The Role of Ethnic Networks in Africa: Evidence from Cross-Country Trade

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Abstract

I investigate the role of ethnic networks on regional African development on the basis of bilateral trade flows. To identify ethnic networks across borders I employ a spatial identification strategy for ethnic networks based on the exogeneity of African political boundaries. I find that ethnic networks in African countries are an important determinant of bilateral trade flows. In particular, ethnic networks decrease the bilateral trade costs in corrupt or distrustful countries. Ethnic networks also affect the choice of exporting through an informational channel that reduces fixed costs of exporting. I find the export value added from one additional network member to be 3.6 US$ of exports in 2010. Considering the average network size of 1.5 million people, ethnic networks contribute a considerable fraction to average trade flows. In terms of trade costs, ethnic network decrease average trade cost as measured by distance by up to 26%.

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1 Introduction

Geographically separated ethnic enclaves tend to generate their own network that span multiple countries. These networks constitute both a barrier and an opportunity to economic development. Ethnic networks may exclude non-members from economically profitable actions but also facilitate them for members, especially across country borders. In countries traversed by mistrust such linkages are potentially more important (Dunlevy 2006) since they act as a source of information, a way to share risks (Fafchamps & Gubert 2007) or to bargain for preferred policies Bates (2008).

In this paper I show that ethnic networks between African countries reduce trade costs significantly. Furthermore, these networks are more effective in overcoming trade barriers in more corrupt or distrustful countries.

African countries are distinctly different from the rest of the world. Figure 1 shows the distribution of ethnicities and countries in Africa. Political borders are not a result of independence struggles or inner African wars but drawn by European colonial powers in the late nineteenth century. This lead to a mixture of ethnicities and tribes both within and across countries. Today, the average African country has more than 10 ethnic groups who often speak their own language such that national identification is often an issue, as country borders were set without considering the ethnic composition. The formation of African states and favoritism of one ethnicity by colonial powers led to ethnic motivated conflicts in the second half of the twentieth century.[1] In elections ethnic identification plays an important role in vote casting (Eifert et al. 2010). If ethnic solidarity also holds across borders, it is likely to affect trade flows between countries.[2]

Empirical evidence for an effect of networks on bilateral trade flows in developing countries is scarce. Peri & Requena-Silvente (2010) and Balnes-Cristóbal (2008) underline the importance of migrants in Spain on the export decision of Spanish firms. The same pattern holds for French firms as Combes et al. (2005) show. For Bolivia Canavire et al. (2006) exemplify the importance of migration for the value of bilateral trade flows and in South-East Asia, Chinese network links

[1] e.g. Rwanda 1994, Congo 1998, Mali 2012, Central African Republic 2014 (although the latter are also of religious nature, the underlying reason is that a minority was favored by French colonialists.) [List incomplete]

[2] One example was the temporary practice of Air Namibia, the major carrier of Namibia, having a stopover in Luanda (Angola) only to refuel due to disputes with the fuel supplier at their main airport. The airline is run by an ethnicity that has strong ties between the two countries and hence uses its credibility in Angola to buy fuel. `http://www.economist.com.na/headlines/2795-air-namibia-increases-frankfurt-flights` and `http://hannamibia.com/uploads/pdf/news/130305093441120.pdf` Additionally, the main supplier of kerosin, Engen, is South African and the ethnicity is only dispersed in Angola and Namibia.

attribute up to 1.4% to trade creation (Felbermayr et al. 2010). However, empirical evidence using all African countries is missing. In this paper I aim at filling that gap and investigate how ethnic networks influence bilateral trade flows between African countries.

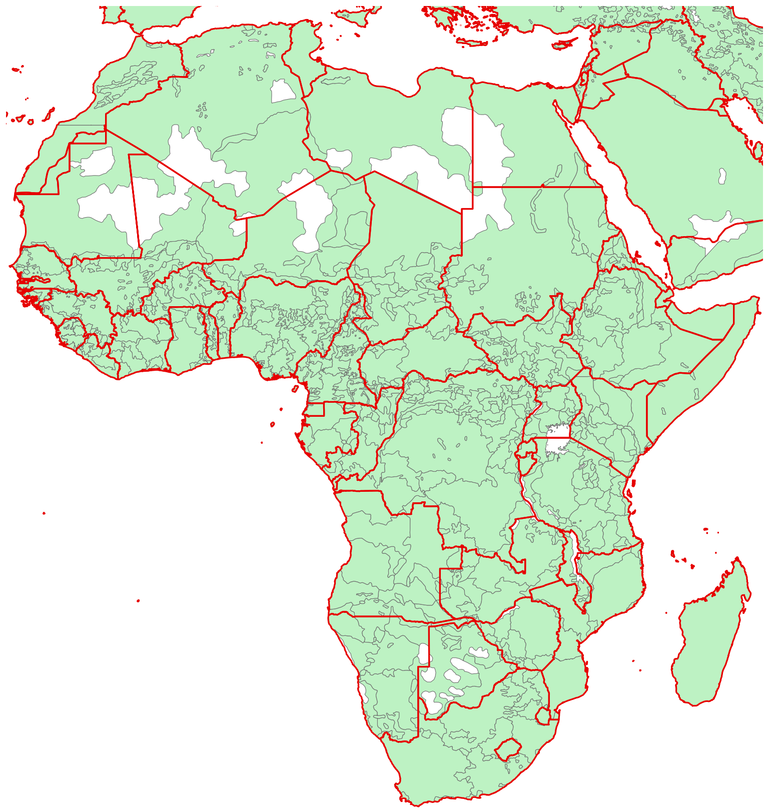


Figure 1: Ethnic (Grey) and Country (Red) Boundaries

Studying the effects of ethnic networks in Africa entails many challenges. First, data quality about African ethnicities is at most questionable. Different names of ethnicities, language barriers and historical ethnic conflicts constitute considerable obstacles for research. Second, conflicts or natural catastrophes might cause migration across borders thus leading to endogeneity of current networks. The U.S. for instance attracts many immigrants due to its economic power and as Woodruff & Zenteno (2007) show, Mexican immigrants use existing networks to migrate, thus creating reversed causality concerns. I aim to overcome these issues using a spatial identification strategy by using ethnic networks as they were in 1960.

The spatial identification strategy I employ is based on the random formation of country borders in Africa. This approach has recently attracted considerable interest among economics due immutability of geographic factors (Nunn 2008, Nunn & Wantchekon 2011, Nunn & Puga 2012, Michalopoulos & Papaioannou 2013, 2014). Using an African map provided by Weidmann et al. (2010) I identify ethnic groups in 1960 and use them as a proxy for ethnic networks today. In a reduced form approach I estimate the effect of ethnicity on bilateral trade flows. Due to the randomness of country borders in Africa with respect to ethnicities I argue that my approach identifies a causal effect. I augment a model by Chaney (2008) with an ethnic specific fix cost function and estimate the elasticity of exports to ethnic networks to be around 0.06. On average increasing an average network by 1% (26,000 people), increases bilateral trade flows by 0.06% or 96,000 US$ in 2010.

The point estimate I find is at the lower end of estimates found in the literature for developed countries (Bandyopadhyay et al. 2008).[3] One explanation is that ethnic networks are less important for bilateral trade in developing countries. This would contradict Dunlevy (2006) who argues that networks are important in corrupt regimes. Considerable heterogeneity of export volumes between African countries might also be an explanation why this estimate is found to be low. Regional African economic integration or political willingness may be different such that not all countries can fully benefit from their ethnic networks.

Another possibility why the coefficients in the literature are higher then the one found in this study are neglected endogeneity concerns. If groups are forced to migrate, they will use network clusters in order to enter new countries (McKenzie & Rapoport 2007). Accordingly, if network clusters are formed by trade flows it causes reverse causality issues. Following this argument empirical results not addressing this point suffer from an upward bias regarding the effect of migration.

This work relates to the literature on networks and trade started by Gould (1994) who investigated the importance of immigrant links for historical US trade flows. To my knowledge, Rauch (1999) is the first study who uses a network/search framework to estimate the networks effect. Both studies use migrant links, instead of migrant stocks or flows, to mitigate endogeneity problems. In a subsequent paper Rauch & Trindade (2002) use the framework to asses the network effect of Chinese migrants in South-East Asia and find that Chinese networks make up 60% of the increase in bilateral trade flows. Felbermayr et al. (2010) and Felbermayr & Toubal (2012) criticize their strategy and augment the initial model by indirect links providing evidence for an upward bias in Rauch & Trindade (2002). In their study the elasticity of Chinese networks and bilateral trade flows is dwarfed by other networks and only estimated at 1.4%.

[3]Generally, most empirical evidence concentrates on migration from developing to developed countries. However, despite the increase since 1970 (Oezden et al. 2012) migration between developing countries still constitutes the largest migration flow. Additionally, ethnic networks in developing countries are especially important since developing countries are often more corrupt (Dunlevy 2006, Svensson 2003, Olken & Barron 2009). Thus, the influence of ethnic networks on bilateral trade flows can be expected to be larger than between developed countries.

In general the US and Canada have been studied extensively (Gould 1994, Dunlevy & Hutchinson 1999, Herander & Saavedra 2005, Dunlevy 2006, White 2007, Partridge & Furtan 2008). Except for Felbermayr et al. (2010) none of these studies address endogeneity concerns as outlined before. Although they include African countries, they do not estimate their model for this subset[4].

As an exception, Balnes-Cristóbal (2008) and Peri & Requena-Silvente (2010) investigate the network effects for bilateral trade flows between developing countries and Spain. Balnes-Cristóbal (2008) investigates the characteristics of immigrants and distinguishes between an information and preference channel. The information channel underlines the importance of better information for the export decision. Immigrants want to consume their home goods in their destination country which is what Balnes-Cristóbal calls the preference channel. Comparing both channels the author finds that an increase in export to those country is mainly driven by increased information, an hypothesis I aim to verify.

