer when we know that it takes a non-negligible amount of trust to migrate, whether legally or illegally. This vicious filter sends away the more capable Africans and leaves behind the less productive ones, producing more poverty, and the circle continues. Of course, poverty and mistrust each taken alone may be a motive for migration but way less than when considering them all together with place disconnect and survival skills.

These findings unearthed the cyclical machine behind how, in Nunn and Wantchekon (2011), mistrust contributes as a causal channel to the poor economic performance among Africans, pointed out earlier by Nunn (2008). I also investigate the intent to migrate using the informed migration within respondents' households, information on preparations towards the intended migration, and the UN international migrants stock and conclude that the intent to migrate outside of Africa is much close to the real overseas migration flow.

10 References

References

Nathan Nunn. The Long-term Effects of Africa's Slave Trades*. *The Quarterly Journal of Economics*, 123(1):139–176, 02 2008. ISSN 0033-5533. doi: 10.1162/qjec.2008.123.1.139. URL https://doi.org/10.1162/qjec.2008.123.1.139.

John Kennan and James R Walker. The effect of expected income on individual migration decisions. *Econometrica*, 79(1):211–251, 2011.

John Kennan and James R Walker. Wages, welfare benefits and migration. *Journal of Econometrics*, 156(1):229–238, 2010.

Diep Phan and Ian Coxhead. Rural–urban migration and remittances in vietnam: Evidence from migrant tracer data. In *Rural-Urban Migration in Vietnam*, pages 167–188. Springer, 2019.

Jillmarie Murphy. Chains of emancipation: Place attachment and the great northern migration in paul laurence dunbar's" the sport of the gods". *Studies in American Naturalism*, 8(2):150–170, 2013.

Kevin E McHugh and Robert C Mings. The circle of migration: Attachment to place in aging. *Annals of the Association of American Geographers*, 86(3):530–550, 1996.

Glen H Elder, Valarie King, and Rand D Conger. Attachment to place and migration prospects: A developmental perspective. *Journal of Research on Adolescence*, 6(4):397–425, 1996.

Valiollah Rostamalizadeh and Ali Ghasemi-Ardahaee. Social factors affecting the migration of rural youth with an emphasis on place attachment. *Journal of Population Association of Iran*, 12(24):43–67, 2018.

Gizem Koşar, Tyler Ransom, and Wilbert Van der Klaauw. Understanding migration aversion using elicited counterfactual choice probabilities. *Journal of Econometrics*, 2021.

Nathan Nunn. Religious conversion in colonial africa. *American Economic Review*, 100 (2):147–52, May 2010. doi: 10.1257/aer.100.2.147. URL https://www.aeaweb.org/articles?id=10.1257/aer.100.2.147.

Nathan Nunn and Leonard Wantchekon. The slave trade and the origins of mistrust in africa. *American Economic Review*, 101(7):3221–52, December 2011. doi: 10.1257/aer.101.7.3221. URL https://www.aeaweb.org/articles?id=10.1257/aer.101.7.3221.

Morgan Kelly. The standard errors of persistence. 2019.

Joseph G Altonji, Todd E Elder, and Christopher R Taber. Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of political economy*, 113(1):151–184, 2005.

Emily Oster. Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204, 2019.

Alberto Alesina and Nicola Fuchs-Schündeln. Good-bye lenin (or not?): The effect of communism on people's preferences. *American Economic Review*, 97(4):1507–1528, 2007.

Michael P Todaro. A model of labor migration and urban unemployment in less developed countries. *The American economic review*, 59(1):138–148, 1969.

John R Harris and Michael P Todaro. Migration, unemployment and development: a two-sector analysis. *The American economic review*, pages 126–142, 1970.

Michael J Greenwood and Gary L Hunt. Migration and interregional employment redistribution in the united states. *The American Economic Review*, 74(5):957–969, 1984.

William J Carrington, Enrica Detragiache, and Tara Vishwanath. Migration with endogenous moving costs. *The American Economic Review*, pages 909–930, 1996.

Gordon B Dahl. Mobility and the return to education: Testing a roy model with multiple markets. *Econometrica*, 70(6):2367–2420, 2002.

Gharad Bryan, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak. Underinvestment in a profitable technology: The case of seasonal migration in bangladesh. *Econometrica*, 82(5):1671–1748, 2014.

Warren Whatley and Rob Gillezeau. The impact of the transatlantic slave trade on ethnic stratification in africa. *American Economic Review*, 101(3):571–76, 2011.

Koen Deconinck and Marijke Verpoorten. Narrow and scientific replication of the slave trade and the origins of mistrust in africa. *Journal of Applied Econometrics*, 28(1): 166–169, 2013.

