Trade and regional economic development

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Abstract

If trade is beneficial, whom do these gains accrue to? In this paper, I assess the impact of elite capture on regional development. African countries provide a unique study ground because the arbitrary placement of country borders during the colonial period provides a source of variation in cross-country connectedness between people in different countries that is independent of economic considerations. Thus, African borders provide both a credible instrument for bilateral trade flows and enable the assignment of trade flows —and their impacts— to individuals. I find that while ethnic networks increase trade flows, increased trade activity decreases subnational economic development, measured by satellite data or individual wealth. I show that this counter-intuitive result comes from elite groups capturing the gains from trade, with detrimental impacts on trust and democratic progress in society.

Keywords: Elite capture, development policy, trade policy

JEL codes: O24, N77, F14

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1 Introduction

Models of trade typically predict that trade increases economic activity. Yet, endogeneity concerns prevent a causal interpretation such that empirical evidence is scarce (Frankel and Romer, 1999; Pascali, 2017; Feyrer, 2019). And even if trade causes growth, elite capture might redistribute welfare to politically dominant groups increasing inequality (Burgess et al., 2015). This study combines these literatures and employs a novel identification strategy to empirically investigate (i) where the gains from trade accumulate and (ii) whether elite capture affects economic and societal development.

Africa provides the ideal setting to study these questions, because the arbitrary placement of country borders during colonization split some ethnic groups into multiple parts, but not others. This 'scramble for Africa' arguably contributed to the relative economic underperformance of, and ethnic favoritism in, African countries today (Alesina et al., 2016; Michalopoulos and Papaioannou, 2016; Clochard and Hollard, 2018; Dickens, 2018). To boost economic development, trade liberalization policies have been touted as a panacea and is part of virtually all major multilateral agreements signed by African countries (Smeets, 2021; Lejarraga, 2022).

I analyze who benefits from trade by calculating groups' and individuals' exposure to exogenous variation in trade activity. I use that colonial powers' placement of country borders in Africa created cross-border networks that exogenously shift export intensity and use pre-colonial population shares of ethnic groups to assign trade exposure to individuals in a shift-share setting.

The analysis reveals three insights. First, real income gains from trade are not shared equally as nighttime light data and individual survey data reveal a negative relationship between trade exposure and welfare. Second, the gains from trade accumulate in ethnic groups in political power, providing suggestive evidence for elite capture. Third, this has negative consequences for individuals' satisfaction with democracy and trust in institutions, effectively undermining the democratic progress. This paper thus yields new insights on the distribution of the gains from trade and casts a shadow on trade policies' impact on regional development.

The analysis unfolds in two parts: How trade flows impact individual welfare and estimating the impact of elite capture on social stability. Estimating the gains from trade requires addressing reversed-causality, as richer countries trade more, and omitted variable biases from government policies or infrastructure increasing trade. Focusing on regional development, I abstract from these concerns and control for confounding factors using country-by-year fixed effects. Instead, utilizing insights from the *shift-share* literature, I capture each groups' exposure to trade flows by aggregating realized bilateral exports to the country-of-origin level (*shift*) and interact this trade activity with each group's pre-colonial population (*share*). Country-by-year and country-by-ethnicity fixed effects then capture the average effect of increased trade activity and ethnic status in each country, respectively, isolating the variation from increased trade exposure of ethnic groups.

Both nighttime light data (2012-2020) at the ethnic-group level and georeferenced data at the individual level from the Afrobarometer (1999-2018) reveal a significant negative relationship between trade exposure and regional economic development. A 10% increase in trade activity reduces nighttime luminosity by 37% and individual welfare by 10%. Groups in power, however, benefit from increased trade activity. Using data on the political status of ethnic groups, I argue that elite capture distorts and redirects the gains from trade, negatively affecting regional economic development in Africa.

Causal identification of elite capture requires addressing the potentially endogenous political status of ethnic groups as well as its interaction with trade activity. If the political status of ethnic groups is determined by an endogenous component capturing each group's propensity to rule and a random component determining whether the group actually rules, country-by-ethnicity fixed effects perfectly capture the endogenous component, isolating the variation of the random shock to its political status.

However, if ethnic groups in political power actively pursue policies to increase trade activity because they tend to benefit from it, the interaction of trade activity and ethnic group may be downward biased. Thus, I utilize the pre-colonial distribution of ethnic groups in all continental African countries and use that not a single country border aligns with a border between ethnic groups. This creates ethnic networks across country borders that is essentially random, as country borders were drawn in 1884 without taking into consideration that countries could become independent more than 60 years later (Michalopoulos and Papaioannou, 2016).

Leveraging the strength of this initial ethnic network across neighboring countries, I obtain a valid instrument that exogenously shifts exports. Similar to Frankel and Romer (1999), I then aggregate predicted exports between neighboring countries ($\widehat{shift}$) and interact this predicted trade activity with population shares (*share*) to instrument realized trade exposure in the *shift-share* estimation on regional development. With F-statistics on the first stage between 29 and 62, the resulting point estimates confirm initial results.

Having established exogenous variation in exports that can be assigned to ethnic groups who, conditional on country-by-year and country-by-ethnicity fixed effects, enter and exit government coalitions, I estimate the impact of trade exposure on social stability. When the gains from trade are not shared with disadvantaged groups, this might lead to lower trust, social stability, and ultimately conflict. Using the Afrobarometer's questions on satisfaction with democracy and trust in institutions, I highlight a significant negative impact on social stability.

Elite capture of the gains from trade thus shape the regional economic development of Africa today. Relocating factories and economic activity into their own ethnic homelands likely explains the negative impacts on trust institutions and satisfaction with democracy: Being left behind by the elites that govern the country, they lose trust and faith in democratic progress. Including trade policies in multilateral agreements might thus add to the growing dissatisfaction with democracy in many developing countries.

These findings contribute to our understanding of Africa's long-run development and the important role its colonial history plays. In related work, Michalopoulos and Papaioannou (2016) show that ethnic groups split across country borders are poorer and lag behind non-split ethnic groups. Split ethnic groups were also less politically centralized in the pre-colonial period, which further emphasizes the fact that they exhibit lower levels of economic development today (Michalopoulos and Papaioannou, 2013). My findings suggest that split ethnic groups with large ethnic networks across borders benefit from increased trade activity, yet these gains from trade disproportionately accumulate with the ethnic groups that hold political power. This is suggestive of a mechanism that aligns with the insights of Dickens (2018), who documents evidence of ethnic favouritism within split groups throughout sub-Saharan Africa.[1] Overall, my results highlight a novel channel through which patterns of development have persisted throughout the African continent.

The findings in this paper also relate to the discussion on whether trade causes growth (Frankel and Romer, 1999). This literature has used gravity equations to study this relationship, exploiting airplanes (Feyrer, 2019), the Suez canal closure (Feyrer, 2021), or the evolution of the steam ship in the 19th century (Pascali, 2017). Similar to papers that broaden the scope of this question to intra-national trade costs (Donaldson and Hornbeck, 2016) or information frictions (Steinwender, 2018), I add a political economy dimension to this question that hitherto has not been studied in the literature.

I also contribute to the emerging discussion on the distributional effects of trade. While it is clear that liberalizing trade generates winners and losers, identifying them empirically was near impossible until the advent of firm-level data. Engel et al. (2021) provides an overview of the distributional effects of trade across regions and demographic groups over time. At the firm level, Baccini et al. (2017) highlight how preferential trade agree-

[1]More broadly, evidence of ethnic favoritism in African politics is well documented in the literature (Frank and Rainer, 2012; Burgess et al., 2015; Kramon and Posner, 2016).

ments increase trade disproportionately for large firms. This evidence is corroborated in the developing countries setting, where Dhingra and Tenreyro (2020) evaluate agribusinesses providing access to farmers and show that while businesses gained, farmers in villages that produced policy-affected crops saw reductions in consumption. Using the staggered implementation of the Africa Growth and Opportunity Act, Desmet and Gomes (2023) show that trade access increases income in general, but decreases it for remote ethnic groups. In contrast to existing studies focusing on tariff reductions, I provide evidence how trade flows differential affect groups based on their power status within government. Thus, my findings add to academic and policy debates on the distributional impacts of trade policies.

This paper is structured as follows. Section 2 presents the data and variable definitions used throughout the paper. Section 3 presents the empirical strategy. Section 4 estimates the effect of trade exposure and elite capture on regional economic development. Section 5 develops a framework for trade between African countries allowing for heterogeneous groups within countries and presents the derived instrument. Section 6 presents the results on regional economic development and social stability using the derived instrument. Section 7 concludes.

2 Data

Trade activity Data on bilateral trade are obtained from UN Comtrade World Bank Integrated Trade Systems from 1990–2020. I use import and export data to maximize coverage of reported trade, acknowledging that the point estimates are likely lower bounds on the true effect of exports between countries.[2] I construct two dependent variables from this data: Exports for country c to destination d on the African continent are aggregated to the country-by-year level $Export_{c,t} = \sum_{d \in D} Export_{c,d,t}$. Exports for each country c to each neighboring country d', $Export_{c,d',t} \forall d' \in D'$ are used to obtain predicted values which are aggregated $\widehat{Export}_{c,t} = \sum_{d' \in D} \widehat{Export}_{c,d',t}$ and used to instrument for $Export_{c,t}$.

Ethnic population The ethnic group of each individual or region is determined by the spatial intersection of the map in Murdock (1959) with modern country borders. In total Africa contains 833 ethnic groups in 48 African countries. The population share of ethnicity e in country c is then calculated by aggregating detailed grid-cell population data

[2] If the data is split up into reported or unreported trade, the true estimate will be $\beta = \left(\beta^{reported} X_{cd}^{reported} + \beta^{unreported} X_{cd}^{unreported}\right) / (X_{cd}^{reported} + X_{cd}^{unreported})$. As long as $\beta^{reported} \leq \beta^{unreported}$, I estimate a lower bound effect.

from the United Nations Environment Program in 1960 to the ethnicity-by-country level.