Peri & Requena-Silvente (2010) support this finding and use an instrumental variable strategy based on historical enclaves. This study also includes some African countries[5] where the estimated elasticity of networks on exports varies between 0.06-0.18. For French enclaves Combes et al. (2005) identifies bilateral intensity of networks by the location of French firms in France and stocks of migrants. However, by instrumenting the latter with historical stocks from 1978 they reject the existance of an endogeneity bias in their data.

The importance of ethnic networks on the African continent has been subject to research for a variety of topics. Fafchamps (2003) using micro level surveys in Benin, Malawi and Madagascar shows the importance of networks in creating trust. Local market vendors however are not affected by ethnic networks as they usually operate within their own ethnicity. Additionally, the information available to a local producer is much more complete than to a producer who exports, making the exporting producer more reliant on trustworthy information.

In a micro level study at the border between Niger and Nigeria Aker et al. (2014) exemplify the effect of ethnic networks on price dispersion of agricultural goods. Within ethnic trade across borders mitigate the price dispersion significantly. Furthermore, the remaining price dispersion is of equal size to the price dispersion between ethnic groups within Niger.

[4]Included countries: Algeria, Egypt, Ethiopia, Ghana, Kenya, Libya, Nigeria, Morocco, South Africa, Sudan and Tunisia.

[5]Included countries: Angola, Algeria, Cape Verde, Gambia, Ghana, Guinea, Guinea-Bissau, Equatorial Guinea, Mali, Morocco, Mauritania, Nigeria, Senegal, Sierra Leone and Tunisia.

In a political economy setting even small ethnic groups can influence local politics. For the case of Kenya Burgess et al. (2013) show that government seats are distributed across ethnicities to foster peace. This view is supported by Francois et al. (2013) who show that government power is often distributed proportionally to population shares which implies that minorities have political power and small ethnic networks are likely to have an effect on trade flows. Since members in political offices can either distribute government contracts or decrease political uncertainty they may decrease the cost of exporting for own ethnicities in other countries.

The remainder of this paper is structured as follows. In section 2 I present a theory of how ethnic networks influence bilateral trade flows. In section 3 I describe the data and in 4 I highlight the empirical strategy and address endogeneity concerns. In section 5 I discuss my baseline results. In section 6 I conduct a series of robustness checks to verify the results. I identify the potential channels in section 7. In section 8 I will discuss my findings and their implication. I conclude in section 9.

2 Theory

In this section I will shortly derive a model of international trade with firm and ethnic heterogeneity. My framework draws from Chaney (2008) and will provide empirical predictions and testable implications.

The economy consists of N countries which contain a subset $e \in E$ predefined ethnicities. Not every ethnicity is present in every country. Further more every economy produces a composite good q_0 and 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:

$$\pi_{ij,ee'}(\omega) = p_{ij}(\omega)q_{ij}(\omega) - c_{ij,ee'}(\omega) \tag{1}$$

Where the price of a good $p_{ij}(\omega)$ is country specific,[6] as is the demand for a good $q_{ij}(\omega)$. $\tau_{ij} > 1$ represent variable trade costs, denoted as "iceberg trade costs". A firm needs to produce τ_{ij}

[6] Although Aker et al. (2014) show that ethnicities affect the prices between two countries, I assume that this is a result of a supply or demand shock.

goods in order to sell one unit in country j. The cost of producing a good $c_{ij,ee'}(\omega)$ are assumed to be ethnic dependent in home e and foreign e' and of the form:

$$c_{ij,ee'}(\omega) = \frac{\tau_{ij}}{\varphi} q_{ij}(\omega) + \left(\frac{L_{j,e'}}{L_j}\right)^{-\eta} f_{ij} \tag{2}$$

Here, φ denotes productivity which every firm draws from a Pareto distribution $G(\varphi) = 1 - \varphi^{-\gamma}$.[7] Here 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.[8] 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.[9] I call the effect of the fraction $\left(\frac{L_{j,e'}}{L_j}\right)^{-\eta}$ the network effect of ethnic ties. This fraction is in 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 decreased costs of acquiring information about the destination country's market structure or market demand. Alternatively, one can interpret it as lower payments to government officials because of ethnic ties or as a proxy for the general trust worthiness of a society. In a society with poorly enforced market rules and a general aura of mistrust, the importance of ethnic networks in order to circumvent failure or bribes is likely to be greater than in well developed markets. This leads to the first set of testable predictions of the model:

Hypothesis 1 *Ethnic networks are more important in countries with poorly enforced rules, lower social norms and lower levels of trust*

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 bureaucratically hurdles. The larger these hurdles, the larger should be the impact of ethnic networks.

[7]Following a great share of the literature I use the Pareto distribution because it mirrors the empirical distributions well Axtell (2001) and is notational convenient.

[8]The cost of producing a good are wages times $c_{ij,ee'}(\omega)$. I do however normalize wages 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.

[9]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 will relax that assumption when I extend the basic framework.

In every country households maximize their utility according to:

$$U = q_0^{1-\mu} \left(\int_{\omega \in \Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}\mu} \tag{3}$$

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 $\mu = 1 - \mu$ 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:

$$q_{ij}(\varphi) = p_{ij}(\varphi)^{-\sigma} P_j^{\sigma-1} \mu \left(1 + \frac{\Pi}{L}\right) L_j \tag{4}$$

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. Hereof, a fraction μ is spend on heterogeneous goods. Combining the profit function, pricing and demand yields the ethnicity dependent productivity cutoff above which firms start to export due to non-negative profits $\pi_{ij,ee'} \geq 0$:

$$\varphi^*_{ij,ee'} = \left(\frac{\sigma}{\sigma-1}\right) \frac{\tau_{ij}}{P_j} \left[\frac{\mu}{\sigma}\left(1 + \frac{\Pi}{L}\right) L_j\right]^{\frac{1}{1-\sigma}} \left(\frac{L_{j,e'}}{L_j}\right)^{\frac{\eta}{1-\sigma}} f_{ij}^{\frac{1}{\sigma-1}} \tag{5}$$

Now, the price index P_j can be solved explicitly by summing all prices from all exporting countries together, taking their productivity cutoffs into account.[10] Then, the productivity cutoff can be expressed in terms of primitives:

$$\varphi^*_{ij,ee'} = \left[\frac{\gamma}{\gamma - (\sigma-1)}\right]^{\frac{1}{\gamma}} \left[\frac{\mu}{\sigma}\left(1 + \frac{\Pi}{L}\right)\right]^{-\frac{1}{\gamma}} L_j^{\frac{\eta-1}{\gamma}} \frac{\tau_{ij}}{\theta_j} f_{ij}^{\frac{1}{\sigma-1}} (L_{j,e'})^{\frac{\eta}{1-\sigma}} \tag{6}$$

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 then the total population.[11] θ denotes the multilateral resistance term that approximates how distant a market is in comparison to all other markets.[12] In order to obtain a testable

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

[11] 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.

[12] $\theta_j = \left[\sum_{k=1}^N f_{kj}^{\frac{\sigma-1-\gamma}{\sigma-1}} \tau_{kj}^{-\gamma} \sum_{e \in E} L_{k,e} (\delta L_{j,e})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}} \right]^{-\frac{1}{\gamma}}$. 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 world wide.

equation, I aggregate individual demand[13] to the standard gravity equation as first noted in Anderson (1979):

$$X_{ij} = \mu \left(1 + \frac{\Pi}{L}\right) L_j f_{ij}^{\frac{\sigma-1-\gamma}{\sigma-1}} \left(\frac{\tau_{ij}}{\theta_j}\right)^{-\gamma} \sum_{e'=e \in E} L_{i,e} (L_{j,e'})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}} \tag{7}$$

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 additionally because $\nu \equiv \frac{\eta(\sigma-1-\gamma)}{1-\sigma} \in [0,1)$ in order to obtain interior solutions for the system of equations.[14] If the number of ethnicities is greater then the number of countries, the system of equations is under identified and cannot be estimated consistently. A workaround is to assume specific values for ν and conduct sensitivity analyses.

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. A famous example of this behavior is the German Beck's brewery that first produced only for the export market and only later allowed their products to be sold in Germany. This feature is similar to capital constraint firms that cannot export in **?** and implies imperfect selection into exporting. Firms that export might have lower productivity than firms that do not creating welfare losses.

The Extensive Margin Having derived the main theoretical equation to be tested empirically, I will focus now on further predictions and implications. At first, I will examine the extensive margin implications by the model.[15] Following Helpman et al. (2008) one can rewrite the equilibrium profits by firms and obtain an indicator Z that defines whether a firm is exporting or not.

$$\pi_{ij,ee'}(\varphi) = \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \frac{\mu}{\sigma}\left(1+\frac{\Pi}{L}\right) L_j \tau_{ij}^{1-\sigma} \varphi^{\sigma-1} P_j^{\sigma-1} - \left(\frac{L_{j,e'}}{L_j}\right)^{-\eta} f_{ij} = 0 \Rightarrow$$

$$Z \equiv \frac{\frac{\mu}{\sigma}\left(1+\frac{\Pi}{L}\right)^{\frac{\sigma-1}{\gamma}} \left(\frac{\tau_{ij}}{\theta_j}\right)^{1-\sigma} \varphi^{\sigma-1} L_j^{(1-\eta)\frac{\sigma-1}{\gamma}}}{L_{j,e'}^{-\eta} f_{ij}} \geq 1 \tag{8}$$

[13] $X_{ij} = L_i \sum_{e'=e \in E} \frac{L_{i,e}}{L_i} \int_{\varphi^*_{ij,e}}^{\infty} q_{ij,ee'}(\varphi) dF(\varphi)$ where $\frac{L_{i,e}}{L_i}$ is the ethnic fraction in country i.