Ross Levine, Chen Lin, and Wensi Xie. The origins of financial development: How the african slave trade continues to influence modern finance. Technical report, National Bureau of Economic Research, 2017.

Lamar Pierce and Jason A Snyder. The historical slave trade and firm access to finance in africa. *The Review of Financial Studies*, 31(1):142–174, 2018.

Laure Athias and Moudo Macina. The legacy of the slave trade: Mistrust in medicine and demand for vaccination in sub-saharan africa. 2020.

Ross Levine, Chen Lin, and Wensi Xie. The african slave trade and modern household finance. *The Economic Journal*, 130(630):1817–1841, 2020.

Adrian Adermon, Mikael Lindahl, and Mårten Palme. Dynastic human capital, inequality, and intergenerational mobility. *American Economic Review*, 111(5):1523–48, May 2021. doi: 10.1257/aer.20190553. URL https://www.aeaweb.org/articles?id=10.1257/aer.20190553.

Carl Müller-Crepon, Yannick Pengl, and Nils-Christian Bormann. Linking ethnic data from africa (leda). *Journal of Peace Research*, page 00223433211016528, 2021.

Robert Mattes, Boniface Dulani, and Emmanuel Gyimah-Boadi. Africa's growth dividend? lived poverty drops across much of the continent. 2016.

Sascha O. Becker, Irena Grosfeld, Pauline Grosjean, Nico Voigtlander, and Ekaterina Zhuravskaya. Forced migration and human capital: Evidence from post-wwii population transfers. *American Economic Review*, 110(5):1430–63, May 2020. doi: 10.1257/aer.20181518. URL https://www.aeaweb.org/articles?id=10.1257/aer.20181518.

Jong-Wha Lee and Robert J Barro. Schooling quality in a cross–section of countries. *Economica*, 68(272):465–488, 2001.

Eric A Hanushek and Dennis D Kimko. Schooling, labor-force quality, and the growth of nations. *American economic review*, 90(5):1184–1208, 2000.

Sharmistha Self and Richard Grabowski. Does education at all levels cause growth? india, a case study. *Economics of Education Review*, 23(1):47–55, 2004.

Surya Bahadur Thapa. Relationship between education and poverty in nepal. *Economic Journal of Development Issues*, pages 148–161, 2013.

John Bellows and Edward Miguel. War and local collective action in sierra leone. *Journal of Public Economics*, 93(11):1144–1157, 2009. ISSN 0047-2727. doi: https://doi.org/10.1016/j.jpubeco.2009.07.012. URL https://www.sciencedirect.com/science/article/pii/S0047272709000942.

Maarten J Voors, Eleonora EM Nillesen, Philip Verwimp, Erwin H Bulte, Robert Lensink, and Daan P Van Soest. Violent conflict and behavior: a field experiment in burundi. *American Economic Review*, 102(2):941–64, 2012.

11 Appendix

11.1 Tables

Table 2: Informed-migartion (SHM) and intent to migrate (ITM)

	ITM			
SHM	0.584***	0.501***	0.435***	0.435***
	(0.0203)	(0.0222)	(0.0230)	(0.0456)
Controls	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
Religion FE	No	No	Yes	Yes
Occupation FE	No	No	Yes	Yes
Clustering	No	No	No	Yes
Observations	15873	13605	12476	12476
R-squared	0.0493	0.105	0.167	0.167
Mean Dep. Var.	0.661	0.667	0.661	0.661

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Intent to migrate (ITM) and Preparation (POM)

	POM			
ITM	0.122***	0.117***	0.105***	0.105***
	(0.0112)	(0.0117)	(0.0125)	(0.0129)
Controls	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
Religion FE	No	No	Yes	Yes
Occupation FE	No	No	Yes	Yes
Clustering	No	No	No	Yes
Observations	4441	3924	3556	3556
R-squared	0.0261	0.0683	0.141	0.141
Mean Dep. Var.	0.447	0.440	0.442	0.442

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Intent to migrate (ITM) (OLS)

	ITM				
IHS(Slave Export)	0.133***	0.0618***	0.0660***	0.0660***	0.0678***
	(0.00680)	(0.00877)	(0.0131)	(0.0167)	(0.0159)
Education		0.0365***	0.0378***	0.0378***	0.0337***
		(0.00513)	(0.00601)	(0.00792)	(0.00811)
SHM					0.312***
					(0.0375)
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	14015	12006	11038	11038	11004
R-squared	0.0267	0.126	0.166	0.166	0.181
Mean Dep. Var.	0.465	0.471	0.467	0.467	0.467