Nighttime lights Data on regional development is derived from the most recent satellite data on nighttime lights (Visible Infrared Imaging Radiometer Suite, VIIRS) at a resolution of 500m at the equator (Elvidge et al., 2021). This data is an improvement over the older DMSP-OLS Nighttime Light Series Elvidge et al. (1997) and the new standard in the literature. Two variables are constructed to measure regional development: $Lid_{e,c,t}$ calculates the fraction of pixels with a luminosity greater than zero for each country-ethnic group observation. $\log(NTL+1)_{e,c,t}$ calculates the logarithm of average luminosity for each country-ethnic group observation.

Household welfare Is derived from the georeferenced version of the Afrobarometer survey rounds 1–7 (BenYishay et al., 2017). The ethnic group of each individual is determined by the spatial intersection of Murdock (1959) with the individual's location. I create three standardized indexes from a list of questions capturing household wealth, satisfaction democracy, and trust in institutions. Appendix C explains the methodology, shows p-values adjusted for multiple hypothesis testing, and lists all questions.

Ethnic power relations The political status of every country-ethnic group observation is derived from Wimmer et al. (2009). The georeferenced data is interesected with the country-ethnic group from Murdock (1959) or the spatial location of the individual. In case an exact match cannot be found, I follow a two step procedure: First, I use the closest ethnic group within 250km in the same country before linking the remaining ethnic groups based on their names and country.[3] $InPower_{e,c,t}$ denotes whether the individual or group belongs to an ethnicity e enjoying a monopoly or dominant status in country c and year t.

Conflict I obtain georeferenced conflict data from https://ucdp.uu.se/. $Conflict_{e,c,t}$ is defined as any conflict occurring in country c, ethnicity e, and year t. Results are robust to using number of conflicts, various definitions of deaths, or conflict intensity.

[3] I use record linking and compare the string differences between ethnic group's names. I only use perfect matches. Results are robust to only using spatial matches.

3 Empirical Strategy

I study the impact of trade exposure on regional economic development and whether elites capture the gains from trade. The unit of observation is a country-ethnic group that is derived from the intersection of the precolonial homelands of ethnic groups (Murdock, 1959) with modern-day country borders. In total, there are 1,383 country-ethnic group observations in each year. The estimation equation is derived from two principles: trade increases regional development and groups differ in their average state of development.

$$Y_{e,c,t} = \beta_1 \log \left(\sum_{d \in D} Export_{c,d,t} \right) + \beta_2 Population\ Share_{e,c} + \alpha_c + \alpha_t + \varepsilon_{e,c,t} \tag{1}$$

$Y_{e,c,t}$ captures regional development as either satellite data capturing luminosity or individual welfare from the Afrobarometer surveys. I expect $\beta_1 > 0$ as trade increases regional development. This coefficient can be interpreted as how much increased trade activity affects regional development *on average*. The sign of β_2 is, however, ambiguous. If larger ethnic groups are more developed and capture *on average* a larger share of the benefit, we would expect $\beta_2 > 0$. Alternatively, if smaller ethnic groups are located close to the capital and occupy influential positions, we would expect $\beta_2 < 0$.

Equation (1) does, however, also capture several factors that compound and bias the treatment effect. First, the sum of exports is correlated with GDP and population, likely biasing the estimate on β_1, motivating the inclusion of economic fixed effects $\alpha_{c,t}$ to hold GDP, population, political system, and aggregate trade flows of country c in each time period t constant. Then, however, β_1 is not identifiable using equation (1). Second, ethnic groups size is likely correlated with economic development, but also to their political status, the fertility of their ethnic homelands, or historical political development (Michalopoulos and Papaioannou, 2013). I thus include country-by-ethnicity fixed effects ($\alpha_{c,e}$) to hold observable and unobservable characteristics for ethnicity e in country c, including its population, homeland size, average economic and political status, as well as conflict prevalence, constant. Then, again, β_2 is not identifiable using equation (1).

Thus, to estimate ethnic-group level exposure to aggregate trade flows and its impact on regional development, I estimate the following equation interacting aggregate bilateral exports with population shares for each group:

$$Y_{e,c,t} = \underbrace{\gamma \log \left(\sum_{d \in D} Export_{c,d,t} \right) \times PopulationShare_{e,c}}_{TradeExposure_{e,c,t}} + \alpha_{c,t} + \alpha_{c,e} + \varepsilon_{e,c,t} \tag{2}$$

Conditional on the large set of fixed effects, *Trade Exposure*$_{e,c,t}$ is identified from the interaction of aggregate bilateral exports from country c to all destinations $d \in D$ with the population share of ethnicity e in country c. The comparison is thus strictly within each country-year observation, comparing ethnic-groups off their long-term average. In this setup, aggregate bilateral exports act as a *shifter* that is assigned to each ethnicity by its *population share*. Standard errors are clustered at the country-ethnic group level.

Contrary to equation (1), where more trade implies larger economic development, the sign of γ is unclear as it captures how trade activity differentially affects ethnic groups: If the gains from trade were proportionally shared among all ethnic groups, we would expect that γ is zero as the average (level-) effect is captured by β_1 inside the country-by-year fixed effects. A positive coefficient would suggest that large ethnic groups capture a disproportionate share of the benefits, redistributing from small ethnic groups to larger ones. A negative coefficient suggests the opposite and is indicative of elite capture.[4]

When estimating the impact of elite capture, I require exogenous variation in each group's political status. This depends on endogenous and random factors: If the endogenous factors can be approximated by each group's historical judicial development, propensity to rule, or economic development today, country-by-ethnicity fixed effects isolate random variation in power status. Then, additionally controlling for country-by-year fixed effects isolates the random variation that determines each group's access to power.

To estimate the impact of elite capture, I interact equation (3) with data on political relations and estimate:

$$Y_{e,c,t} = \gamma\ TradeExposure_{e,c,t} + \delta\ TradeExposure_{e,c,t} \times InPower_{e,c,t} + \alpha_{c,e} + \alpha_{c,t} \times InPower_{e,c,t} + \varepsilon_{e,c,t}$$

In this setup, γ captures how much ethnic groups benefit from increased trade flows if they are not in political control. Groups that are in political power then gain an additional δ from additional trade exposure. $\alpha_{c,t} \times InPower_{e,c,t}$ controls for the average political status of country c in time period t, such that δ measures the extent of elite capture.

4 Results

In Table 1, I use nighttime light satellite imagery to assess whether the gains from trade are equally shared among all ethnic groups. Columns (1) and (2) present results on the fraction of pixels lid for each country-ethnic group. The results suggest that a 10% increase in trade results in a 37% decrease in the fraction of pixels lid.[5] If the group is in

[4] This interaction does not capture a simple urban/rural divide in which rural areas are larger with lower population density and thus fewer nighttime lights. Size, location, population density is held constant by $\alpha_{c,e}$.

[5] A potential concern is differential population density across ethnic groups. Country-by-ethnicity fixed effect capture all constant characteristics, including population density.

power, however, the interaction term in column (2) suggest a 15% increase in nighttime luminosity.[6] These results carry over when considering average luminosity in columns (3) and (4).

Table 1 suggests significant elite capture of the gains from trade. The negative point estimate suggests that most ethnic groups in African countries do not benefit from increased trade activity. The gains from trade are squarely located with the group in power, redistributing wealth towards their own group.

These group-level estimates from nighttime lights carry over to individual estimates using the Afrobarometer Surveys. Here, I construct a standardized measure of relative household welfare and use it to assess whether the gains from trade accumulate with individuals. The same picture emerges in Table 2: A 10% increase in exports decreases household welfare by 10% of a standard deviation for groups not in power, and increases welfare by 4.6% of a standard deviation for groups in power.

Table 1 and 2 thus provide evidence that the gains from trade are not shared proportional to each ethnic groups' population share. This result cannot be explained by time-varying country factors or time-invariant characteristics of ethnic groups such as population density, pre-colonial distributions, or the ethnic group being split; country $\times$ year and ethnic $\times$ country fixed effects absorb these confounders completely. These results are also not driven by outliers as dropping countries individually does not alter the estimate significantly (Figure A.1).[7]

4.1 Mechanism

There are two explanations how powerful elites can benefit from increased economic activity; Bribery and redirection of economic activity. While bribery is certainly widespread among African countries, with many ruling parties benefiting their own group, the focus of this paper lies on the redirection of economic activity. In the spirit of the road building exercise in Burgess et al. (2015), the redirection of economic activity could be the construction or upgrading of roads that attract new businesses, or in the outright relocation of businesses to the ethnic homelands of powerful elites.

Both mechanisms predict that exposure to manufacturing exports has worse impacts on regional development than agriculture or resource exports. Whereas resources and agricultural fields are immutably fixed in space, factories can be relocated. Table A.1

[6]Calculated from 10% of the average log exports (13.87) times the point estimate relative to fraction of lid pixels (0.033) on average and for groups in power (0.088).

[7]Following (Borusyak et al., 2022) I also cluster the standard error at the level that provides exogenous variation; in this case the ethnic group. Standard errors are smaller and thus not reported.

provides suggestive evidence in favor of such relocation as manufacturing exports are the only type of exports that significantly affects regional development.

5 Trade in Africa: A gravity equation

Even conditional on country-by-year fixed effects capturing economic activity and country-by-ethnicity effects capturing ethnic relations, my findings could be biased. Larger ethnic groups are more likely to be split into multiple countries, are less likely to gain power, and are less likely to be economically integrated (Michalopoulos and Papaioannou, 2013, 2016). Conversely, smaller ethnic groups are more likely to be closer to the centers of economic and political power. Then, their ability to relocate economic activity towards their homelands might create a reversed causality bias in the interaction term in trade exposure. Do groups benefit from increased trade exposure, or is trade exposure increased because they benefit from it?

In order to assess the severity of this bias, I begin by developing a gravity-type equation that incorporates heterogeneous ethnic groups across multiple country pairs. Then, I exploit the quasi-exogenous placement of borders and use pre-colonial ethnicity shares in each exporting country —and their connections to the importing country— to highlight the importance of ethnic networks in shaping and directing export flows. This provides an exogenous shifter in trade flows uncorrelated with the current political status of ethnic groups.