[14] I further require that $\gamma > (\sigma-1)$ and $\eta < \frac{(\sigma-1)}{\gamma}$.

[15] The extensive margin of trade is defined as the number of firms newly starting to export after a reduction in trade costs. In contrast, the intensive margin amounts to export value adjustments of already existing firms.

That is, the probability of exporting to another country $\Pr[Z \geq 1]$ increases in the ethnic population abroad. In fact, for a specific ethnicity, increasing the ethnic homogeneity in favor of a firms ethnicity in the destination country increases the probability of exporting. The advantage of this formulation is the ability to investigate the effect of networks on the extensive margin of trade. Furthermore, there should be a positive relationship between the number of ethnic connections between two countries and the number of firms actively trading.[16]

Hypothesis 2 *Number of firms exporting is increasing in the number of ethnic connections between two countries*

The second hypothesis states that ethnic heterogeneity is beneficial for firms exporting, because they serve as an entry door to an export market.[17] Assuming that the first firm that is exporting is the firm with the largest ethnic population in the destination country, equation (8) gives a consistent estimate of η.

Ethnic Specific Fixed Costs So far I have assumed that networks only exist within ethnicities and ignored networks that exist between ethnicities. It is however reasonable to assume that every ethnicity can create networks with other ethnicities in order to conduct trade. In the following I will relax the 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 ethnicities 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 ethnicities. Hence, I assume there exists a matrix $F_{E \times E}$ that reflects this ordering between every possible combination of ethnicities. The cost of producing and exporting are then given by:

$$c_{ij,ee'}(\varphi) = \frac{\tau_{ij}}{\varphi} q_{ij}(\varphi) + \left(\frac{L_{j,e'}}{L_j} \right)^{-\eta} f_{ij} f_{ij,ee'} \tag{9}$$

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 as before but they also have to invest

[16] This relationship becomes even more clear when calculating the number of exporters $\#EX_{ij} = \sum_{e \in E} L_{i,e} \int_{\varphi^*_{ij,ee'}}^{\infty} dG(\varphi) = \frac{\gamma - (\sigma-1)}{\gamma} \frac{\sigma}{\mu} \left(1 + \frac{\Pi}{L}\right) L_j^{1-\eta} \left(\frac{\tau_{ij}}{\theta_j}\right)^{-\gamma} f_{ij}^{\frac{\gamma}{1-\sigma}} \sum_{e'=e \in E} L_{i,e} L_{j,e}^{\frac{\eta}{\gamma} \frac{1}{\sigma-1}}$ which is increasing in the number of ethnic connections if the increase does not affect $L_{i,e}$ or $L_{j,e'}$.

[17] This relationship holds as long as the exponent on market size L_j is greater then the exponent on ethnic population $L_{j,e'}$. The resulting condition $\frac{\sigma-1}{\gamma} \geq \frac{\eta}{1-\eta}$ is fulfilled by the data.

in ethnic relations in order to mitigate them and export. 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 networks within ethnicities can emerge. The gravity equation is then given by:

$$X_{ij} = L_j\mu\left(1+\frac{\Pi}{L}\right) f_{ij}^{1-\frac{\gamma}{\sigma-1}}\left(\frac{\tau_{ij}}{\theta_j}\right)^{-\gamma}\sum_{e\in E} L_{i,e}(L_{j,e'})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}} f_{ij,ee'}^{1-\frac{\gamma}{\sigma-1}} \tag{10}$$

Now, the network effect is not only within an ethnicity, but also between ethnicities. If the fixed costs of creating networks between ethnicities are low enough, this specification should fit the data better. Combining the findings on the extensive margin formulation and the ethnic specific fixed costs, ethnicities 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 ethnicities and further underlines the importance of testing the first hypothesis.

3 Data

Geographical information I use spatial data based upon the Geo-referencing of Ethnic Groups (henceforth: GREG) from the *Atlas Narodov Mira* (Weidmann et al. 2010). It has been used in various applications and shows the ethnic distribution around the world in 1960, as seen by Russian scientists. Population count data is obtained from the United Nations Environment Program / Global Resource Information Database with a spatial resolution of 4 kilometer.

Country information African trade data is obtained from the World Bank Integrated Trade Survey that employs the UN comtrade dataset which covers all countries from 1950-2010. Measures of trust are obtained from the Afrobarometer 2005 as used in Nunn & Wantchekon (2011). Perceived corruption indexes are obtained from the Afrobarometer 2008. I employ the Uppsala University Department of Peace and Conflict Research data set for the information of conflict[18] incidences in Africa. To control for colonial ties between countries I use "The Issue Correlates

[18]Conflict in the data is defined as "a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths."

of War" colonial history data set from Hensel (2009). The complete set of controls and their statistics can be seen in Table 14 in the appendix.

4 Empirical Strategy

I aim to consistently and causally estimate the following gravity equation:

$$X_{ij,t} = \mu \left(1 + \frac{\Pi_t}{L_t}\right) L_{j,t} f_{ij,t}^{\frac{\sigma-1-\gamma}{\sigma-1}} \left(\frac{\tau_{ij}}{\theta_j}\right)^{-\gamma} \sum_{e'=e\in E} L_{i,e,t}(L_{j,e',t})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}} \tag{11}$$

The first term can be approximated by per capita GDP in both countries $\mu\left(1+\frac{\Pi}{L}\right)L_{j,t} = exp(y_j + y_i + \mu_i + \mu_j)$ where all errors are normal distributed with mean zero and y denotes the logarithm of per capita GDP. As it is common in the literature (Helpman et al. 2008, e.g.) I proxy the variable trade costs by the geographic distance d_{ij} between the importer and exporters most central points $\ln(\tau_{ij}) = \ln(d_{ij}) + \mu_\tau$. Fixed costs f_{ij} can be approximated by bilateral characteristics[19] and importer and exporter fixed effects $f_{ij} = exp(\phi_j IM + \phi_i EX + \phi_{ij}\Phi_{ij} + \mu_{f_{ij}})$ as can be the multilateral resistance term $\theta_j = exp(\delta_j IM + \delta_i EX + \mu_\theta)$.

In the network component of equation (11) $\sum_{e'=e\in E} L_{i,e,t}(L_{j,e',t})^{\frac{\eta(\sigma-1-\gamma)}{1-\sigma}}$, the ethnic population in both countries is calculated using the population weighted ethnic share of each ethnicity in 1960 as obtained by the GREG map multiplied by the total population in country i or j at time t. For the exponent on the foreign ethnic population $\nu \equiv \frac{\eta(\sigma-1-\gamma)}{1-\sigma}$ I choose three values, $\nu = \{1, 0.5, 0.2\}$, to capture increasing firm heterogeneity, or holding the degree of firm heterogeneity fixed, increasing the elasticity of substitution.[20] Thus, the main empirical equation is:

$$\begin{aligned} X_{ij,t} =& \beta_1 \ln(\text{Ethnic Network}_t,\ \nu) + \beta_2 y_{i,t} + \beta_3 y_{j,t} + \beta_4 \ln(d_{ij}) \\ &+ (\delta_j + \phi_j)IM + (\delta_i + \phi_i)EX + \phi_{ij}\Phi_{ij,t} + \gamma_{ij,t}\Gamma_{ij,t} + \epsilon_{ij,t} \end{aligned} \tag{12}$$

where $\epsilon_{ij,t} = \mu_{i,t} + \mu_{j,t} + \mu_{f_{ij}} + \mu_{\theta,t} + \mu_\tau$ is iid and $N(0, \sigma_\epsilon)$. $\Gamma_{ij,t}$ contains time-varying country characteristics and a linear time trend.[21] Equation (12) will then be estimated using the established procedure in the literature. I compare estimates using ordinary least squares, Poisson Pseudo Maximum Likelihood (PPML) and a Heckman Two-Step estimation. This is

[19] The bilateral characteristics used are: common border, sharing a language, sharing a colonial history and sharing a border that contains a river.

[20] Although $\nu < 1$ I keep the unit value for its interpretative simplicity.

[21] Having year fixed effects does not change the results.

necessary due to different distributional assumptions of each procedure. As Santos-Silva & Tenreyro (2006) show in their influential work, ignoring non-linearities in the error term can lead to biased estimates. Furthermore, due to a large proportion of zeros in trade data the PPML estimation is superior to an ordinary least squares regression. Another way to reduce the resulting bias from ignoring zeros in trade data is to use a Heckman-Two-Step procedure as used in Helpman et al. (2008). Both procedures estimate the equation non-linearly and report elasticities but have different distributional assumptions in the error term. While the Heckman-Two-Step procedure estimates a selection equation and then an ordinary least squares regression that assigns the weight of an observation in the regression according to its importance, the PPML assigns each observation the same weight.[22] Using the Heckman Two-Step estimation, however, requires a selection equation with a variable that does not affect the export flows.