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Intent to migrate (ITM) and Slave Exports (Ordered Logit)

	ITM				
ITM					
IHS(Slave Export)	0.307***	0.134***	0.212***	0.212***	0.216***
	(0.0155)	(0.0226)	(0.0375)	(0.0505)	(0.0501)
Education		0.121***	0.135***	0.135***	0.124***
		(0.0140)	(0.0173)	(0.0279)	(0.0285)
SHM					0.714***
					(0.0959)
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	14015	12006	11039	11039	11005
Mean Dep. Var.	0.465	0.471	0.467	0.467	0.467

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Intent to migrate (ITM) and Slave Exports (IV-2sls)

	ITM				
IHS(Slave Export)	0.0953***	0.0631***	0.0475	0.0475	0.0618
	(0.0164)	(0.0167)	(0.0383)	(0.0468)	(0.0433)
Education		0.0292***	0.0378***	0.0378***	0.0334***
		(0.00558)	(0.00649)	(0.00780)	(0.00817)
SHM					0.434***
					(0.0454)
Instrument	Distance	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	15915	13639	12511	12511	12477
Mean Dep. Var.	0.661	0.667	0.662	0.662	0.661

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Intent to migrate (ITM) and Slave Exports (IV-2sls – To Outside of Africa)

	ITM				
IHS(Slave Export)	0.186***	0.134***	0.110**	0.110**	0.116**
	(0.0158)	(0.0161)	(0.0374)	(0.0388)	(0.0380)
Education		0.0365***	0.0368***	0.0368***	0.0325***
		(0.00513)	(0.00605)	(0.00636)	(0.00638)
SHM					0.312***
					(0.0293)
Instrument	Distance	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	14015	12006	11039	11039	11005
R-squared	0.0225	0.121	0.165	0.165	0.180
Mean Dep. Var.	0.465	0.471	0.467	0.467	0.467

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Years of Education (OLS)

	Year Educ.				
IHS(Slave Export)	0.0491**	0.0616***	0.129***	0.120**	0.123**
	(0.0150)	(0.0157)	(0.0206)	(0.0410)	(0.0413)
SHM					0.163***
					(0.0420)
Instrument	Distance	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	14135	12081	11105	11105	11051
R-squared	0.000754	0.407	0.554	0.554	0.556
Mean Dep. Var.	3.410	3.418	3.408	3.408	3.408

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Years of Education (Ordered Logit)

	Year Educ.				
IHS(Slave Export)	0.00348	-0.0424**	0.165***	0.154**	0.157**
	(0.0119)	(0.0136)	(0.0251)	(0.0502)	(0.0512)
SHM					0.168**
					(0.0516)
Instrument	Distance	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	16055	13718	12577	12577	12520
Mean Dep. Var.	3.406	3.409	3.398	3.398	3.399

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Years of Education (IV-2sls)

	Year Educ.				
IHS(Slave Export)	0.322***	0.0382	0.213***	0.213*	0.218*
	(0.0324)	(0.0308)	(0.0541)	(0.0983)	(0.0993)
SHM					0.105*
					(0.0418)
Instrument	Distance	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	16055	13718	12577	12577	12520
R-squared	.	0.379	0.545	0.545	0.546
Mean Dep. Var.	3.406	3.409	3.398	3.398	3.399

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Years of Education (IV-2sls – To Outside of Africa)

	Year Educ.				
IHS(Slave Export)	0.386***	-0.0276	0.282***	0.282**	0.293**
	(0.0358)	(0.0421)	(0.0690)	(0.0916)	(0.0921)
SHM					0.153***
					(0.0382)
Instrument	Distance	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	14135	11050	10151	10151	10114
R-squared	.	0.408	0.558	0.558	0.559
Mean Dep. Var.	3.410	3.430	3.426	3.426	3.426

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Years of Education – IV-2sls – Nunn and Wantchekon (2011)

	Year Educ.			
IHS(Slave Export)	-0.00643	-0.0395	0.226***	0.226**
	(0.0274)	(0.0256)	(0.0378)	(0.0861)
Instrument	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
Religion FE	No	No	Yes	Yes
Occupation FE	No	No	Yes	Yes
Clustering	No	No	No	Yes
Observations	21624	21102	20939	20939
R-squared	0.000420	0.194	0.479	0.479
Mean Dep. Var.	3.077	3.106	3.105	3.105

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Reach of Intent to migrate (ROM) (OLS)