5.1 A stylized model of trade

In the trade literature, the value of bilateral exports is modeled in gravity-type equations (Anderson, 1979). Here, the value of trade is correlated with the size of the exporter and importer economy and the geographic distance between them, as larger and more geographically close economies trade more. In this framework, the addition of a stock or flow of migrants is used to estimate the impact of migration:

$$\log(X_{cd,t}) = \beta \log(PS(c)_{d,t}) + \Gamma_{cd,t} + \alpha_{c,t} + \alpha_{d,t} + \varepsilon_{c,d,t} \tag{3}$$

Here the log of exports from the exporting country c to destination d, $\log(X_{cd,t})$, is correlated with the population share of people from country of origin c in destination country d ($PS(c)_{d,t}$). Controlling for country ($\alpha_{c,t}$) and destination ($\alpha_{d,t}$) fixed effects interacted with time period fixed effects and bilateral characteristics ($\Gamma_{cd,t}$), β identifies the effect of the population share on the log of exports. The elasticity $\beta > 0$ indicates that trade flows increase if the trading partners share a larger network.

Implicitly, equation (3) assumes that migrants to destination d identify with the nationality of their country of origin c.[8] African countries however, combine a multitude of ethnic groups, each with their own identity. Thus, allowing for multiple ethnic groups (e) from the set of ethnic groups in each country ($e \in E_c \cap E_d$), the general form of equation (3) is given by:

$$\log(X_{cd,t}) = \beta \underbrace{\log\left(\sum_{e \in E_c \cap E_d} PS_{c,t,e} \times PS_{d,t,e}\right)}_{Ethnic\ Connections_{cd}} + \Gamma_{cd,t} + \alpha_{c,t} + \alpha_{d,t} + \varepsilon_{c,d,t} \tag{4}$$

where $PS_{c,t,e} \in (0,1]$ is the population share of an ethnicity e that is common to country c and d, relative to the population of country c at time t. This formulation nests equation (3) if country c has only one ethnic group with $PS_{c,t,e} = 1$. Equation (4) correlates bilateral exports to the probability of a co-ethnic relationship (match) when randomly drawing two individuals from each country. It captures the idea that it is easier to trade with someone from your own ethnicity, but does not exclude the possibility of trading with other ethnic groups.

The formulation of equation (4) is supported by three observations. First, it is the empirical equivalent of an otherwise standard model of international trade (Melitz, 2003; Chaney, 2008) that adds an ethnicity-specific fixed cost capturing lower entry costs into an export market for ethnically connected firms.[9]

Second, the interpretation is equivalent to the search and matching literature where a match is defined when two individuals of the same characteristics are drawn. Since these characteristics are stochastic, the likelihood of a match is given in probabilities. Here, characteristics are distributed along ethnic lines and thus the fraction of the population representing an ethnicity in the importing country is equivalent to the likelihood that an exporting firm from the exporting country finds a match in the importing country.

[8] The underlying equation is of the form $PS(c)^{\beta}_{d,t} = ({}^{Pop(c)_{d,t}}/{}_{Pop_{d,t}})^{\beta}$. The population of migrants from country c in destination d at time t ($Pop(c)_{d,t}$) is denominated by the population size of destination d at time t ($Pop_{d,t}$). The implicit assumption is that all migrants form c identify with country c, and not with a subgroup e. That is, $({}^{Pop(c)_{c,t}}/{}_{Pop_{c,t}})^{\beta} \approx 1$. Combining these yields $PS^{\beta}_{d,t} = ({}^{Pop(c)_{d,t}}/{}_{Pop_{d,t}} \times {}^{Pop(c)_{c,t}}/{}_{Pop_{c,t}})^{\beta}$.

[9] These costs can be lower information costs, more reliable information about market structures or bribes, and fewer cases of fraud between business partners. In Appendix D, I show that equation (4) follows if firms face a fixed cost of exporting $PS^{-\eta}_{c,e} f_{cd}$ with $\eta \in [0,1)$ providing concavity for the impact of fixed costs f_{cd} on the exporting firms' profits. These fixed costs represent costs of setting up a distribution network, informing about markets, administration and paying for permits. A similar model has been suggested by Krautheim (2012) and it nests the established Chaney (2008) model with $\eta = 0$.

Then, the estimated β can be interpreted as an elasticity that captures the change in match probability of each ethnicity when its population changes on either side of the border.[10] This interpretation is similar to the standard in equation (3); both can be interpreted as a probability of drawing two connected people in each country. Equation (4), however, incorporates the heterogeneous population structures in African countries and allows for a large amount of subgroups within two countries that are connected.

Third, an alternative interpretation of the coefficient β is akin to iceberg trade costs: Ethnic connections capture the 'ethnic distance' between two countries. The ethnic composition of a country can be reflected by a vector $\overrightarrow{e_c}$ that contains the population shares of all possible ethnic groups $e \in E$. The product $\overrightarrow{e_c} \times \overrightarrow{e_d}$ then results in a linear distance measure between countries c and d in terms of ethnicity. Then, similar to the interpretation of larger geographic distances between countries reducing trade, larger 'ethnic distances' also reduce trade by capturing increasing dissimilarity between countries.

Every regression follows the standard in the trade literature and includes time-specific country- and destination fixed effects and country-destination pair characteristics (Γ_{cd}).[11] A positive point estimate, $\beta > 0$, suggests that a larger population on either side of the border for a connected ethnicity yields larger trade flows.

I estimate this equation at the country-destination by year level. The final sample consists of 46 African countries in 91 country pairs with 182 country-destination relationships that share a border. Due to unobserved trade, the sample is further reduced to 169 observations from 1990–2020. Since the exploited variation is at the country-pair level, I cluster the standard errors at this level. I report estimates using ordinary least squares and show robustness to using weighted least squares, a panel estimation with country specific year fixed effects, the Poisson-Pseudo-Maximum-Likelihood estimator as suggested by Santos-Silva and Tenreyro (2006), as well as sectoral exports in Tables B.2-B.4.

5.2 Identification assumption of bilateral exports

Using stocks of migrants to estimate the effect of migration on trade flows is likely biased as economic activity attracts trade and migration flows similarly. In addition, borders are not set at random and instead reflect spheres of influence and historical economic activity,

[10] The probability that two randomly drawn individuals are not from the same ethnicity is non-zero, but is captured by the country and destination fixed effects in equation (4). This model can be amended to allow for inter-ethnic trade, assuming an increasing cost of trade for ethnic groups that are further away from each other (Appendix D).

[11] Country-destination pair characteristics include the log of the distance, number of ethnic connections, sharing a colonial history or language, linguistic and genetic similarity, and geographical features of the border (Table B.2).

such that the direction of a potential omitted variable bias is unclear. To address reversed causation and omitted variable bias, I argue that (i) the local dispersion of ethnic groups and (ii) the borders between African countries are placed without the intention to increase trade, migration, or economic activity in modern times.

First, to address endogenous sorting, I obtain exogenous variation in ethnic connections from the precolonial distribution of 833 ethnic groups (Murdock, 1959). I combine the geographic location of each group with grid-cell population data in 1960 to obtain population estimates of ethnic enclaves and their home population at the time of independence. In contrast to modern population figures, my measure of ethnic connectedness is unaffected by migration, catastrophes, hunger, or civil conflict dispersing people across Africa since independence.[12] Similar to the existing literature (Munshi, 2003; McKenzie and Rapoport, 2007), this strategy solves the reverse causality problem if populations were randomly placed in countries.

This assumption is fulfilled as African borders were drawn in 1884 at the Berlin conference. These borders do not reflect the interest of ethnic groups or African countries, but the interest of their colonizers. Most country borders feature parts that follow either latitudinal or longitudinal lines since the exact geography of Africa was largely unknown at the Berlin conference. The exogeneity of these borders has been extensively used in the literature on culture and development, price dispersion across borders as well as ethnic fractionalization (Alesina et al., 2011; Aker et al., 2014; Michalopoulos and Papaioannou, 2014).

I argue that these borders were arbitrarily drawn and do not reflect the interests of ethnic groups; to the contrary, they divide them into more than one country. The only determinant of an ethnic group being divided across two counties is its geographical size (Michalopoulos and Papaioannou, 2013, 2016).[13] To address remaining endogeneity concerns, I only use borders where ethnic groups have been split when estimating the impact of ethnic networks on trade flows. I thus abstract from comparing influential with negligible ethnic groups and use a balanced sample across similar ethnic groups.

My instrument thus exploits the political process in Berlin 11884 splitting the contiguous ethnic homelands into disjoint parts. As the border is drawn, the population shares of ethnicity e in country c is random, as its exact geography was unknown to the colon-

[12]Naturally, this measure includes migration until 1960. However, results are robust to using precolonial- or modern-day population figures (Table B.5).

[13]Using data on historical characteristics of tribes, neither nomadic status, the size of local communities, nor historical institutions predict a future divide into more countries. Estimating all characteristics jointly to account for correlations between variables, the size of ethnic groups is the only determinant that predicts the division into multiple countries (Table B.1).

izers. Then, conditional on sharing a border, moving the border then randomly changes the population shares.[14]

5.3 First stage results

Figure 1 plots the strength of the instrument (left) and the correlation between predicted and realized aggregated trade flows (right). I estimate equation (4) in the left panel, and plot the residualized variation in cross-border trade flows (y-axis) and the size of the cross-border network (x-axis) controlling for country and destination fixed effects interacted with time periods and border covariates.

In this country-destination panel between neighboring countries, exports increase by 0.17% when networks increase by 1% with an F-statistic of 9.92. This result is robust to using a less demanding set of fixed effects, controlling for regional trade agreements and conflict, using a Poisson-Pseudo-Maximum-Likelihood (PPML) estimator, or only exploiting the country-destination level variation in networks in a weighted regression (Tables B.2-B.4).

Using this variation, I predict export flows between all neighboring countries and aggregate them at the country-by-year level. The resulting variable then measures the predicted trade activity of country c with its neighbors d, as shifted by the exogenous network. In the right panel of Figure 1, I correlate these aggregated predicted trade flows between neighboring countries (x-axis) with aggregated realized trade flows with all African countries (y-axis). Neighboring countries are a major destination for exports as even controlling for country and year fixed effects, a one percent increase in aggregated predicted trade flows with neighboring increases realized trade flows with all countries by 0.39%.