Rewriting the selection equation in (8) in estimation format becomes:

$$\begin{aligned} \Pr[Z_{ij} > 1] :=& \eta l_{j,e'} + \beta_2^s y_i + \beta_3^s y_j + \beta_4^s d_{ij} + (\sigma - 1)\log(\varphi) \\ &+ (\delta_j + \phi_j) IM + (\delta_i + \phi_i) EX + \phi_{ij}\Phi_{ij} + \epsilon_{ij} = 0 \end{aligned} \tag{13}$$

Here, $l_{j,e'}$ is the logarithm of the maximum foreign ethnic population and β^s is the regression coefficient from the selection equation. This selection equation provides a consistent estimate of η if $l_{j,e'}$ is uncorrelated to the omitted productivity variable φ.[23]

Identification Strategy I use the GREG map by Weidmann et al. (2010) to obtain an exogenous variation of ethnic shares across country borders. The ethnic dispersion in African countries today is driven by independence struggles resulting in civil wars, migration and the initial dispersion across countries. Furthermore, the ethnic shares are often unknown, incomplete or collected from different sources at different points in time.[24] Thus, I focus on the initial dispersion across countries and argue that the resulting distribution is as good as random. The *Atlas Narodov Mira* was created by Russian scientists in the early 1960, thus showing the ethnic distribution when many African countries gained independence.[25] The resulting country bor-

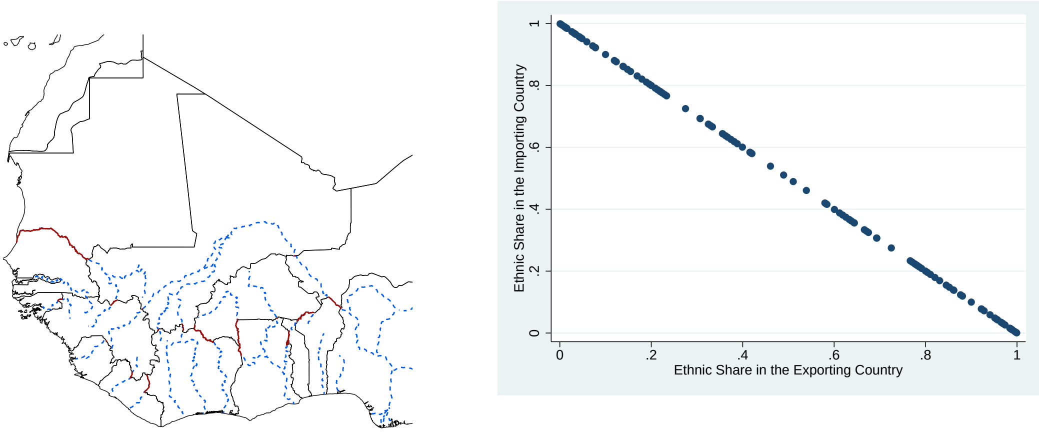
[22]Due to considerable heterogeneity in the economic activity of African countries, these assumptions can be of interpretative importance when comparing estimates.

[23]This assumption implies that the expected productivity is independent of the ethnicity when drawing from $G(\varphi)$.

[24]See [e.g.] CIA World Factbook: `https://www.cia.gov/library/publications/the-world-factbook/`

[25]France retreated from most of its possessions in 1958-192, Britain did it in 1957-1965 and Belgium in 1960-1962.

Figure 2: Randomness of Borders and Ethnic Shares



(a) Rivers (Blue) in West Africa

(b) Share of Ethnicities in the Importing and Exporting Country

ders, most of which are still valid today, were decided by the political powers in Europe. These borders were set without taking economic or political consequences into account (Michalopoulos & Papaioannou 2014) and most importantly, without the knowledge of the future population of the countries they were forming. Furthermore, as Alesina et al. (2011) show, 80% of African political boundaries follow either latitudinal or longitudinal lines and thus often combined various ethnic groups that were then supposed to form a working democracy. This mixture of ethnicities proved menacing in the second half of the twentieth century as civil war broke out in several countries.[26] Identification with the own country is often of secondary importance to identification with the own ethnicity (Alesina et al. 2011), possibly also to form a group that can bargain for rents (Bates 2008).

The argument for random ethnic shares in African countries also holds when the country border is, or contains, a river. As long as ethnicities did not settle alongside rivers in order to have political or economical advantages in the event of nation founding ethnic shares are still random. When comparing country borders and rivers in West-Africa in Figure 2a there are countries that have multiple rivers passing through countries without having a river as a boundary, supporting the initial claim.

If country borders were set to split ethnicities in a certain way Figure 2b would show a concentration of values. The values, however, are spread across the complete unit interval supporting the randomness assumption. Additionally, Michalopoulos & Papaioannou (2013) show that

[26] Sudan 1955,1983, 1987-today, Algeria 1991-2002, Chad 1965-2002 (with breaks), Somalia 1977, 1991-today, Uganda 1982-1986, Rwanda 1994 Ivory Coast 2002-2007, Guinea-Bissau 1998-1999, Libera 1989-2003 (with break). List incomplete.

Figure 3: Construction of the ethnic network variable

with the exception of landmass and water area, other potentially important factors are not systematically different across separated and non-separated ethnicities.[27] Thus supporting my claim that based on observables, ethnic shares are as good as random across countries.

To identify the ethnic population I interact the geographic size of an ethnicity in each country with population raster data from the United Nations Environment Program. Using a more recent version of this data would generate a bias towards ethnicities that contain large cities, due to increased urbanization in Africa.[28] Although I use the spatial information where these ethnicities were located, I do not require individual members to live inside the same area as in 1960. I rather require them to live in the same country and have the same population growth as all other ethnicities.[29] Using this procedure I account for 245 million people in 1960, which is 85% of the figure reported in popular media.[30]

[27] Although showing it for a different input provided by Murdock (1959) that uses pre-colonial data, it is likely to hold here as well.

[28] See United Nations (2002) for percentage of urban population in 1950: Botswana 0.4%, Lesotho 1 %, Rwanda 1.8% up to 6.2% in 2000, Mozambique 2.5%, Malawi 3.5% up to 14.7% in 2000, Chad 3.9% Niger 4.9% up to 20.6% in 2000, Guinea 5.5%. Median in 1950 was 9.6% while in 2000 the median lies at 36.4%.

[29] Although this claim is violated for individual ethnicities due to expulsion or genocide, on average this claim is likely to hold. To be more precise I require that the ethnic share in 1960 is a good proxy for the ethnic shares in 1989-2010 and any deviation from the 1960 network share is random. The resulting measurement error will be addressed in the robustness section.

[30] Imputing the population shares until today and compare the resulting ethnic shares with the next best from the CIA World Factbook, the numbers have a correlation of 0.85.

The construction of the ethnic network variable is shown in Figure 3 by the example of Angola and Namibia. The ethnic network variable contains the blue shaded ethnicities on both sides of the country border (red). In this case, four ethnicities[31] cross the border and their population share is calculated taking the other ethnicities (green) and the population raster data into account.

The resulting data set contains 2,256 (48×47) country pairs over a time span of 22 years of which 492 pairs share at least one ethnicity. If a country shares an ethnicity, the ethnic shares are on average 33.6% and the network size is on average 1.5 million people. I focus on the period 1989-2010 to have enough time between independence and observation and to be able to use detailed conflict data. In total 67.7% of all possible trade connections are zero trade or missing.

5 Baseline Results

The baseline results are reported in Table 1. In the first column I estimate equation (12) using an ordinary least squares approach and present the main dependent ethnic network variable with three values for the exponent. Using unity as the exponent ν, a 1% increase in the ethnic network across countries increases the exports by 0.1%.

In the average country-pair with ethnic connections, the reported elasticity implies that an increase in the network size on either side of the border by approximately 26,000 members, increases the average exports between those countries by 96,000 USD in 2010. In a back of the envelop calculation, comparing this effect to the average trade flow of country-pairs without ethnic connections, it would increase their exports by 0.3%.[32]

Another way of interpreting the results would be to consider trade costs. The coefficient on distance in the equations are -1.068 with a standard error of 0.106 in the specification using ordinary least squares and -0.388 with a standard error of 0.068 in the PPML specification. The estimated reduction in trade cost for an average country ranges between 16.3% and 25.9% in the OLS and PPML specification respectively.[33]

The next two rows in Table 1 can be thought of in two ways. The first interpretation is an increase in the degree of firm heterogeneity relative to the elasticity of substitution $\gamma \downarrow$ to fit

[31] The ethnicities are Herero, Bushmen, Ovambo and Wayeye

[32] Assuming linear elasticities that are equal across countries.

[33] The average for log(Ethnic Network) is 11.23 and for distance as a proxy for trade costs 6.84. Then the calculation done here is $\frac{0.106*11.23}{1.068*6.84} = 16.3$.

Table 1: Baseline results

	(1)	(2)	(3)
Estimation Technique:	OLS	PPML	Heckman
Dependent Variable:	log(Exports)	Exports	log(Exports)
log(Ethnic Network)	0.1062***	0.0613***	0.1149***
	(0.0147)	(0.0192)	(0.0153)
log(Ethnic Network, exp=0.5)	0.1372***	0.0751***	0.1483***
	(0.0194)	(0.0257)	(0.0202)
log(Ethnic Network, exp=0.2)	0.1605***	0.0822***	0.1731***
	(0.0236)	(0.0309)	(0.0245)
N	15641	15945	49402

Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. The second and third row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). The first column uses an ordinary least squares estimator and the second the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). The third column uses a Heckman Two-Step procedure where the selection equation features the maximum ethnic population abroad, as given by equation (8). Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the data while the second interpretation is to decrease the importance of the ethnic network abroad $\eta \downarrow$. The resulting coefficients are larger than before indicating greater elasticities. The interpretation is however not as straightforward as in the unitary case. While before the ethnic population in both countries share an elasticity, the latter two cases separate the elasticities for the domestic and destination country ethnic population. Hence, although network size in the destination country matters, estimates suggest that the amount of firms being able to use this network matters more.[34]

In column two I estimate the preferred specification using the Poisson Pseudo Maximum Likelihood estimator. Assuming a Poisson distribution for the export flows and equal variance across countries the estimated elasticities drop but remain highly significant. Again, increasing the degree of firm heterogeneity, increases the importance of ethnic networks.