	ROM				
IHS(Slave Export)	0.0970***	0.0949***	0.0629***	0.0629***	0.0644***
	(0.00517)	(0.00554)	(0.00981)	(0.0128)	(0.0126)
Education		0.0360***	0.0398***	0.0398***	0.0370***
		(0.00389)	(0.00460)	(0.00642)	(0.00669)
SHM					0.262***
					(0.0272)
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	15844	13570	12448	12448	12409
R-squared	0.0217	0.119	0.165	0.165	0.182
Mean Dep. Var.	0.494	0.497	0.494	0.494	0.493

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: ROM and Slave Exports (Ordered Logit)

	ROM				
IHS(Slave Export)	0.226***	0.246***	0.171***	0.171***	0.180***
	(0.0134)	(0.0156)	(0.0297)	(0.0361)	(0.0367)
Education		0.107***	0.122***	0.122***	0.117***
		(0.0117)	(0.0145)	(0.0194)	(0.0212)
SHM					0.761***
					(0.0788)
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	15844	13570	12449	12449	12410
Mean Dep. Var.	0.494	0.497	0.494	0.494	0.493

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Reach of Intent to migrate (ROM) (IV-2sls)

	ROM				
IHS(Slave Export)	0.120***	0.0813***	0.115***	0.115***	0.113***
	(0.0118)	(0.0137)	(0.0293)	(0.0333)	(0.0327)
Education		0.0358***	0.0385***	0.0385***	0.0358***
		(0.00390)	(0.00464)	(0.00627)	(0.00653)
SHM					0.263***
					(0.0269)
instrument	Distance	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Religion FE	No	No	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	15844	13570	12449	12449	12410
R-squared	0.0205	0.118	0.163	0.163	0.181
Mean Dep. Var.	0.494	0.497	0.494	0.494	0.493

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Informed-migartion (SHM) and Slave Trades

	SHM			
IHS(Slave Export)	0.0285***	0.0281***	-0.00549	-0.00549
	(0.00274)	(0.00299)	(0.00499)	(0.0133)
urban/rural		0.0254**	0.0187*	0.0187
		(0.00802)	(0.00812)	(0.0109)
security index		0.0143***	0.0140***	0.0140***
		(0.00347)	(0.00353)	(0.00408)
news index		0.0356***	0.0369***	0.0369***
		(0.00237)	(0.00247)	(0.00324)
lived poverty		-0.00549	-0.00105	-0.00105
		(0.00418)	(0.00430)	(0.00542)
share_district		0.00128	-0.0110	-0.0110
		(0.0113)	(0.0119)	(0.0321)
total_missions_area		-50.64***	6.873	6.873
		(10.35)	(12.13)	(17.24)
Controls	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
Religion FE	No	No	Yes	Yes
Clustering	No	No	No	Yes
Observations	16007	14192	14192	14192
R-squared	0.00668	0.0347	0.0641	0.0641
Mean Dep. Var.	0.224	0.222	0.222	0.222

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Informed-migartion (SHM) and Slave Trades (IV-2sls)

	SHM			
ihs_export_area	0.0506***	0.0415***	0.0231	0.0231
	(0.00632)	(0.00737)	(0.0157)	(0.0284)
urban/rural		0.0183*	0.0182*	0.0182
		(0.00879)	(0.00840)	(0.0104)
security index		0.0145***	0.0137***	0.0137***
		(0.00347)	(0.00360)	(0.00387)
news index		0.0357***	0.0363***	0.0363***
		(0.00237)	(0.00254)	(0.00325)
lived poverty		-0.00507	-0.00196	-0.00196
		(0.00419)	(0.00439)	(0.00544)
share_district		-0.0130	-0.0235	-0.0235
		(0.0134)	(0.0129)	(0.0278)
total_missions_area		-50.08***	3.082	3.082
		(10.35)	(13.21)	(18.13)
Instrument	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes
Country FE	No	No	Yes	Yes
Religion FE	No	No	Yes	Yes
Clustering	No	No	No	Yes
Observations	16007	14192	13679	13679
R-squared	0.00263	0.0334	0.0710	0.0710
Mean Dep. Var.	0.224	0.222	0.222	0.222

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Intent to migrate (ITM) (OLS)