6 Instrumental variables estimation

In this section, I present results instrumenting realized aggregated trade flows with their predicted values from Figure 1. The instrument is based on exogenous cross-country networks formed by colonial powers imposing country borders. These networks positively affected trade flows between neighboring countries, isolating the exogenous variation in exports, thus alleviating remaining reversed causality concerns. The procedure is as follows:

[14]In contrast to Frankel and Romer (1999) and Deij et al. (2021), I do not use fixed geographic factors, but exploit political factors splitting ethnic groups as an instrument.

$$Export_{c,d',t} = \log Ethnic\ Connections_{cd'} + \Gamma_{cd'} + \alpha_{c,t} + \alpha_{d',t} + \varepsilon_{c,d',t} \tag{Dyad}$$

$$\sum_{d \in D} Export_{c,d,t} = \gamma \sum_{d \in D'} \widehat{Export}_{c,d',t} + \alpha_{c,t} + \alpha_{c,e} + \varepsilon_{c,e,t} \tag{FS}$$

$$Y_{e,c,t} = \beta \sum_{d \in D} Export_{c,d,t} \times Population\ Share_{e,c} + \alpha_{c,t} + \alpha_{c,e} + \varepsilon_{c,e,t} \tag{IV}$$

In the first step, exports from country c to neighboring destination $d' \in D'$ are predicted using exogenous shocks to ethnic connections between c and d' (Dyad). These predicted values are aggregated for all neighboring countries D' and plugged into the first stage stage (FS) to predict total trade activity of country c at time t: $\sum_{d \in D} Export_{c,d,t}$.

Table 3 presents results estimating equation (IV) in odd columns and its corresponding reduced form in even columns. The first stage F-statistic range from 29.4 in the nighttime light data to 65.5 in the Afrobarometer data.[15] The IV coefficients are similar to the OLS: The coefficient on fraction of pixels lid (-0.012) is only one standard error larger than the OLS estimate in the first column of Table 1 (-0.008). The same relationship emerges with household welfare, where the IV coefficient (-0.087) is slightly larger than the OLS estimate in Table 2 (-0.069). These results are robust to using the PPML estimator in the first stage (Table B.6-B.7).

Reduced-form results on the interaction with power status to assess the extent of elite capture are generally consistent with OLS results. Ethnic groups that are in power benefit from increased trade activity in terms of nighttime luminosity and household welfare.

6.1 Results on social stability

The fact that the gains from trade are captured by elites presents a threat to society at large. When the gains from trade are not uniformly shared, it might lead to lower trust, social stability, and ultimately conflict in disadvantaged groups.

As the Afrobarometer is mainly a survey about political values, I construct two indices capturing 'satisfaction with democracy' and 'trust in institutions' from questions listed in Appendix C. These questions set the Afrobarometer apart from the DHS that mainly captures health-related questions. I show the average effect of trade exposure on these indices in Table 4. A 10% increase in trade activity reduces satisfaction with democratic values by 28% of a standard deviation and trust in institutions by 11% of a standard deviation.

[15] The differences arise from different time frames, 2012-2020 in the former and 1999-2018, respectively.

Finally, I use georeferenced conflict data to assess the impact on violent conflict in Africa. The point estimates in columns (5) and (6) suggest that the counteracting forces of economic prosperity on conflict are still dominating. Conflict incidence, defined as any conflict in that country-ethnic group observation, is decreasing with increasing trade exposure. These counteracting forces are, however, decreasing. Trade exposure in 2020 decreases conflict 60% less than it did in 1990 with the numbers of conflicts increasing (Figure A.2).

7 Conclusion

Does trade cause growth and for whom? The results in this paper provide evidence that trade causes growth at the regional level, but only for members of ruling coalitions. Ethnic groups belonging to cross-border ethnic networks are, by construction, at the border of countries and are less likely to be in power of an entire country. However, even though these ethnic groups help bridge the gap between two countries and increase trade, the gains from trade are concentrated among the group that is in power. Relocating factories and economic activity into their own ethnic homelands likely explains the negative impacts on trust institutions and satisfaction with democracy: Being left behind by the elites that govern the country, they lose trust and faith in democratic progress.

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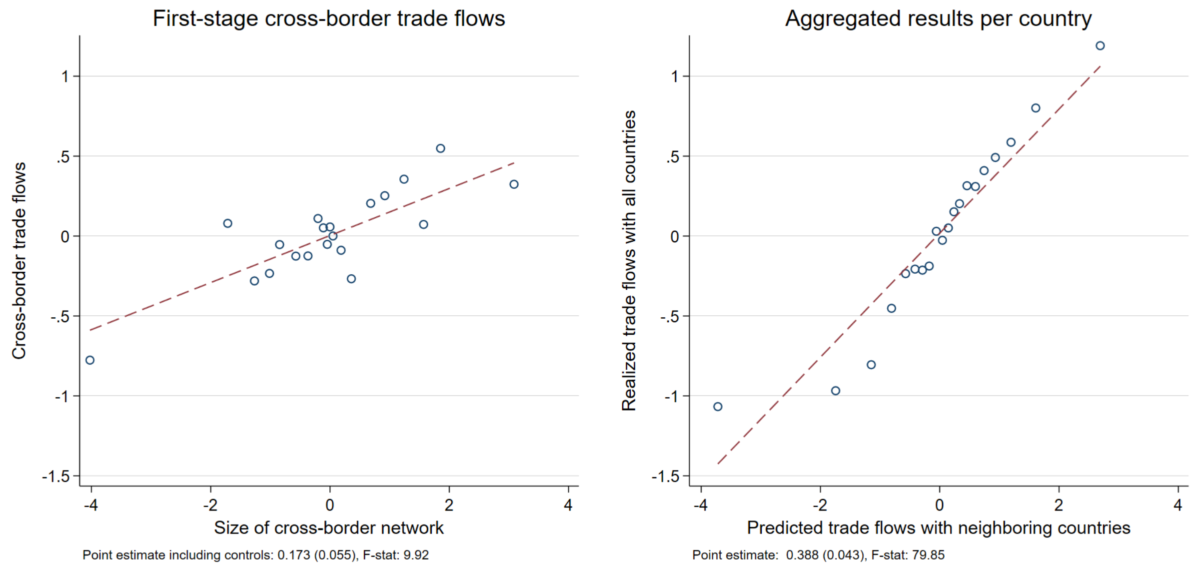
Figure 1: First stage relationship of the instrument



Notes: This figure plots the residualized variation between the size of the cross-border network and the cross-border trade flows (left) as well as the correlation of aggregated predicted and realized trade flows (right). The linear fit is shown with the dashed line in each panel and its slope and F-statistic noted below.

Table 1: Trade exposure and the gains from trade
Using nighttime light satellite imagery

	Fraction lid		Average luminosity	
	(1)	(2)	(3)	(4)
Trade Exposure	-0.008***	-0.009***	-0.029**	-0.024**
	(0.003)	(0.003)	(0.012)	(0.011)
Trade Exposure × In Power		0.010**		0.028*
		(0.004)		(0.016)
Country × year fixed effect	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes
Observations	10,314	8,541	10,314	8,541
Mean dependent variable	0.033	0.034	0.106	0.116

In this table, I show how trade exposure impacts economic development as measured by nighttime luminosity. Columns (1) and (3) represent the instrumental variables estimation, columns (2) and (4) the reduced form evidence. *Trade Exposure* is defined as realized trade flows to all African countries aggregated to the country-by-year level and interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$. *Country × year fixed effects* account for total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Fraction lid* is calculated as the fraction of pixels not zero and *Average luminosity* as the log of average luminosity in each country-ethnic group observation plus one. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Trade exposure and the gains from trade
Household welfare from the Afrobarometer

	Household welfare			
	(1)	(2)	(3)	(4)
Trade Exposure	-0.067***	-0.068**	-0.069***	-0.076**
	(0.023)	(0.032)	(0.025)	(0.034)
Trade Exposure $\times$ In Power		0.037***		0.036***
		(0.014)		(0.013)
Country $\times$ year fixed effect	Yes	Yes	Yes	Yes
Country $\times$ ethnicity fixed effects	Yes	Yes	Yes	Yes
Individual controls			Yes	Yes
Observations	221,880	197,166	218,950	194,775

In this table, I show how trade exposure impacts household welfare as measured by the Afrobarometer *Trade Exposure* is defined as realized trade flows to all African countries aggregated to the country-by-year level and interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$. *Country $\times$ year fixed effects* account for total trade flows, GDP, and population. *Country $\times$ ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Individual controls* are a full set of age, gender, education, and urban dummies. *Household welfare* represents a standardized index constructed from 9 variables asked in 7 rounds of the Afrobarometer. Details in the Appendix. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Trade exposure and the gains from trade
IV results

	Fraction lid		Average luminosity		Household welfare	
	(1) IV	(2) RF	(3) IV	(4) RF	(5) IV	(6) RF
Trade Exposure	-0.012***		-0.028**		-0.087***	
	(0.004)		(0.012)		(0.026)	
Predicted Trade Exposure		-0.008***		-0.019**		-0.076**
		(0.002)		(0.008)		(0.030)
Predicted Trade Exposure × In Power		0.007*		0.025		0.039***
		(0.004)		(0.015)		(0.013)
Country × year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls					Yes	Yes
Reduced form		Yes		Yes		Yes
Observations	10,128	8,398	10,128	8,398	217,809	193,671
First Stage F-Test	29.452		29.452		65.556	

In this table, I show how trade exposure impacts economic development as measured by nighttime luminosity (columns 1-4) and household welfare (columns 5-6). *Trade Exposure* is defined as realized trade flows to all African countries aggregated to the country-by-year level and interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$ instrumented by *Predicted Trade Exposure*. *Fraction lid* is calculated as the fraction of pixels not zero, *Average luminosity* as the log of average luminosity in each country-ethnic group observation plus one, and *Household welfare* represents a standardized index constructed from 9 variables asked in 7 rounds of the Afrobarometer *Country* × *year fixed effects* account for total trade flows, GDP, and population. *Country* × *ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Individual controls* are a full set of age, gender, education, and urban dummies. The first stage F statistic is given in the last row. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Trade exposure and society
Democracy, trust, and conflict