In column three I use the total available data and estimate the selection equation (8) using a Heckman Two-Step procedure. The selection equation requires an estimate for the ethnic population in the destination country $L_{j,e'}$ that does not affect the value of trade flows. Hence, I use the logarithm of the maximum ethnic network population that affects selection into exporting, but only in combination with the home ethnic population affects trade flows. The estimated

[34]The coefficient does not significantly draw from per capita GDP in both countries or any other covariate [Results not shown.]

value for the importance of the ethnic networks is $\eta = 0.03$ which is below the condition for interior solutions when the exponent is 0.5 or 0.2.[35] The results suggest that there is indeed a selection bias, the coefficients from column one and three are however not statistically different.

6 Robustness

Ethnic networks do have a strong and economically meaningful impact on bilateral trade flows. In this section I will explore the robustness of the results in various ways. At first I check whether data quality poses a threat to my results. Since 67.7% of the possible importer and exporter pairs contain non-reported trade, I verify that these observations are not missing systematically. To do so, I employ three different treatments of the dependent variable. First, I assume that every non-reported trade flow is actually zero trade flow. This is labeled "All-Zero" in Table 2 and refers to a specification where I use the complete available data set and trust its reliability. Second, I assume that non-reported trade is only zero trade after I have observed this trading connection at least once. In Table 2 I refer to this specification as "Zero-after-Observing" in column two. The underlying assumption here is that data availability only started when this importer-exporter pair first traded with each other. Third, I impute the trade flows between two countries using the last observations value-to-GDP ratio. I refer to this specification as "Impute-after-Observing" in Table 2, column three. Here I assume that after the first time trade between the importer-exporter pair has been observed, instead of no trade, there was non-reported trade for the next years.

If the results are due to systematical under-reporting bilateral trade-flows the results from at least one of the above treatments should vary significantly from the baseline results. The results from the PPML regression in Table 2, however, are not statistically different from the previously obtained results in the baseline. I do not report results from ordinary least squares or the Heckman Two-Step procedure since for the former the logarithm of zero is undefined and the latter uses the complete data set by default.

The second test for data quality is how sensitive the results are with respect to the number of years chosen. In the baseline I include all observations for 1989-2010, together with non-reported trade. In Table 3 I only take importer-exporter pairs into account when they have been trading

[35] I keep on reporting the unitary coefficient due to its interpretative simplicity. The condition is $\eta < \frac{\sigma-1}{\gamma}$ which can be obtained by using the value for η in the exponent: $\eta^{\frac{(\sigma-1)-\gamma}{1-\sigma}} = \nu \Rightarrow \frac{\sigma-1}{\gamma} = \frac{\eta}{\nu+\eta}$ which holds for $\nu < 1 - \eta$.

Table 2: Definition of the data

	(1)	(2)	(3)
Estimation Technique:		PPML	
Dependent Variable:		Exports	
Definition of Dep. Variable:	"All-Zero"	"Zero-after-Observing"	"Impute-after-Observing"
log(Ethnic Network)	0.0630***	0.0673***	0.0485**
	(0.0203)	(0.0200)	(0.0238)
log(Ethnic Network, exp=0.5)	0.0785***	0.0834***	0.0598**
	(0.0271)	(0.0268)	(0.0298)
log(Ethnic Network, exp=0.2)	0.0875***	0.0923***	0.0672**
	(0.0327)	(0.0324)	(0.0333)
N	43320	23294	23294

Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. The second and third row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). The estimation method is the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). Heckman-Two-Step results are omitted since they use the full sample. OLS results are omitted since the logarithm of zero is undefined. Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

for at least five or ten years. Data quality might have increased over time, such that more importer-exporter pairs previously non-reported were added to the data. Reporting trade might be correlated via unobservables with ethnic connections and thus systematically under-report the actual trade flows. Then only using importer-exporter pairs that reported trade continuously over the last five or ten years corrects for that selection bias. Additionally, increased proficiency and lowering the costs of acquiring the firm level data by the local governments might have helped decreasing the misreporting of trade values, further improving the reliability of the estimates.

In Table 3 I run the baseline for those importer-exporter pairs that I observer continuously for at least five or ten years. Sample size decreases but the estimates are not statistically different from the baseline results. [36]

Controlling for sample selection and non-reporting trade I failed to reject the hypothesis that the ethnic network elasticity is 0.06 in the preferred PPML estimation. However, due to considerable heterogeneity in economic activities between African countries, one country can influence the baseline results to a great extend. In Figure 4 I verify the sensitivity of the estimates when leaving one country out as an exporter and importer and re-estimate the gravity equation in

[36]The coefficient actually increases when I only take recent years. [Results not shown]

Table 3: Restricting years

	(1)	(2)
Estimation Technique:	OLS	PPML
Dependent Variable:	log(Exports)	Exports
Minimum 5 years		
log(Ethnic Network)	0.1085***	0.0777***
	(0.0192)	(0.0220)
log(Ethnic Network, exp=0.5)	0.1389***	0.0959***
	(0.0250)	(0.0290)
log(Ethnic Network, exp=0.2)	0.1612***	0.1047***
	(0.0303)	(0.0343)
N	9015	9058
Minimum 10 years		
log(Ethnic Network)	0.0970***	0.0710***
	(0.0211)	(0.0215)
log(Ethnic Network, exp=0.5)	0.1236***	0.0784***
	(0.0271)	(0.0274)
log(Ethnic Network, exp=0.2)	0.1435***	0.0766***
	(0.0326)	(0.0312)
N	7596	7620

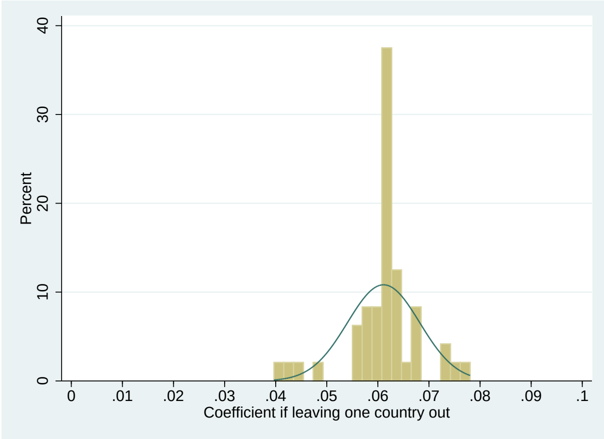
Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. The second and third (fifth and sixth) row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). The first column uses an ordinary least squares estimator and the second the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). The first break implies that every importer-exporter pair has to be observed for at least 5 years, the second break for at least 10 years. Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(12). Figure 4 shows the histogram of the elasticity in 48 regressions that each leaves one country out and a normal distribution to compare.[37] If one country would influence the results, the figure would show a value that is lower then two standard deviations away from the original result (0.0613 [0.0192]) in Table 1. All estimates, however, lie within that two standard deviation interval. Hence, despite the heterogeneity in economic analysis, no country influences the result to a great extent.

Having ruled out data issues, I continue to test for the validity of my theoretical model. I assumed that all ethnicities that cross the border are of importance because they reduce the bilateral fixed costs of exporting. If ethnic membership however also affects variable trade

[37] Another possible way to account for the heterogeneity in economic activity is to divide the bilateral exports by the total exports of a country. The results for the PPML are not statistically different, while the OLS results drop. See Table 15 in the Appendix.

Figure 4: Histogram of the coefficient when leaving one county out in the regression



The above shows the regression coefficients of log(Ethnic Network) in a PPML regression on exports.

costs, then the estimation equation would be misspecified. I aim to test the model by dropping every ethnic connection and its network, when the ethnicity does not have an important border crossing in its original area.[38] Variable trade costs also include bribery at the border and if ethnic membership decreases bribery payments, then these ethnic networks should be more important than others. Thus, the estimated elasticities should be larger then the baseline results. The results are shown in Table 4 where I re-estimate the baseline only using ethnicities with border crossings. Using ordinary least squares the estimates drop significantly and vanish when employing the PPML specification. The results for the PPML estimation show strong evidence, while the others give at least weak evidence, for the correct specification of my model.

Ethnic population in every country today is calculated using the population shares in 1960 and multiplying them with the population figures from the year of observation. As there is a lot of migration within Africa due to economic possibilities or conflicts, ethnic shares may vary significantly during the years. Although I control for conflict, the resulting measurement error might still be substantial in a subset of countries with large migration patterns. In the following I propose an assessment of the severity of the measurement error in the ethnic network variable. At first I will create the network variable in 1960 and leave it constant for all future observations, factoring out population growth and variations in the ethnic shares. The resulting elasticity in Table 5 is a reduced form effect of the ethnic network in 1960 on export flows in the years 1989-2010. The results using the PPML estimator do not change significantly, supporting the hypothesis that the measurement error is not substantial. In columns (1) and (3) where I

[38]I define border crossing as a main customs station at a relatively frequented, possibly paved, road.