	ITM				
IHS(Slave Export)	0.0682***	0.0701***	0.0711***	0.0711***	0.0734***
	(0.0133)	(0.0131)	(0.0138)	(0.0194)	(0.0164)
Age		-0.0109***	-0.0144***	-0.0144***	-0.0146***
		(0.00315)	(0.00331)	(0.00422)	(0.00426)
Age^2		-0.00000142	0.0000418	0.0000418	0.0000448
		(0.0000349)	(0.0000368)	(0.0000383)	(0.0000379)
Male		0.176***	0.161***	0.161***	0.148***
		(0.0189)	(0.0201)	(0.0261)	(0.0259)
Urban		0.0947***	0.0454*	0.0454	0.0427
		(0.0205)	(0.0229)	(0.0238)	(0.0223)
Remittance		0.202***	0.153***	0.153***	0.0744*
		(0.0227)	(0.0244)	(0.0300)	(0.0304)
Education		0.0502***	0.0369***	0.0369***	0.0329***
		(0.00564)	(0.00645)	(0.00786)	(0.00830)
Poverty			0.0628***	0.0628***	0.0609***
			(0.0118)	(0.0143)	(0.0137)
Security			0.0481***	0.0481***	0.0450***
			(0.00966)	(0.0119)	(0.0119)
News			0.0613***	0.0613***	0.0520***
			(0.00805)	(0.00974)	(0.0103)
Ethnic Frac.			-0.0836*	-0.0836*	-0.0826*
			(0.0326)	(0.0366)	(0.0383)
Missionnaries			-32.79	-32.79	-42.36
			(33.84)	(38.33)	(38.38)
SHM					0.436***
					(0.0456)
Controls	No	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Religion FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	14544	14078	12510	12510	12476
R-squared	0.0893	0.132	0.145	0.145	0.169
Mean Dep. Var.	0.656	0.656	0.662	0.662	0.661

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Years of Education (OLS)

	Year Educ.				
IHS(Slave Export)	0.115***	0.125***	0.134***	0.113**	0.115**
	(0.0203)	(0.0194)	(0.0194)	(0.0386)	(0.0392)
Age		-0.00166	0.00115	0.00356	0.00359
		(0.00462)	(0.00470)	(0.00546)	(0.00541)
Age^2		-0.000259***	-0.000282***	-0.000236***	-0.000235***
		(0.0000512)	(0.0000521)	(0.0000642)	(0.0000637)
Male		0.425***	0.428***	0.231***	0.227***
		(0.0275)	(0.0279)	(0.0358)	(0.0356)
Urban		0.692***	0.665***	0.276***	0.275***
		(0.0295)	(0.0301)	(0.0444)	(0.0447)
Remittance			0.149***	-0.0242	-0.0408
			(0.0338)	(0.0316)	(0.0341)
Poverty			-0.201***	-0.117***	-0.118***
			(0.0159)	(0.0192)	(0.0192)
Security				0.0254	0.0256
				(0.0135)	(0.0137)
News				0.428***	0.426***
				(0.0147)	(0.0150)
Ethnic Frac.				-0.196**	-0.196**
				(0.0613)	(0.0618)
Missionnaries				172.4*	172.0*
				(74.15)	(74.32)
SHM					0.103*
					(0.0423)
Instrument	Distance	Distance	Distance	Distance	Distance
Controls	No	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Religion FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	14673	14655	14113	12622	12564
R-squared	0.416	0.469	0.480	0.546	0.547
Mean Dep. Var.	3.390	3.391	3.388	3.397	3.397

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Reach of Intent to migrate (ROM) (OLS)

	ROM				
IHS(Slave Export)	0.0609***	0.0594***	0.0629***	0.0629***	0.0644***
	(0.00954)	(0.00933)	(0.00981)	(0.0128)	(0.0126)
Age		-0.00589**	-0.00740**	-0.00740**	-0.00759**
		(0.00225)	(0.00237)	(0.00276)	(0.00283)
Age^2		-0.0000186	0.00000264	0.00000264	0.00000552
		(0.0000250)	(0.0000262)	(0.0000238)	(0.0000236)
Male		0.102***	0.0870***	0.0870***	0.0788***
		(0.0135)	(0.0144)	(0.0165)	(0.0165)
Urban		0.0904***	0.0477**	0.0477**	0.0457**
		(0.0147)	(0.0164)	(0.0170)	(0.0161)
Remittance		0.153***	0.115***	0.115***	0.0664*
		(0.0163)	(0.0174)	(0.0262)	(0.0272)
Education		0.0521***	0.0398***	0.0398***	0.0370***
		(0.00404)	(0.00460)	(0.00642)	(0.00669)
Poverty			0.0427***	0.0427***	0.0409***
			(0.00839)	(0.00949)	(0.00935)
Security			0.0351***	0.0351***	0.0326***
			(0.00688)	(0.00869)	(0.00864)
News			0.0529***	0.0529***	0.0475***
			(0.00574)	(0.00620)	(0.00631)
Ethnic Frac.			-0.0556*	-0.0556	-0.0538
			(0.0232)	(0.0303)	(0.0330)
Missionnaries			-17.37	-17.37	-22.20
			(24.04)	(25.05)	(25.00)
SHM					0.262***
					(0.0272)
Controls	No	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Religion FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Clustering	No	No	No	Yes	Yes
Observations	14479	14010	12448	12448	12409
R-squared	0.0990	0.149	0.165	0.165	0.182
Mean Dep. Var.	0.491	0.489	0.494	0.494	0.493