	Satisfaction with Democracy		Trust in Institutions		Conflict Incidence	
	(1)	(2)	(3)	(4)	(5)	(6)
Trade Exposure	-0.207***	-0.227***	-0.127***	-0.127**	-0.066**	-0.058*
	(0.056)	(0.075)	(0.049)	(0.063)	(0.027)	(0.032)
Country × year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes		
Observations	218,950	217,809	218,950	217,809	34,538	33,361
First Stage F-Test		65.556		65.556		81.842

In this table, I show how trade exposure impacts household welfare as measured by the Afrobarometer *Trade Exposure* is defined as realized trade flows to all African countries aggregated to the country-by-year level and interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$. *Country × year fixed effects* account for total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Individual controls* are a full set of age, gender, education, and urban dummies. *Satisfaction with Democracy* and *Trust in Institutions* represent standardized indexes constructed from variables asked in 7 rounds of the Afrobarometer. Details in the Appendix. *Conflict Incidence* is a binary variable whether the UCDP records a conflict in that country-ethnic group observation and year. The first stage F statistic is given in the last row. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For Online Publication: Appendix
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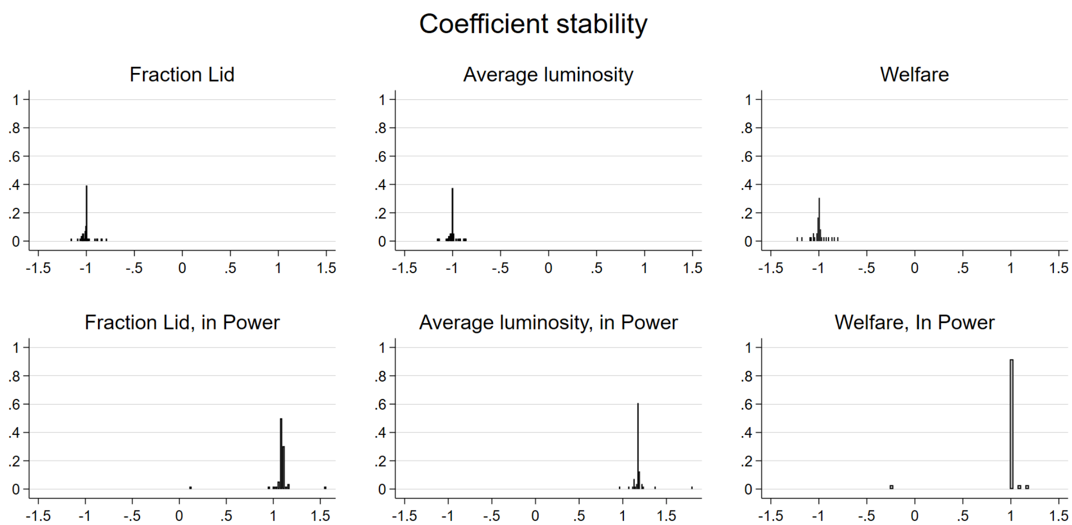
This appendix provides supporting evidence to the main paper. I cover the following topics:

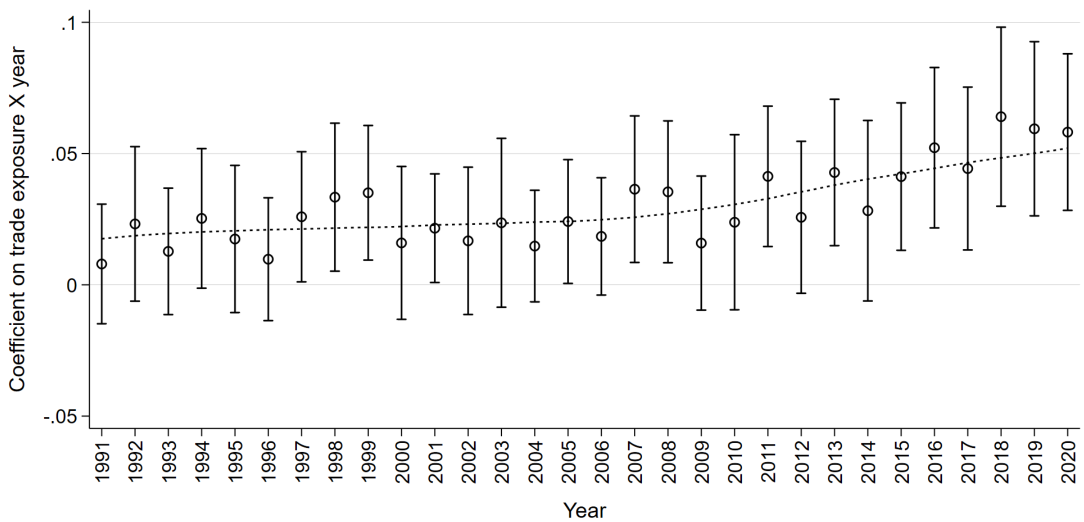
A Supporting Evidence

Figure A.1: Coefficient stability for the main regressions in Table 1 and 2



Notes: This figure plots the distribution of point estimates when dropping one country at a time relative to the average effect. 1 implies that the point estimate is the same, 0.5 implies its 50% smaller.

Figure A.2: Trends in trade exposure and conflict



Notes: This figure plots point estimates from the interaction between *Trade exposure* and *Year* on conflict incidence. The average effect of *Trade exposure* on conflict incidence is -0.15. The increasing pattern suggests that the counteracting effect of economic prosperity on conflict is decreasing.

Table A.1: Trade exposure and the gains from trade
Sectoral exports and nighttime light satellite imagery

	Fraction lid				Average luminosity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trade Exposure	-0.008***				-0.029**			
	(0.003)				(0.012)			
Exposure to manufacturing exports		-0.004**				-0.021**		
		(0.002)				(0.010)		
Exposure to agriculture exports			-0.002				-0.007	
			(0.002)				(0.005)	
Exposure to resource exports				-0.003				-0.008
				(0.003)				(0.006)
Country × year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,314	10,845	10,845	10,845	10,314	10,845	10,845	10,845

In this table, I show how trade exposure in various sectors impacts economic development as measured by nighttime luminosity. Columns (1) and (3) represent the instrumental variables estimation, columns (2) and (4) the reduced form evidence. *Trade Exposure*, *Exposure to manufacturing exports*, *Exposure to agriculture exports*, and *Exposure to resource exports* are defined as realized trade flows to all African countries aggregated to the country-by-year level in that sector and interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$. *Country × year fixed effects* account for total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Trade Exposure* is identified only from the interaction of the two. *Fraction lid* is calculated as the fraction of pixels not zero and *Average luminosity* as the log of average luminosity in each country-ethnic group observation plus one. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Instrumental variables strategy

Table B.1: Determinants of being divided:
Historical characteristics of ethnic groups in Murdock (1959)

	Ethnic group is divided between two or more countries							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log Population in 1960	0.041***	0.008						0.015
	(0.013)	(0.015)						(0.021)
	[0.011]	[0.011]						[0.017]
log Ethnic Area		0.109***						0.138***
		(0.019)						(0.022)
		[0.013]						[0.016]
log Population Density			-0.031**				-0.050***	
			(0.015)				(0.021)	
			[0.011]				[0.014]	
Cities				-0.087			-0.084	-0.046
				(0.055)			(0.059)	(0.060)
				[0.050]			[0.051]	[0.049]
Mean Size of Local Communities					0.013		0.020*	0.004
					(0.012)		(0.011)	(0.011)
					[0.011]		[0.011]	[0.011]
Political Centralization						0.036	0.038	-0.072
						(0.055)	(0.053)	(0.050)
						[0.051]	[0.051]	[0.051]
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	833	833	833	441	441	441	441	441
Adjusted R-squared	0.022	0.086	0.014	0.017	0.014	0.011	0.038	0.134

Every column shows the point estimate from a regression on the probability of an ethnicity being divided between two or more countries. Geographic Controls include latitude, longitude, and their product. log Population in 1960 taken from UNEP SIOUX grid cell data. log Ethnic Area is the total expansion area of an ethnicity as given by the Murdock map. Data in columns (4)–(8) taken from Michalopoulos and Papaioannou (2013) and coded as follows. 'Cities': If at least one ethnicity that crosses the border historically had permanent or complex settlements. 'Political Centralization' If at least one ethnicity that crosses the border historically had a jurisdictional level beyond the local level: centralized tribe$\geq$2, where 'centralized tribe' is the count variable of jurisdictional level beyond the local level (range: 0-3). Standard errors corrected for spatial correlation within 500km shown in parenthesis. Lower cutoffs decrease the standard errors to the robust standard errors level shown in brackets. Symbols reflect the significance level for spatially corrected standard errors: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Ethnic connections and trade flows
log(Exports) between neighboring countries

	OLS			PPML
	(1)	(2)	(3)	(4)
Ethnic connections	0.183**	0.173**	0.210***	0.278***
	(0.078)	(0.070)	(0.080)	(0.066)
	[0.044]	[0.055]	[0.058]	[0.107]
Linguistic distance		-5.270**	-4.840**	-8.222***
		(2.167)	(1.908)	(0.964)
		[-0.049]	[-0.050]	[-0.128]
Genetic distance		26.575***	24.480***	31.519***
		(5.242)	(5.279)	(5.445)
		[-0.085]	[-0.051]	[0.346]
Regional trade agreements			-0.279	-0.301
			(0.523)	(0.462)
			[-0.009]	[-0.036]
log(# Conflict)			-0.597	-0.212
			(0.576)	(0.337)
			[-0.007]	[-0.019]
log(# Civilian deaths)			0.500	0.246
			(0.308)	(0.218)
			[0.006]	[0.013]
log(# Deaths)			0.035	0.046
			(0.131)	(0.077)
			[0.001]	[-0.002]
lnUnknown			0.124	0.052
			(0.252)	(0.128)
			[0.000]	[0.011]
Country-pair controls	Yes	Yes	Yes	Yes
Exporter and importer $\times$ year fixed effects	Yes	Yes	Yes	Yes
Conflict controls	4195	4195	4195	4198