Table 4: Results when only including the ethnicity that has a border crossing

	(1)	(2)	(3)
Estimation Technique:	OLS	PPML	Heckman
Dependent Variable:	log(Exports)	Exports	log(Exports)
log(Ethnic Network)	0.0748***	0.0087	0.0784***
	(0.0155)	(0.0194)	(0.0160)
log(Ethnic Network, exp=0.5)	0.0966***	0.0110	0.1016***
	(0.0205)	(0.0250)	(0.0212)
log(Ethnic Network, exp=0.2)	0.1155***	0.0117	0.1220***
	(0.0256)	(0.0293)	(0.0264)
N	15641	15945	49402

Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. Networks are calculated using only the ethnicity that has a border crossing. Hence, it ignores ethnicities that are in non contingent countries. The second and third row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). The first column uses an ordinary least squares estimator and the second the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). The third column uses a Heckman two-step procedure where the selection equation features the maximum ethnic population abroad, as given by equation (8). Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

employ the ordinary least squares estimation and the Heckman Two-Step procedure, however, the elasticities drop significantly. This drop is due to factoring out population growth which might be substantial in some African countries. It appears that the assumption about how to weight each observation is important for the results.[39]

By factoring out population growth I am, however, unable to assess the size of the measurement bias that results from changes in ethnic shares over time directly. The ethnic network variable I construct is only a proxy for the actual ethnic network that exists today. It measures the underlying variable x^* only with a possibly non-classical measurement error γ_G:

$$x_G = \gamma_G x^* + \epsilon_G \tag{14}$$

Here the ethnic network variable I construct from the GREG data x_G only measures x^* with a factor $\gamma_G > 0$ and a random error term ϵ_G. When using this variable the estimated elasticity is a function of the factor γ_G and the underlying variable x^*:

$$\beta^{x_G} = \beta \left(\frac{\gamma_G \sigma^2_{x^*}}{\gamma^2_G \sigma^2_{x^*} + \sigma^2_{\epsilon_G}} \right) = \beta \cdot R_G \tag{15}$$

[39]Since the OLS weights each observation by its size and the PPML assumes equal weight, the assumption can make a difference if the variances of the observations are large enough.

Table 5: Results when omitting population growth

	(1)	(2)	(3)
Estimation Technique:	OLS	PPML	Heckman
Dependent Variable:	log(Exports)	Exports	log(Exports)
log(Ethnic Network)	0.0619***	0.0463***	0.0677***
	(0.0076)	(0.0105)	(0.0078)
log(Ethnic Network, exp=0.5)	0.0816***	0.0598***	0.0892***
	(0.0101)	(0.0141)	(0.0104)
log(Ethnic Network, exp=0.2)	0.0997***	0.0709***	0.1091***
	(0.0125)	(0.0174)	(0.0129)
N	15641	15945	49402

Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. Networks are calculated using the population in 1960. The second and third row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). The first column uses an ordinary least squares estimator and the second the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). The third column uses a Heckman two-step procedure where the selection equation features the maximum ethnic population abroad, as given by equation (8). Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Where β^{x_G} is the regression coefficient in the baseline results.[40] I can argue that if $\frac{\sigma^2_{x^*}}{\sigma^2_{x_G}} > \gamma_G$, the attenuation factor R_G is less than unity and the estimated coefficient is downward biased. However, I want to employ a method used by Krueger & Lindahl (2001) and use a second proxy x_M to factor out the attenuation factor directly. They assume a classical measurement error $\gamma_G = \gamma_M = 1$ and regress two inputs for schooling on each other to obtain the attenuation factor. I extend their method to non-classical measurement errors if either γ_G or γ_M is known. Then, by regressing two inputs on each other I obtain:

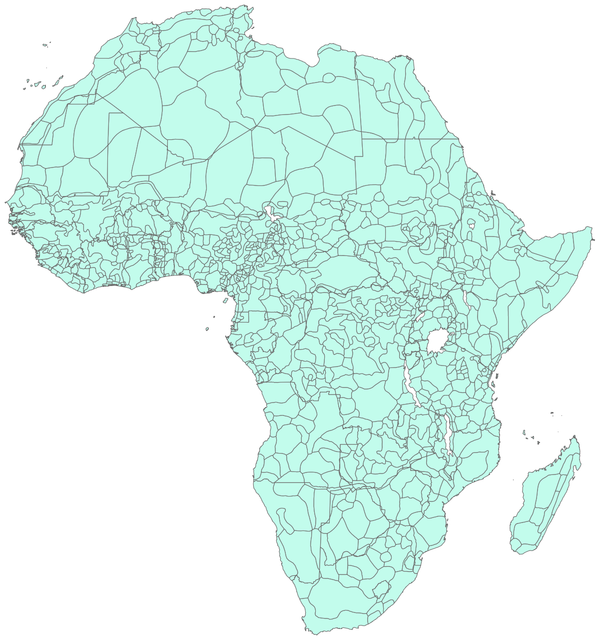
$$\beta^{x_M x_G} = \frac{cov(x_G, x_M)}{var(x_g)} \xrightarrow{p} \frac{\gamma_G \gamma_M \sigma^2_{x^*}}{\gamma^2_G \sigma^2_{x^*} + \sigma^2_{\epsilon_G}} = \gamma_M \cdot R_G \tag{16}$$

Here, the resulting coefficient is a function of the attenuation factor R_G and the non-classical measurement error in the other data set γ_M. The advantage of this procedure is that I do not need to know the variance of the underlying variable x^* nor the variance of the error term $\sigma^2_{\epsilon_G}$ in order to get an unbiased estimate for β. The necessary assumption is that the error terms are uncorrelated ($corr(\epsilon_G, \epsilon_M) = 0$).

Hence, I use the map in Figure 5 provided by Murdock (1959) that shows pre-colonial ethnic distribution in Africa. This map has been used by Nunn & Wantchekon (2011), Michalopoulos

[40] Under the assumption that $corr(\epsilon_G, x^*) = corr(\epsilon_G, x_G) = 0$.

Figure 5: Ethnic and country boundaries as provided by Murdock (1959)



& Papaioannou (2013) and Michalopoulos & Papaioannou (2014) in various applications. It has on average more ethnic groups (25 vs 10.5), more ethnicities (835 vs 214) and a smaller ethnicity share (2.6% vs 5.2%) than the GREG map, but the assumption on the error terms $corr(\epsilon_G, \epsilon_M) = 0$ are supported in two ways.[41] First, the map shows ethnic distribution years before the GREG map and second while the *Atlas Narodov Mira* was created by Russian scientist, the Murdock map was published in America at the height of the cold war, almost at the same time.

A further advantage of using the Murdock map as a secondary input is that Nunn & Wantchekon (2011) give a correlation of 0.55 for the location of a respondent and its ethnicity as indicated by the map. This correlation is the factor γ_M I need to factor out the attenuation bias R_G.[42] Thus, the true β can be estimated as:

$$\beta = \frac{\beta^{x_G}}{\beta^{x_G, x_M}} \cdot \gamma_M \tag{17}$$

The results are shown in Table 6. As long as $\gamma_M < \beta^{x_M x_G}$ I estimate the coefficient with an upward bias and vice versa if $\gamma_M > \beta^{x_M x_G}$. However, using the correlation provided by Nunn

[41] Using the Murdock map yields qualitatively the same results, but the GREG map coincides exactly with the first population raster data which is why I chose to use it as a primary input.

[42] Since $\gamma_M = \frac{cov(x_M, x^*)}{var(x^*)} = \frac{corr(x_M, x^*)\sigma^2_{x^*}}{\sigma^2_{x^*}} = corr(x_M, x^*)$

Table 6: Attenuation factor R, R^2 and the covariate adjusted attenuation factor R'.

	(1) log(Ethnic Network)	(2) log(Ethnic Network, exp=0.5)	(3) log(Ethnic Network, exp=0.2)
$\beta^{x_M x_G}$	0.5502	0.5575	0.5675
R *using* $\gamma_M = 0.55$	1.0004	1.0136	1.0318
R^2	0.6089	0.6112	0.6104
R' cond. on cov.	1.0010	1.0350	1.0816
Estimated β^{x_G}	0.0613	0.0751	0.0822
True β in PPML	0.0612	0.0726	0.0760

$\beta^{x_M x_G}$ is the regression coefficient from a regression that has the first row from the Murdock Data as an independent variable and the GREG variable as a dependent variable. The second row estimates the attenuation factor R using $R = \beta^{x_M x_G}/\gamma_M$ The R^2 is from a regression using the GREG ethnic distance/network as a independent variable on all covariates. The $R' = \frac{R_G - R^2}{1-R^2}$ when conditioning on covariates is a formula provided by Krueger & Lindahl (2001). Although only the coefficient from the poisson-pseudo-maximum-likelihood regression is reported, the attenuation factor R' is the same for all estimated coefficients.

& Wantchekon (2011) results in no significant changes in the elasticities. I reject the existence of a substantial measurement error and neglect it in further analyses.

Having discussed data quality issues and potential measurement errors I found strong support for the coefficients in the baseline results. Ethnic networks have a strong positive effect on bilateral exports and the resulting elasticity is of economic meaning. The preferred Poisson Pseudo Maximum Likelihood specification yields the lowest elasticity, but is most robust to the threats discussed here. Hence, I will almost exclusively employ the PPML specification when I investigate the channels through which ethnic networks affect bilateral exports.

7 Channels

In this section I test the empirical predictions derived from the model in section 2. To test the first prediction

Hypothesis 1 *Ethnic networks are more important in countries with poorly enforced rules, lower social norms and lower levels of trust*

I use the Afrobarometer data that contain trust and corruption measures as used by Nunn & Wantchekon (2011) and interact them with the ethnic network variables. Since the data is based on a questionnaire the resulting value is ordinal and not directly interpretable. To circumvent

Table 7: Investigating trust channels

	(1)	(2)	(3)
Estimation Technique:		PPML	
Dependent Variable:		Exports	
log(Ethnic Network)	0.0795**		
	(0.0324)		
log(Ethnic Network, exp=0.5)		0.1031**	
		(0.0448)	
log(Ethnic Network, exp=0.2)			0.1187**
			(0.0576)
Ethnic × Trust Own Ethnicity	0.1499	0.2142	0.2767
	(0.2244)	(0.2952)	(0.3595)
Ethnic × Trust Other Ethnicity	-0.3944*	-0.5196*	-0.6509*
	(0.2082)	(0.2831)	(0.3579)
Ethnic × General Trust	-0.6812***	-0.8316**	-0.9298**
	(0.2446)	(0.3300)	(0.4154)
Ethnic × Trust Neighbors	0.2324	0.2929	0.3616
	(0.2027)	(0.2754)	(0.3479)
N	5308	5308	5308

Each column is a regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. I employ the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). The second and third row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). Rows (4)-(7) show the interaction effect of the ethnic variable with measures of trust for the destination country as obtained by the Afrobarometer 2005. The standard deviations of the trust measures are (in order of appearance): 0.32/0.29/0.08/0.33. The network coefficients without the trust measures in that reduced sample are 0.0911(0.0294), 0.1173(0.0406) and 0.1354(0.0516) for the exponent $\nu = 1, 0.5$ and 0.2, respectively. The sample is reduced since the measures of trust are only available for 15 destination countries. Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

this I aggregate the individual answers to an country average and demean by the African wide mean. This way, the coefficient can be interpreted compared to all other African countries.