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

11.2 Figures

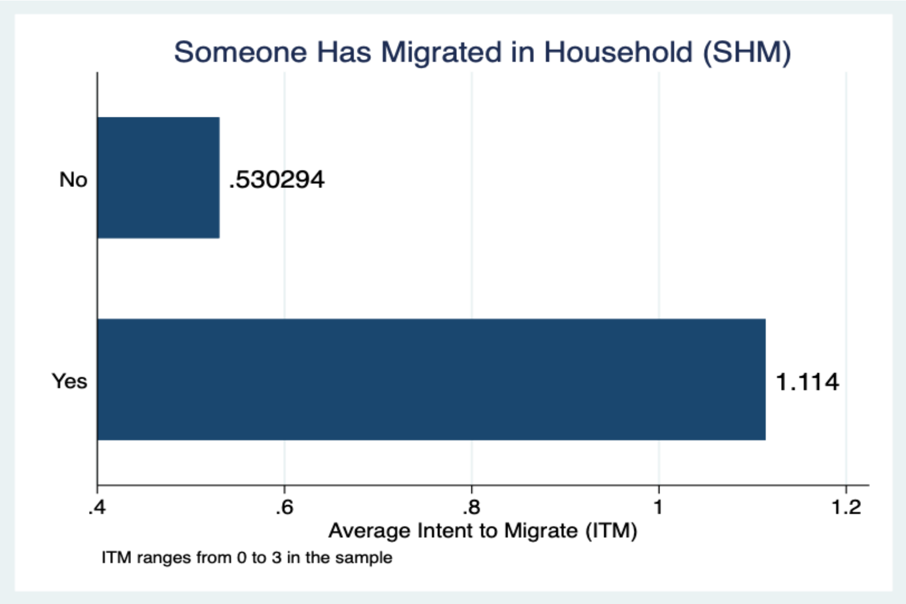
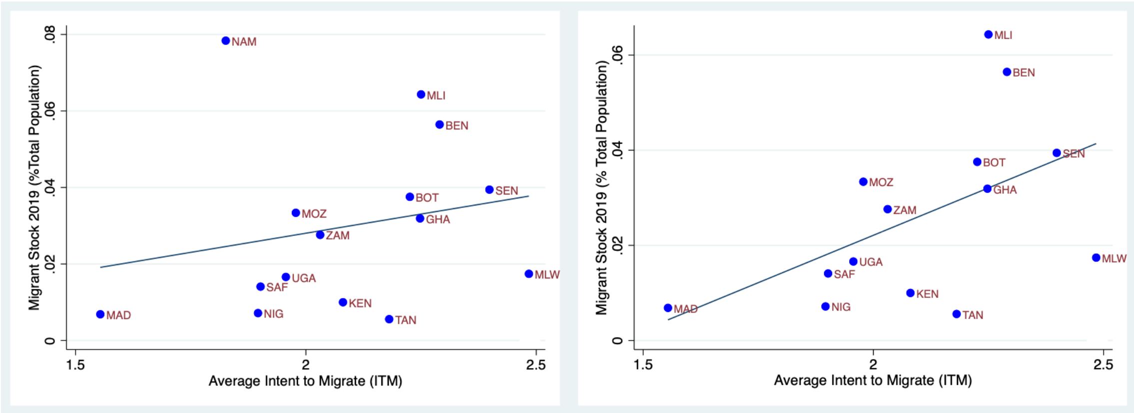
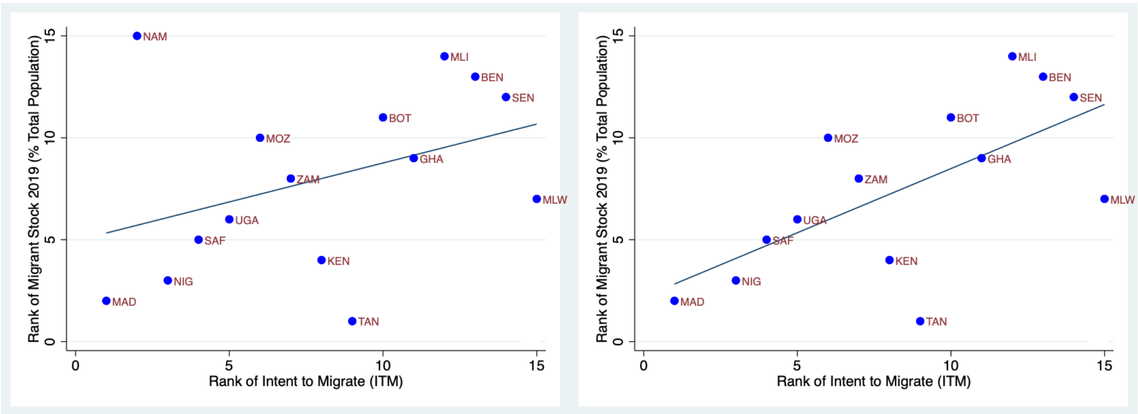