In this table, I show that ethnic connections predict bilateral exports per capita between neighboring countries. *Ethnic connections* are defined as the log ethnic match probability as defined in equation (4) and capture the likelihood of drawing two individuals from either country with the same ethnicity. Sample consist of bordering countries in Africa and includes country and destination by year fixed effects in all regressions. The main dependent variable are the logarithm of bilateral exports per current capita in the years 1992–2018. The following country-pair controls are added in all columns: log length of the border, log distance between capitals, a binary variable indicating whether parts of the border is a river, a mountain above 1,000 or 2,000 meter. The number of ethnic groups shared between the countries, whether the countries share a colonial past or judicial language, and log border fractionalization (Alesina et al., 2011). Linguistic and genetic distance $\in [0, 1]$ captures the similarity between the countries (Spolaore and Wacziarg, 2015). Regional trade agreements for the years 1989-2020 are obtained from Mario Larch's Regional Trade Agreements Database from Egger and Larch (2008). Conflict at the country level is obtained from UDCP https://ucdp.uu.se/. Inference is made on the basis of standard errors clustered by each country-pair, as shown in parenthesis. Two-way clustered standard errors allowing for separate home- and foreign-clusters shown as robustness in brackets. OLS and PPML denote the estimation method. Significance denoted by standard errors clustered by the country pair: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Ethnic connections and trade flows
Weighted exports between neighboring countries

	OLS			PPML
	(1)	(2)	(3)	(4)
Ethnic connections	0.125	0.158*	0.142**	0.147**
	(0.091)	(0.087)	(0.061)	(0.066)
	[0.066]	[0.074]	[0.057]	[0.085]
Country-pair controls		Yes	Yes	Yes
Weighted regression			Yes	Yes
Observations	169	169	4,195	4,195

In this table, I show that ethnic connections predict bilateral exports per capita between neighboring countries, when the data is collapsed to the level of variation in this setting: the country-destination pair. *Ethnic connections* are defined as the log ethnic match probability as defined in equation (4) and capture the likelihood of drawing two individuals from either country with the same ethnicity. Sample consist of bordering countries in Africa and includes country and destination by year fixed effects in all regressions. The main dependent variable are the logarithm of bilateral exports per current capita in the years 1992–2018. The following country-pair controls are added in all columns: log length of the border, log distance between capitals, a binary variable indicating whether parts of the border is a river, a mountain above 1,000 or 2,000 meter. The number of ethnic groups shared between the countries, whether the countries share a colonial past or judicial language, and log border fractionalization (Alesina et al., 2011). Linguistic and genetic distance $\in [0,1]$ captures the similarity between the countries (Spolaore and Wacziarg, 2015). Inference is made on the basis of standard errors clustered by each country-pair, as shown in parenthesis. Two-way clustered standard errors allowing for separate home- and foreign-clusters shown as robustness in brackets. Significance denoted by standard errors clustered by the country pair: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Ethnic connections and trade flows
Sectoral exports between neighboring countries

	log(Export)	log(Manufacturing)	log(Agriculture)	log(Resources)
	(1)	(2)	(3)	(4)
Ethnic connections	0.171**	0.258***	0.144**	0.068
	(0.070)	(0.074)	(0.070)	(0.108)
	[0.054]	[0.055]	[0.075]	[0.097]
Country-pair controls	Yes	Yes	Yes	Yes
Exporter and importer $\times$ year fixed effects	Yes	Yes	Yes	Yes
Conflict controls	4199	4199	4199	4199

In this table, I show that ethnic connections predict bilateral exports per capita between neighboring countries. *Ethnic connections* are defined as the log ethnic match probability as defined in equation (4) and capture the likelihood of drawing two individuals from either country with the same ethnicity. Sample consist of bordering countries in Africa and includes country and destination by year fixed effects in all regressions. The main dependent variable are the logarithm of bilateral exports per current capita in the years 1992–2018. The following country-pair controls are added in all columns: log length of the border, log distance between capitals, a binary variable indicating whether parts of the border is a river, a mountain above 1,000 or 2,000 meter. The number of ethnic groups shared between the countries, whether the countries share a colonial past or judicial language, and log border fractionalization (Alesina et al., 2011). Linguistic and genetic distance $\in [0, 1]$ captures the similarity between the countries (Spolaore and Wacziarg, 2015). Inference is made on the basis of standard errors clustered by each country-pair, as shown in parenthesis. Two-way clustered standard errors allowing for separate home- and foreign-clusters shown as robustness in brackets. Significance denoted by standard errors clustered by the country pair: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Ethnic connections and trade flows
Alternative population data

	OLS			
	(1)	(2)	(3)	(4)
Ethnic connections	0.173**			
	(0.070)			
	[0.055]			
Ethnic connections, pre-colonial population		0.109**		
		(0.053)		
		[0.037]		
Ethnic network according to model			0.211**	
			(0.086)	
			[0.068]	
Ethnic connections, Ethnologue data today				0.146
				(0.111)
				[0.074]
Country-pair controls	Yes	Yes	Yes	Yes
Exporter and importer $\times$ year fixed effects	Yes	Yes	Yes	Yes
Conflict controls	4195	4195	4195	4195

In this table, I show that ethnic connections predict bilateral exports per capita between neighboring countries. *Ethnic connections* are defined as the log ethnic match probability as defined in equation (4) and capture the likelihood of drawing two individuals from either country with the same ethnicity. *Ethnic connections, pre-colonial population* are defined by the population figures for each ethnic group as recorded in Murdock (1959), multiplied with their population share in 1960 to obtain country-by-ethnic group population figures. *Ethnic network according to model* is defined following the model in Appendix D. *Ethnic connections, Ethnologue data today* are defined by current day population shares by ethnicity in each country. Sample consist of bordering countries in Africa and includes country and destination by year fixed effects in all regressions. The main dependent variable are the logarithm of bilateral exports per current capita in the years 1992–2018. The following country-pair controls are added in all columns: log length of the border, log distance between capitals, a binary variable indicating whether parts of the border is a river, a mountain above 1,000 or 2,000 meter. The number of ethnic groups shared between the countries, whether the countries share a colonial past or judicial language, and log border fractionalization (Alesina et al., 2011). Linguistic and genetic distance $\in [0,1]$ captures the similarity between the countries (Spolaore and Wacziarg, 2015). Inference is made on the basis of standard errors clustered by each country-pair, as shown in parenthesis. Two-way clustered standard errors allowing for separate home- and foreign-clusters shown as robustness in brackets. Significance denoted by standard errors clustered by the country pair: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: IV Results: Trade exposure and the gains from trade
Using a PPML estimation in the first stage

	Fraction lid		Average luminosity		Household welfare	
	(1) IV	(2) RF	(3) IV	(4) RF	(5) IV	(6) RF
Trade Exposure	-0.010***		-0.027**		-0.082***	
	(0.004)		(0.012)		(0.025)	
Predicted Trade Exposure		-0.006***		-0.018**		-0.076**
		(0.002)		(0.008)		(0.030)
Predicted Trade Exposure × In Power		0.005		0.022		0.037***
		(0.005)		(0.017)		(0.013)
Country × year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls					Yes	Yes
Reduced form		Yes		Yes		Yes
Observations	10,128	8,398	10,128	8,398	217,809	193,671
First Stage F-Test	29.690		29.690		64.480	

In this table, I show how trade exposure impacts economic development as measured by nighttime luminosity. *Trade Exposure* is defined as realized trade flows to all African countries aggregated to the country-by-year level and interacted with the population share of ethnicity e: $\sum_{d\in D} Export_{c,d,t} \times PopulationShare_{e,c}$ instrumented by *Predicted Trade Exposure*. *Country × year fixed effects* account for total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Trade Exposure* and *Predicted Trade Exposure* are identified only from the interaction of the two. *Fraction lid* is calculated as the fraction of pixels not zero, average luminosity as the log of average luminosity in each country-ethnic group observation plus one. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Trade exposure and society
Using a PPML estimation in the first stage

	Satisfaction with Democracy		Trust in Institutions		Conflict Incidence	
	(1)	(2)	(3)	(4)	(5)	(6)
Trade Exposure	-0.207***	-0.205***	-0.127***	-0.123**	-0.066**	-0.064*
	(0.056)	(0.067)	(0.049)	(0.060)	(0.027)	(0.033)
Country × year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes		
Observations	218,950	217,809	218,950	217,809	34,538	33,361
First Stage F-Test		64.480		64.480		85.875

In this table, I show how trade exposure impacts household welfare as measured by the Afrobarometer *Trade Exposure* is defined as realized trade flows to all African countries aggregated to the country-by-year level and interacted with the population share of ethnicity e: $\sum_{d\in D} Export_{c,d,t} \times PopulationShare_{e,c}$. *Country × year fixed effects* account for total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Trade Exposure* is identified only from the interaction of the two. *Individual controls* are a full set of age, gender, education, and urban dummies. *Satisfaction with Democracy* and *Trust in Institutions* represent standardized indexes constructed from variables asked in 7 rounds of the Afrobarometer. Details in the Appendix. *Conflict Incidence* is a binary variable whether the UCDP records a conflict in that country-ethnic group observation and year. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Afrobarometer questions

In this Appendix, I highlight the methodology and questions that go into creating the standardized indexes for household wealth, satisfaction with democracy, and trust in institutions.

Standardized Index Following Anderson (2008), I standardize each question within these three categories and sum the standardized outcomes, weighting each question by the inverse of the covariance matrix of the standardized outcomes. The four indices address concerns of multiple hypothesis testing and aggregate changes that individual questions only measure imperfectly. I also present results for individual questions with estimated p-values and false discovery rate-adjusted p-values, computed using the procedure outlined in Anderson (2008).

The individual questions are shown in Tables C.2–C.4 at the example of the Afrobarometer Round 7. All questions are recoded such that higher values in the question would correspond a positive impact of trade exposure. For example, question q8a "*Over the past year, how often, if ever, have you or anyone in your family: Gone without enough food to eat?*" is recoded such that the meaning is reversed: While in q8a higher values imply *more* food insecurity, the recoded variable has higher values for *less* food insecurity.