I show the results in Table 7. The interaction terms for trusting other ethnicities and general trust in the destination country shows support for the first hypothesis. If trust in other ethnicities decreases by one standard deviation, the elasticity of ethnic networks increase by 150 %.[43] The same decrease in the measure of general trust in society yields an increase by 60%. Although insignificant, the coefficient on trusting the own ethnicity is positive, indicating the same qualitative result as a decrease in the trust of other ethnicities.

[43]Calculated as follows: $-0.3944 \times 0.29 = 0.1144$ which is 1.44 times the original value for the elasticity on networks in the first column.

Table 8: Investigating corruption channels

	(1)	(2)	(3)
Estimation Technique:		PPML	
Dependent Variable:		Exports	
log(Ethnic Network)	0.0768***		
	(0.0279)		
log(Ethnic Network, exp=0.5)		0.0915**	
		(0.0383)	
log(Ethnic Network, exp=0.2)			0.0991**
			(0.0484)
Ethnic × corr. Tax	-0.3819**	-0.4537**	-0.5332**
	(0.1523)	(0.1981)	(0.2436)
Ethnic × corr. Law	0.4791***	0.5875***	0.6784***
	(0.1405)	(0.1901)	(0.2411)
Ethnic × Bribe the Police	0.2331	0.2465	0.2647
	(0.2633)	(0.3552)	(0.4463)
Ethnic × Bribe for Permit	0.3633*	0.4645*	0.5391*
	(0.1885)	(0.2544)	(0.3194)
N	6314	6314	6314

Each column is a regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. I employ the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). The second and third row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). Rows (4)-(7) show the interaction effect of the ethnic variable with measures of corruption or bribing for the destination country as obtained by the Afrobarometer 2008. The standard deviations of the corruption measures are (in order of appearance): 0.28/0.27/0.16/0.31. The network coefficients without the corruption measures in that reduced sample are 0.0856(0.0253), 0.1067(0.0348) and 0.1231(0.0435) for the exponent $\nu = 1, 0.5$ and 0.2, respectively. The sample is reduced since the measures of corruption are only available for 18 destination countries. Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To investigate the second part of the first prediction, how important ethnic networks are in countries with poorly enforced rules and lower social norms, I employ the same method as before and interact the ethnic network variable with measures of corruption and bribery. The results in Table 8 show that ethnic networks are more important in countries with a more corrupt law system and where bribery for permits is more common. A one standard deviation increase in either increases the importance of ethnic networks by 170% and 150% respectively.

The results I present in Table 7 and 8 show strong support for the first hypothesis. Ethnic networks are more important in countries with lower levels of governance and lower levels of social integrity. To approach the second hypothesis

Table 9: Interaction effect with bilateral characteristics

	(1)	(2)	(3)	(4)	(5)
Estimation Technique:			PPML		
Dependent Variable:			Exports		
log(Ethnic Network)	0.0613***	0.0650***	0.0909***	0.0727***	0.0944***
	(0.0192)	(0.0186)	(0.0192)	(0.0190)	(0.0194)
Ethnic × River		-0.0706			-0.0249
		(0.0483)			(0.0638)
Ethnic × Border			-0.1002***		-0.0761*
			(0.0268)		(0.0390)
Ethnic × Language				-0.0848***	-0.0720**
				(0.0256)	(0.0326)
N	15945	15945	15945	15945	15945

Each column is a separate regression of the dependent variable on the column variables, covariates and importer and exporter fixed effects. I employ the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Hypothesis 2 *Number of firms exporting is increasing in the number of ethnic connections between two countries*

I first look into how bilateral characteristics influence networks in Table 9. Including all interaction terms in column (5) the results show a negative impact of sharing a border and having a larger network. The same qualitative result holds for sharing a language. Ethnic networks become more important as distance between two countries increase and the official languages differ. In light of these results I choose to investigate the selection channel in order to test the second hypothesis.

Using disaggregated data at the 2-digit level I first investigate which products influence the importance of ethnic networks in Table 10. I interact the main independent variable with all sectors and estimate the baseline equation. The results show that semi and non durable consumer goods influence the importance of ethnic networks, without changing the original estimate significantly.[44] Since foods are a separate category, the result indicate that historical trade routes for food are not an important factor for todays staple consumption.[45] Other consumption goods are however affected, which hints at a preference channel through which

[44]Total number of sectors is 21, including food, industrial supplies, fuels, capital, passenger motor cars, consumer goods and other. In table 10 I omit insignificant interaction terms and product code dummies.

[45]Likely because non-market purchased food is coming from international companies.

Table 10: Results with disaggregated data, interaction effects

	(1)	(2)	(3)
		Sector Exports	
log(Ethnic Network)	0.0638^{***}		
	(0.0178)		
log(Ethnic Network, exp=0.5)		0.0782^{***}	
		(0.0237)	
log(Ethnic Network, exp=0.2)			0.0858^{***}
			(0.0286)
Interaction, code 6 and ethnicity	0.0348^{***}	0.0416^{***}	0.0442^{**}
	(0.0116)	(0.0150)	(0.0178)
Interaction, code 61 and ethnicity	0.0039	0.0049	0.0049
	(0.0171)	(0.0224)	(0.0266)
Interaction, code 62 and ethnicity	0.0406^{**}	0.0480^{**}	0.0497^{**}
	(0.0162)	(0.0202)	(0.0231)
Interaction, code 63 and ethnicity	0.0297^{**}	0.0364^{**}	0.0395^{**}
	(0.0119)	(0.0154)	(0.0185)
N	160619	160619	160619

Estimation Methods: Poisson-pseudo-maximum-likelihood. Importer and exporter fixed effects included, product category fixed effects included. Interaction, code and ethnicity means an interaction between the product category and the main dependent variable in row (1-3). Code 6: consumer goods (61: durable, 62: semi durable, 63: non durable). Insignificant interaction terms omitted here. Standard errors are clustered within each importer-exporter pair and given in parentheses.* $p < 0.10$, ** $p < 0.05$, ***

ethnic networks affect the available selection of product variety. This result stands in contrast to Balnes-Cristóbal (2008) who find the information channel dominates the preference channel.[46]

In the following I test the second hypothesis by first introducing a second more disaggregated data set and compare the results to the original data. The second data set features the SIC 4-digit industry classification with 443 sectors in the years 2007-2010. As shown in Table 16 in the Appendix, the results from both data sets are statistically indistinguishable. To test the second hypothesis I aim to estimate the selection equation (8):

$$\begin{aligned}\Pr[Z_{ij} > 1] :=& \eta l_{j,e'} + \beta_2^s y_i + \beta_3^s y_j + \beta_4^s d_{ij} + (\sigma - 1)\log(\varphi) \\ &+ (\delta_j + \phi_j)IM + (\delta_i + \phi_i)EX + \phi_{ij}X_{ij} + \epsilon_{ij} = 0 \end{aligned} \tag{18}$$

The number of sectors exporting T_{ij} to country j can then be expressed as $E(T_{ij}|X_{ij}) = S \cdot \Pr[Z_{ij} > 1]$, where S is the number of sectors covered by the data. The second hypothesis

[46]Here, the channels are additive with the information channel being the network variable.

suggests that $E(T_{ij}|X_{ij})$ is a function of the maximum ethnicity in country j that has an ethnic connection to the exporter i $l_{j,e'}$ and the number of ethnic connections between the two countries. Since ethnic connections open a doorstep into an export market they are expected to positively affect the export decision of individual firms, and therewith sectors.[47]

The outcome variable of a regression on $E(T_{ij}|X_{ij})$ is count data and Santos-Silva & Tenreyro (2014) suggest to use a Bernoulli (pseudo) maximum likelihood approach, here labeled "Flex". In Table 11 I compare the marginal effects from both data sets, obtained by using either a Poisson or a Flex approach. Having a larger maximum ethnicity increases the number of sectors that exports by 0.1871 in the original data set and 3.5283 in the new data. Directly testing the second hypothesis with the variable "# Ethnic Connections", however, yields only weak support of the second hypothesis. In the original data set only the Flex specification supports the hypothesis, while in the new data set both estimates just reject the hypothesis at the 10% level.

While the theoretical model is largely confirmed by my results, the second hypothesis is questionable. One possibility is the misspecification I explore in equation (10). It is likely that there also exist inter-ethnic networks that are active across borders. I assume that these networks bear a cost $f_{ij,ee'}$ that a firm has to pay to learn about that ethnicity and create a network. Every firm can create multiple inter-ethnic networks and thus trade between countries is facilitated. However, since the fixed costs for exporting is higher, fewer firms will export to the destination country. This explanation might lead to the low coefficients on ethnic connections in Table 11. Additionally, trade volumes are reduced since the additional cost increase the productivity necessary to export profitably.