Figure 4

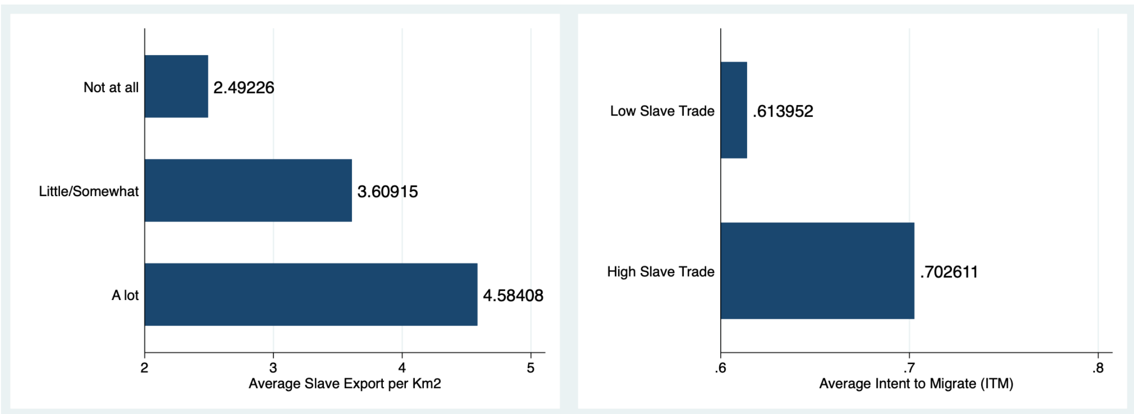


(a) With Namibia (b) Without Namibia



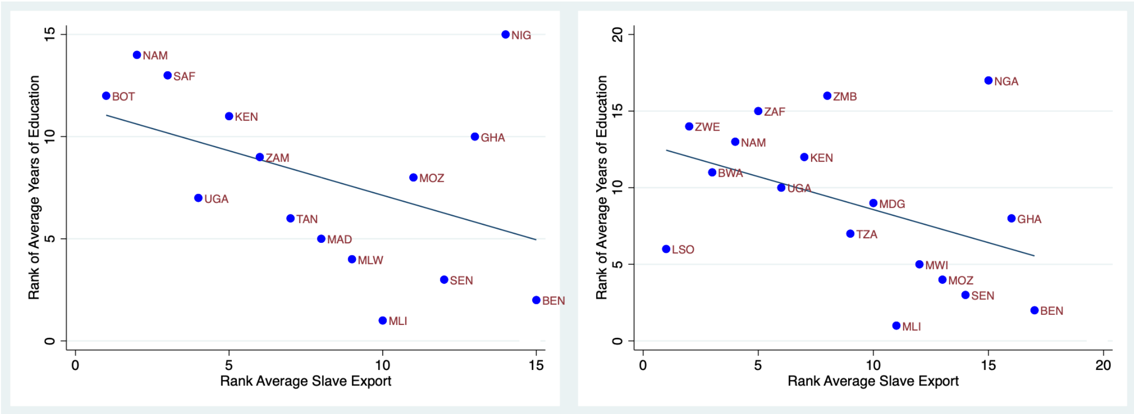
(c) With Namibia (d) Without Namibia

Figure 5: ITM and International Migrant Stock 2019 (Real and Rank)