Table C.1: Trade exposure and the gains from trade
Individual responses and multiple hypothesis testing

	(1)	(2)	(3)	(4)
	beta	s.e.	*p*-value	FDR adj. *p*-value
Household welfare				
Country Condition	-0.125	0.086	0.145	0.159
Household Condition, Compared	-0.025	0.071	0.728	0.282
Household Condition	-0.133	0.078	0.088	0.124
Household Condition, Past	-0.189	0.136	0.165	0.159
Days with Food	-0.130	0.051	0.011	0.032
Days with Water	-0.212	0.083	0.010	0.032
Days with Cash	-0.046	0.055	0.400	0.282
Days with Fuel	-0.167	0.066	0.011	0.032
Satisfaction with Democracy				
Status of Democracy	-0.213	0.079	0.007	0.007
Satisfied with Democracy	-0.184	0.100	0.068	0.024
Freedom of Speech	-0.377	0.110	0.001	0.002
Trust in Institutions				
Trust in President	-0.320	0.166	0.053	0.092
Trust in Electoral Commission	-0.167	0.082	0.043	0.092
Trust in Ruling Party	-0.234	0.164	0.154	0.092
Trust in Traditional Leaders	-0.122	0.066	0.063	0.092

Notes: Results on all individual questions from the Afrobarometer survey. P-values run individually in column (3), p-values adjusted for Multiple Hypotheses Testing in column (4).

Table C.2: Variables and questions in the Afrobarometer
Household welfare

Variable	Question Number	Question Text
Country Condition	q4a	In general, how would you describe: The present economic condition of this country?
Household Condition, Compared	q5	How do you rate your living conditions compared to those of other people in your country?
Household Condition	q4b	In general, how would you describe: Your own present living conditions?
Household Condition, Past	q6	Looking back, how do you rate economic conditions in this country compared to twelve months ago?
Days with Food	q8a	Over the past year, how often, if ever, have you or anyone in your family: Gone without enough food to eat?
Days with Water	q8b	Over the past year, how often, if ever, have you or anyone in your family: Gone without enough clean water for home use?
Days with Cash	q8e	Over the past year, how often, if ever, have you or anyone in your family: Gone without a cash income?
Days with Fuel	q8d	Over the past year, how often, if ever, have you or anyone in your family: Gone without enough fuel to cook your food?

Notes: The table lists the individual questions included in Table C.1 under the category *Household welfare*. All variables are recoded such that higher values imply higher welfare. Question number and text refer to the Afrobarometer Round 7 questionnaire.

Table C.3: Variables and questions in the Afrobarometer
Satisfaction with Democracy

Variable	Question Number	Question Text
Status of Democracy	q35	In your opinion, how much of a democracy is your country today?
Satisfied with Democracy	q36	Overall, how satisfied are you with the way democracy works in your country?
Freedom of Speech	q42a	In your opinion, how often, in this country: Do people have to be careful of what they say about politics

Notes: The table lists the individual questions included in Table C.1 under the category *Satisfaction with Democracy*. All variables are recoded such that higher values imply higher satisfaction with democracy. Question number and text refer to the Afrobarometer Round 7 questionnaire.

Table C.4: Variables and questions in the Afrobarometer
Trust in Institutions

Variable	Question Number	Question Text
Trust in President	q43a	How much do you trust each of the following, or haven't you heard enough about them to say: The President?
Trust in Electoral Commission	q43c	How much do you trust each of the following, or haven't you heard enough about them to say: Electoral commission
Trust in Ruling Party	q43e	How much do you trust each of the following, or haven't you heard enough about them to say: The Ruling Party?
Trust in Traditional Leaders	q43j	How much do you trust each of the following, or haven't you heard enough about them to say: Traditional leaders?

Notes: The table lists the individual questions included in Table C.1 under the category *Trust in Institutions*. All variables are recoded such that higher values imply higher trust in institutions. Question number and text refer to the Afrobarometer Round 7 questionnaire.

D Technical Appendix

In this section, I derive a model of international trade with firm and ethnic heterogeneity to provide a motivation for the main estimation equation (4). My framework draws on Chaney (2008) and nests the standard model while remaining tractable.

The economy consists of N countries which contain a subset $e \in E$ of predefined ethnic groups. Not every ethnicity is present in every country. Furthermore, every economy produces a homogeneous composite good q_0, as well as horizontally differentiated goods $q(\omega)$. Any firm of ethnicity $e \in E$ producing a heterogeneous good $\omega \in \Omega$ from country $i \in N$, uses its ethnic counterpart $e' \in E$ in country $j \in N$ to maximize the expected profits from selling in market $j \in N$ according to:

$$\pi_{ij,ee'}(\omega) = p_{ij}(\omega)q_{ij}(\omega) - c_{ij,ee'}(\omega) \tag{5}$$

Where the price of a good $p_{ij}(\omega)$ is country specific, as is the demand for a good $q_{ij}(\omega)$.[16] $\tau_{ij} > 1$ represent variable trade costs, denoted as "iceberg trade costs". A firm needs to produce τ_{ij} goods in order to sell one unit in country j. The cost of producing a good $c_{ij,ee'}(\omega)$ is assumed to be ethnic dependent in home e and foreign e' and of the form:

$$c_{ij,ee'}(\omega) = \frac{\tau_{ij}}{\varphi} q_{ij}(\omega) + \left(\frac{L_{j,e'}}{L_j}\right)^{-\eta} f_{ij} \tag{6}$$

Here, φ denotes productivity which every firm draws from a Pareto distribution $G(\varphi) = 1 - \varphi^{-\gamma}$.[17] γ represents the degree of firm heterogeneity, with increasing values denoting decreasing firm heterogeneity. Firms learn about their productivity when drawing from $G(\varphi)$ and, subsequently, decide to pay country pair specific fixed costs f_{ij} in order to serve market j.[18] These fixed costs are mitigated by the fraction of the population in country j that is of the same ethnicity $e' = e \in E$ as the owner of the firm.[19] I call the effect of

[16] Although Aker et al. (2014) show that ethnic groups affect the prices between two countries, I assume that this is a result of a supply or demand shock. However, including a demand shock here would create a simple demand shift in the gravitiy equation. Alternatively, one could divide the product space into goods consumed by ethnic groups which would yield a result similar to including different sectors.

[17] Following the literature standard I use the Pareto distribution as it mirrors the empirical distributions well (Axtell, 2001) and is notational convenient.

[18] The cost of producing a good are wages times $c_{ij,ee'}(\omega)$. Due to the production in the freely traded homogeneous good q_0 wages in both sectors are normalized to unity to simplify the expressions. Furthermore, since there are infinitely many possible firms of each ethnicity, I can characterize the costs of producing variety ω simply by the ethnicity and the productivity of the firm φ.

[19] A similar approach has been undertaken by Krautheim (2012) where the fraction is the number of domestic firms active in the destination market. In the following, I assume that every ethnicity has at least one member in every country. I can relax this assumption and assume that there is an additional fixed cost

the fraction $\left(\frac{L_{j,e'}}{L_j}\right)^{-\eta}$ the network effect of ethnic ties. This fraction lies within the unit interval and raised to the power of $\eta \in \left[0, \frac{\sigma-1}{\gamma}\right)$ that gives the importance of ethnic networks in decreasing the fixed costs of exporting. It can be interpreted as a decreased costs of acquiring information about the market structure in the destination country or market demand. Alternatively, its interpretation permits lower payments to government officials because of ethnic ties or it serves a proxy for the general trust-worthiness of a society. Empirical evidence by Grossman et al. (2006) suggests that factors like cultural distance and institutional development are particular relevant for the fixed cost of exporting. Ethnic networks should then be beneficial when firms try to circumvent bureaucratic hurdles. The larger the hurdles, the larger should be the impact of ethnic networks.

In every country, households maximize their utility according to:

$$U = q_0^{1-\mu} \left(\int_{\omega \in \Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}\mu} \tag{7}$$

That is, they consume a freely traded homogeneous good q_0 and consume every available variety of the heterogeneous good ω. The share of income spent on the heterogeneous good is given by μ and the elasticity of substitution is given by $\sigma > 1$. Standard results lead to a pricing of $p_{ij}(\varphi) = \frac{\sigma}{\sigma-1}\frac{\tau_{ij}}{\varphi}$ and a demand:

$$q_{ij}(\varphi) = p_{ij}(\varphi)^{-\sigma} P_j^{\sigma-1} \mu \left(1 + \frac{\Pi}{L}\right) L_j. \tag{8}$$

Here, $\left(1 + \frac{\Pi}{L}\right) L_j$ denotes the fraction of world capital Π and labor L income that belongs to country j.[20] Hereof, a fraction μ is spend on heterogeneous goods. Combining the profit function, pricing and demand yield the ethnicity dependent productivity cutoff above which firms start to export due to non-negative profits $\pi_{ij,ee'} \geq 0$:

$$\varphi^*_{ij,ee'} = \left(\frac{\sigma}{\sigma-1}\right) \frac{\tau_{ij}}{P_j} \left[\frac{\mu}{\sigma}\left(1 + \frac{\Pi}{L}\right) L_j\right]^{\frac{1}{1-\sigma}} \left(\frac{L_{j,e'}}{L_j}\right)^{\frac{\eta}{1-\sigma}} f_{ij}^{\frac{1}{\sigma-1}} \tag{9}$$

The price index P_j can be solved explicitly by summing all prices from all exporting countries together, taking their productivity cutoffs into account.[21] Then, the productivity cutoff can be expressed in terms of primitives:

to pay when dealing with non co-ethnic members. The results are robust.

[20]Due to the sector that produces the homogeneous goods, wages are driven down to unity.

[21]$P_j = \left(\sum_{k=1}^{N} L_k \sum_{e \in E} \int_{\varphi^*_{kj,ee'}}^{\infty} \left(\frac{\sigma}{\sigma-1}\frac{\tau_{kj}}{\varphi}\right)^{1-\sigma} dG(\varphi)\right)^{\frac{1}{1-\sigma}}$.

$$\varphi^*_{ij,ee'} = \left[\frac{\gamma}{\gamma-(\sigma-1)}\right]^{\frac{1}{\gamma}} \left[\frac{\mu}{\sigma}\left(1+\frac{\Pi}{L}\right)\right]^{-\frac{1}{\gamma}} L_j^{\frac{\eta-1}{\gamma}} \frac{\tau_{ij}}{\theta_j} f_{ij}^{\frac{1}{\sigma-1}} (L_{j,e'})^{\frac{\eta}{1-\sigma}} \tag{10}$$

As in Chaney (2008), the total foreign population decreases the cutoff due to market size effects $L_j^{\frac{\eta-1}{\gamma}}$. This effect is dampened by $\frac{\eta}{\gamma}$ because the ethnic population has a stronger effect on the cutoff than the total population.[22] θ denotes the multilateral resistance term that approximates how distant a market is in comparison to all other markets.[23] Equation (10) suggests that much of the ethnic network effect will work through the extensive margin of trade. If the fixed costs of exporting are higher due to corruption, the cutoff for ethnically connected and non-connected firms increases, but to a lesser extent for the former group.[24]

In order to obtain a testable equation, I aggregate individual demand[25] to an network extended gravity equation:

$$X_{ij} = \mu\left(1+\frac{\Pi}{L}\right) L_j f_{ij}^{\frac{\sigma-1-\gamma}{\sigma-1}} \left(\frac{\tau_{ij}}{\theta_j}\right)^{-\gamma} \sum_{e\in E_i\cap E_j} L_{i,e}(L_{j,e'})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}} \tag{11}$$

Total exports between any pair of countries increase in market size $\mu\left(1+\frac{\Pi}{L}\right)L_j$ and multilateral resistance θ and decrease in variable trade cost τ_{ij} and fixed costs f_{ij}. The network term is increasing the total trade flows since $\nu \equiv \frac{\eta(\sigma-1-\gamma)}{1-\sigma} \in [0,1)$ in order to obtain interior solutions for the system of equations.[26] If the number of ethnic groups is greater then the number of countries, the system of equations is under-identified and individual parameters in ν cannot be identified. A way around is to assume specific

[22] The original cutoff in Chaney (2008) can be recovered by setting $\eta = 0$. The effect of the foreign ethnic population is greater since $\frac{\eta}{\gamma} < \frac{\eta}{\sigma-1}$ due to the assumption $\gamma > \sigma - 1$ that guarantees interior solutions.

[23] $\theta_j = \left[\sum_{k=1}^N f_{kj}^{\frac{\sigma-1-\gamma}{\sigma-1}} \tau_{kj}^{-\gamma} \sum_{e\in E} L_{k,e}(L_{j,e})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}}\right]^{-\frac{1}{\gamma}}$. A popular example is the comparison between Portugal and Spain with New Zealand and Australia. Similar in terms of GDP, the latter trade relatively more with each other due to their distance to all other markets in the world.

[24] Putting it differently, in a world where all the fixed cost consist of corruption and trust, the ethnic networks are paramount to exporting. We should observe only ethnically connected firms. A similar exercise can be done by changing the cost function into a part which is ethnic dependent (trust and corruption) and a part that is non ethnic dependent. Then ethnic networks do not matter when there is no ethnic dependent fixed costs, but matter a lot when there is no non ethnic dependent fixed cost.

[25] $X_{ij} = L_i \sum_{e'=e\in E} \frac{L_{i,e}}{L_i} \int_{\varphi^*_{ij,ee'}}^{\infty} dG(\varphi)$, where $\frac{L_{i,e}}{L_i}$ is the ethnic fraction in country i. An alternative summation would be to include the non ethnic population in foreign and their cutoffs: $X_{ij} = L_i \left[\sum_{e\in E_i\cap E_j} \frac{L_{i,e}}{L_i} \int_{\varphi^*_{ij,ee'}}^{\infty} dG(\varphi) + \sum_{e'\neq E_i\cap E_j} \frac{L_{i,e}}{L_i} \int_{\varphi^*_{ij,ee'}}^{\infty} dG(\varphi)\right]$. The second term would be condensed to the part in Chaney (2008).

[26] I further require that $\gamma > (\sigma - 1)$ and $\eta < \frac{(\sigma-1)}{\gamma}$ to guarantee an interior solution.

values for ν and conduct sensitivity analyses. Specifically, if ν takes on the value one, the ethnic network variable leads to a search and matching interpretation and gives the likelihood that two randomly selected firms from both countries are of the same ethnicity, when controlling for population size.

The introduction of ethnic heterogeneity in the framework of Melitz (2003) and Chaney (2008) introduced a second source of heterogeneity that creates a particular feature regarding export decisions. Firms owned by an ethnic minority might first export to other markets and only later serve their home market. This feature is similar to capital-constraint firms that cannot export in Chaney (2016) and implies imperfect selection into exporting. Firms that export might have lower productivity than firms that do not and, thus, create welfare losses.

The empirical equivalent of this equation is given by:

$$\log(X_{ij,t}) = \beta \log \left(\sum_{e \in i \cap j}^{E} L_{i,e} (L_{j,e'})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}} \right) + \Gamma_{ij,t} + \delta_i + \delta_j + \varepsilon_{ij,t} \tag{12}$$

Since the importer and exporter fixed effect also capture population in each country and $(L_j \times L_i)^{-1} = -\log L_j - \log L_i$ one can rewrite the equation as:

$$\log(X_{ij,t}) = \beta \log \left(\sum_{e \in i \cap j}^{E} \frac{L_{i,e}}{L_i} \times \frac{(L_{j,e'})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}}}{L_j} \right) + \Gamma_{ij,t} + \delta_i + \delta_j + \varepsilon_{ij,t} \tag{13}$$

which as $\frac{\eta(\sigma-1-\gamma)}{1-\sigma} \to 1$ approaches equation (4). This equation can be interpreted as a search and matching model, where the population in the importing country has to incur a penalty, thus needs a larger population to have the same effect on trade as the exporting population.

D.1 Inter-ethnic Trade

So far I assumed that connections can only exist within ethnic groups and neglected the possibilities of inter-ethnic connections. Here, I relax this initial assumption and assume that every ethnicity has an implicit (weak) ranking of every other ethnicity. Then, for every ethnicity I can order the other ethnic groups according to the cost they have to incur in order to conduct business with them. This cost is similar to the fixed costs discussed earlier, in the sense that it reflects learning costs between ethnic groups. Therefore, I assume there exists a matrix $F_{E \times E}$ that reflects this ordering between every possible combination of ethnic groups. The cost of producing and exporting are then given by:

$$c_{ij,ee'}(\varphi) = \frac{\tau_{ij}}{\varphi} q_{ij}(\varphi) + \left(\frac{L_{j,e'}}{L_j}\right)^{-\eta} f_{ij} f_{ij,ee'} \tag{14}$$

with $f_{ij,ee'}$ being an element from $F_{E\times E}$. Here bilateral fixed costs are disentangled from ethnic specific cost. Every firm has to incur bilateral fixed costs to set up the firm, but also have to invest in ethnic relations in order to mitigate the additional ethnic specific fixed costs.[27] The gravity equation is then given by:

$$X_{ij} = L_j \mu \left(1 + \frac{\Pi}{L}\right) f_{ij}^{1-\frac{\gamma}{\sigma-1}} \left(\frac{\tau_{ij}}{\theta_j}\right)^{-\gamma} \sum_{e \in E \cap E'} L_{i,e} (L_{j,e'})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}} f_{ij,ee'}^{1-\frac{\gamma}{\sigma-1}} \tag{15}$$

Now, the effect of ethnic match probabilities is not only measured within ethnic groups, but also between ethnic groups. If the fixed costs of creating ties between ethnic groups are low enough, this specification should fit the data better. Combining the findings on the extensive margin formulation and the ethnic specific fixed costs, ethnic groups have a two fold effect on trade flows. They increase the number of firms exporting in distrustful environments by affecting the extensive margin. However, trade volumes between two countries are negatively affected by the ethnic specific fixed costs. Then if these fixed costs represent trust or corruption issues, the above model puts a strong emphasis on reducing corruption and increase trust among ethnic groups.

D.2 Empirical results from the theoretical Model

Table D.1 presents the empirical results to estimating the theoretical model on trade flows between all African countries using OLS in odd columns and PPML in even. The point estimates are not statistically different from the baseline empirical results in Table B.2, and allowing for inter-ethnic trade increases the importance of ethnic networks, as expected.

[27] The basic model is a special case of this case where the off diagonal elements of $F_{E\times E}$ are assumed to be so high that only within ethnicity connections can occur.

Table D.1: Ethnic connections and trade flows
log(Exports) between all countries

	OLS	PPML	OLS	PPML	OLS	PPML
	(1)	(2)	(3)	(4)	(5)	(6)
log(Size of Network)	0.130^{***}	0.085^{***}				
	(0.024)	(0.024)				
	[0.033]	[0.027]				
log(Size of Network, exponent=0.2)			0.197^{***}	0.131^{***}		
			(0.038)	(0.038)		
			[0.054]	[0.049]		
log(Size of Network, allowing for inter-ethnic networks)					0.859^{***}	1.282^{***}
					(0.156)	(0.178)
					[0.369]	[0.245]
Country-pair controls	Yes	Yes	Yes	Yes	Yes	Yes
Exporter and importer $\times$ year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,983	38,271	37,983	38,271	37,983	38,271

In this table, I show that ethnic connections predict bilateral exports per capita between all countries using the models empirical equation. *log(Size of Network* is estimating equation (12) with the exponent on foreign ethnic population $L_{j,e'}^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}}$ being set to one. *log(Size of Network* is estimating equation (12) with the exponent on foreign ethnic population $L_{j,e'}^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}}$ being set to 0.2 based on reasonable values for the elasticity of substitution σ, the pareto parameter γ and η based on the assumption that $\gamma > (\sigma - 1)$ and $\eta < {}^{(\sigma-1)}/_{\gamma}$. *log(Size of Network, allowing for inter-ethnic networks* estimates equation (15) Sample consist of all countries in Africa and includes country and destination by year fixed effects in all regressions. The main dependent variable are the logarithm of bilateral exports per current capita in the years 1992–2018. The following country-pair controls are added in all columns: log length of the border, log distance between capitals, the number of ethnic groups shared between the countries, whether the countries share a colonial past or judicial language. Linguistic and genetic distance $\in [0, 1]$ captures the similarity between the countries (Spolaore and Wacziarg, 2015). Inference is made on the basis of standard errors clustered by each country-pair, as shown in parenthesis. Two-way clustered standard errors allowing for separate home- and foreign-clusters shown as robustness in brackets. OLS and PPML denote the estimation method. Significance denoted by standard errors clustered by the country pair: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$