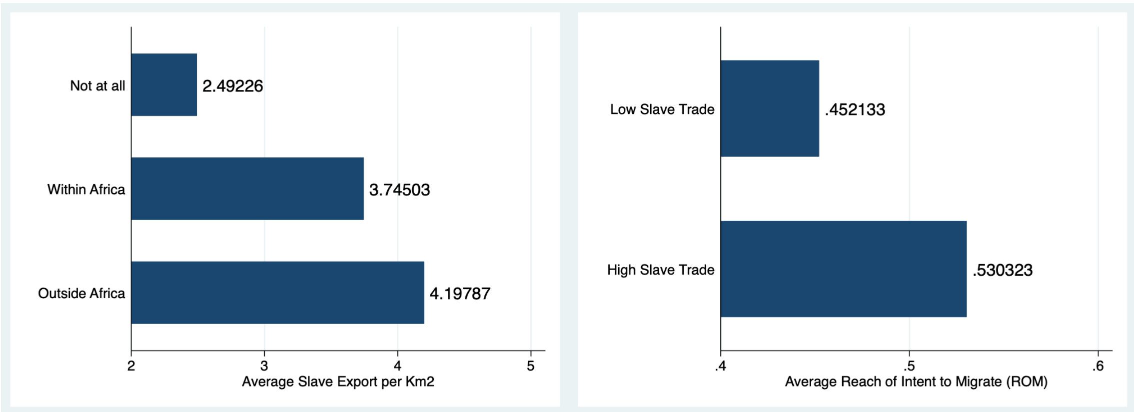
(a) (b)

Figure 6: Intent to Migrate and Slave Exports per Km2



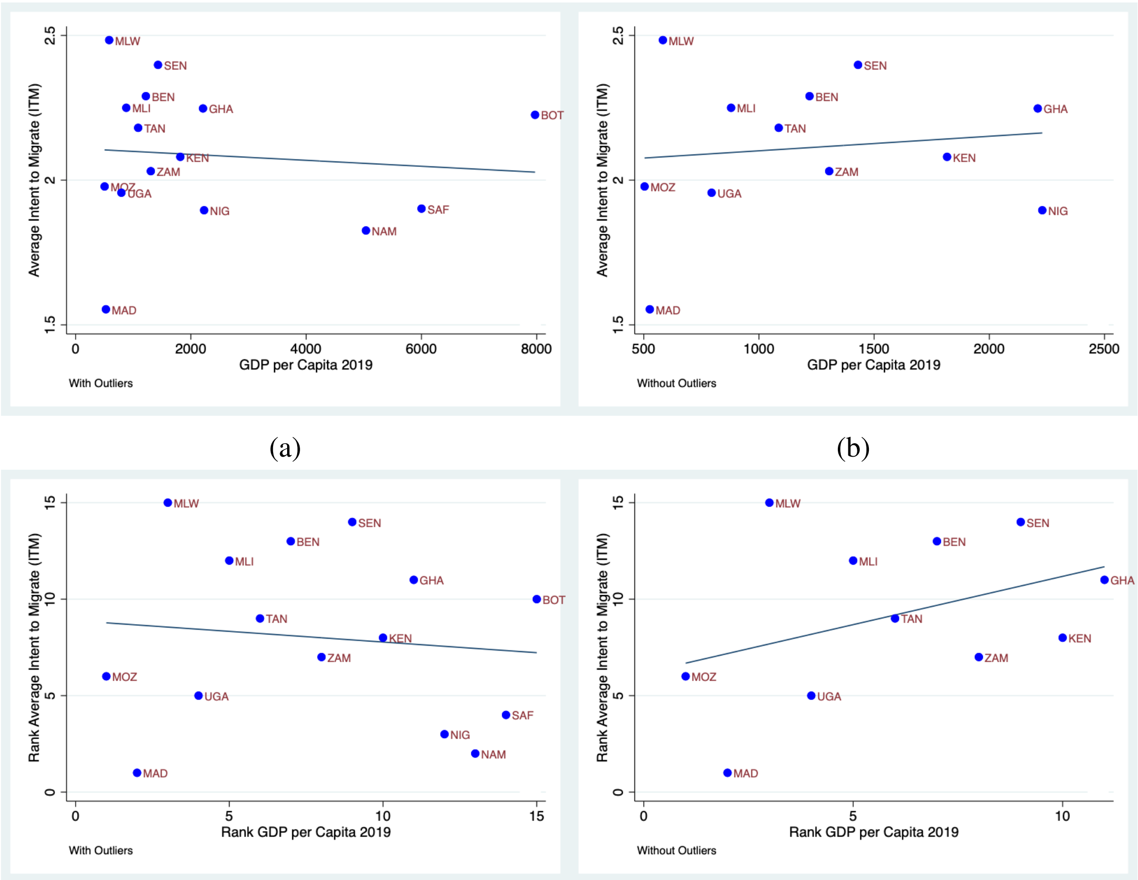
(a) (b) Nunn and Wantchekon (2011)

Figure 7: Years of Education and Slave Trade at Country Level



(a) (b)

Figure 8: Reach of Intent to Migrate and Slave Exports



(a) (b)

(c) (d)

Figure 9: GDP per Capita 2019 and Intent to Migrate