In the first three rows of Table 12 I assume that these fixed costs are proportional to the distance between the ethnicities. In the last row I assume a value on the exponent $\nu = 0.2$, use the value for $\eta = 0.03$ and infer on the size of the fix cost exponent. This exponent is then 6.67 and thus indicate highly convex fixed costs as proxied by the distance between the ethnicities.[48] Regression results indicate a better fit to the data and a higher estimated elasticity for every specification. This elasticity, however, is not the elasticity of intra-ethnic networks but the elasticity of fixed cost weighted intra- and inter-ethnic networks. A decrease in the fixed cost of

[47] A stronger assumption would be that every sector has exactly one firm exporting. Then the ethnicity of the CEO of that firm matters for the individual decision to export. Then, more ethnic connections increase the likelihood that a randomly chosen firm has a CEO that has an ethnic connection to the importing country j.

[48] This exponent implies a ratio $\frac{\gamma}{\sigma-1} = 7\frac{2}{3}$. Chaney (2008) argues for a ratio of 2 in his paper. Despite my belief that the firm heterogeneity is lower in Africa, which would imply a higher ratio, I estimated the empirical specification with this estimate which gave an exponent of ν. The results are indistinguishable.

Table 11: Extensive margin with count data

	(1)	(2)
Estimation Technique:	Poisson	Flex
Dependent Variable:	# of Sectors Active	
Original Data:		
Max. Ethnic Network Abroad β	0.2427***	0.1871***
	(0.0561)	(0.0625)
# Ethnic Connections	0.1204	0.2546*
	(0.1052)	(0.1442)
N	15983	15983
SIC-4 Data:		
Max. Ethnic Network Abroad β	1.7994***	3.5283***
	(0.5232)	(1.0141)
# Ethnic Connections	1.7557	3.6533
	(1.0812)	(2.2373)
N	2203	2203

Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. The coefficients show the marginal effect at means for the respective regression. The first column is a poisson regression on the number of active sectors and the second uses a Flex approach as suggested by Santos-Silva & Tenreyro (2014). The number of sectors in the original data is 21 and 443 in the SIC-4 data. I exclude zero trade flows. Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

network formation by one percent, increases trade volumes by 0.14 percent in the specification with the lowest point estimate.

The above results suggest that ethnic networks are more important in countries that are less trustful, less governed and more corrupt. Furthermore, I find some evidence that the number of ethnic connections increases the amount of sectors that export. Investigating an extension with ethnic dependent fixed costs greatly increases the elasticity and highlights another finding. Ethnic networks can also exist between ethnicities, even though they are more costly to form. Reducing these inter ethnic fixed costs can significantly increase trade flows and therewith economic performance in African countries.

Table 12: Model extension with ethnic dependent fixed costs

	(1)	(2)
Estimation Technique:	OLS	PPML
Dependent Variable:	log(Exports)	Exports
log(Ethnic Network, linear fixed costs)	2.0665***	1.4422***
	(0.1111)	(0.1889)
log(Ethnic Network, exp=0.5, linear fixed costs)	2.0710***	1.4507***
	(0.1099)	(0.1804)
log(Ethnic Network, exp=0.2, linear fixed costs)	2.0499***	1.4237***
	(0.1086)	(0.1722)
log(Ethnic Network, exp=0.2, convex fixed costs†)	0.2641***	0.1406***
	(0.0146)	(0.0212)
N	14978	15269

Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. The first column uses an ordinary least squares estimator and the second the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). In the first three rows I assume linear ethnic fixed costs, that is the exponent on $f_{ij,ee'}$ in the augmented gravity equation $1-\frac{\gamma}{\sigma-1}$ is equal to -1. In the last row I take a structural approach and first estimate $\eta = 0.03$ and then assume that the exponent $\frac{\nu(\gamma-(\sigma-1))}{\sigma-1} = 0.2$ and compute $1-\frac{\gamma}{\sigma-1}$ which I assume to be -6.67. Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

8 Discussion

In the baseline result I estimate that the value added per additional network member is approximately 3.6 US$.[49] Compared to the median value added per worker in PPP US$ to non-exporting firms (6.5US$, Yoshino 2008), the 3.6 US$ gained by each network member is substantial. These 3.6 US$ are non-exclusive to every firm and lead to more exports by already exporting firms as well as to new firms entering the export market. If these networks were shut down, the potential losses would amount to 17.4% of yearly export volumes.[50] The effect of networks on exports becomes stronger, the more recent the data.[51] A part of this increase is due to increased data quality and another by the increased population in Africa. Slowly developing governance and social integrity failed to decrease the importance ethnic ties and generate possibilities for all firms. As shown in Table 7 and 8 these factors can influence trade volumes indirectly via the effectiveness of ethnic networks. Lower levels of governance decrease

[49] In 2010: An additional 26,000 member increase exports by 96,000 US$.

[50] Calculated by predicting the trade flows without ethnic networks and correcting for small samples. Results not shown.

[51] Table 3 and not displayed results.

Table 13: Instrumental Variable Approach for the logarithm per capita GDP.

First Stage Estimation :	(1) OLS	(2) PPML	(3) PPML (Fixed cost specification)
Instrument:		log(Ethnic Network, exp=0.2)	
First stage F-test†:	49.93	6.99	43.98
Second Stage: Dep. Variable:		log(per capita GDP)	
log total trade flows	0.5704**	1.0870***	1.2005***
	(0.2609)	(0.2318)	(0.1629)
Observations	1054	1054	1033
R^2	0.898	0.909	0.909

Each column is a separate instrumental variable estimation where the first stage is estimated using the instrument log(Ethnic Network, exp=0.2). In column (3), the fixed cost specification as in equation (10) is employed with an exponent for the fixed cost of -6.67 and η=0.03, as previously estimated. The second stage is an regression of the predicted yearly trade volumes of a country on the logarithm of per capita GDP. The standard error are not corrected for the sandwich theorem. Standard errors are clustered within each importer-exporter pair and given in parentheses. The number of observations decrease to the number of countries $\times$ year. † The F-test corresponds to the estimation in column (1) and (2) in Table 1 as well as column (3) in Table 12.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the economic potential of a country and hence trade volumes. Ethnic networks, however, can help to overcome, or at least attenuate, the negative effects for international trading partners. These ethnic networks still seem to be largely exclusive as the fixed costs for creating an inter-ethnic network seem to remain at a high level (Table 12). A decrease in ethnic specific fixed costs increases the network creation between importer and exporters and hence increases trade flows. Fostering cultural exchange could thus be a way to increase networking and to overcome inefficiencies in government structures.

African bilateral trade, however, is still underdeveloped. Only 8-9% of exports by African countries are bound to stay within Africa.[52] Nevertheless, growth rates from 2001-2005 show that the inner African market gains importance and grew by more then 20% yearly, compared to only 12.7% growth in exports to the rest of the world (Yoshino 2008). Using the data at hand this figure rose to 49 billion US$ in 2010, a growth rate of again 21.6%[53]. With the rise of economic activity in Africa, ethnic networks, and the reduction of the ethnic specific fixed costs with it, are likely to become more important in the future.

[52]26.5 billion US$ Yoshino (2008). In the available data that figure stands at 18.4 billion US$.

[53]Using my data: 2005 18.4 billion US$ to 49 billion US$ in 2010.

From an employment perspective, ethnic networks have also an effect on GDP. If networks facilitate the access to export markets, general employment is likely to increase since exporting firms have a larger workforce (Yoshino 2008, Page & Soderbom 2012). Hence, enabling productive network members to set up their own firm might increase employment and lift people out of poverty. There is some evidence that a larger number of exporters increase GDP growth in African countries (Soderbom & Teal 2003). Since the way I model ethnic networks has no direct effect on GDP besides the effect through export values, I instrument export values by these networks to solve the reverse causality concerns between GDP and exports. The second stage results I find in Table 13 show a positive and significant effect of export volumes on GDP supporting the correlation found by Soderbom & Teal (2003). Firms use or create ethnic networks to facilitate exporting to new markets. The resulting knowledge and wealth spillovers then impact per capita GDP in both countries positively. However, this is not the total effect of ethnicities on GDP through conflicts or mistrust that are factored out In the way I create my instrument and only partially covered by bilateral characteristics and importer and exporter fixed effects in both stages of the regression.

The results I found for trust and corruption also support common empirical findings that investments in infrastructure and administration are needed to foster integration. Ethnic networks, however, can help to overcome some of these barriers and account for some of the differences regarding the export intensities of various countries. As Wood & Jordan (2000) for Uganda and Zimbabwe show, Zimbabwe outperforms Uganda in terms of exports even though they are predicted to have similar levels of manufacturing exports. The authors argue that this discrepancy between prediction and reality can be explained by the lack of adequate infrastructure in Uganda and investments in their export sector in Zimbabwe. Additionally, as I have shown above, Zimbabwe profits from a larger ethnic network to surrounding countries and its positive effect on trade flows.

9 Conclusion

The above analysis provides evidence that ethnic networks form and direct export flows between African countries. By deriving a variant of a model based on the Chaney (2008) model I am able to asses the importance of fix costs of exports as determinants of export flows.
The preferred specification suggests an elasticity of export flows to ethnic networks in importing and exporting countries of 0.06 which translates into potential yearly losses of shutting down that network of 17.4%. Using an approach by Krueger & Lindahl (2001) and adapting it to the

case of non-classical measurement error I am able to show that my proxy for ethnic networks is not affected by an attenuation bias. I do find some evidence for the positive selection into exporters, given ethnic connections and ethnic population size. In an extension with ethnic dependent fix costs to form networks I show that these cost matter immensely for export volumes. Finally, instrumenting trade volumes by ethnic networks I am able to establish a positive relation between exports and per capita GDP growth.

Researchers having reliable ethnic population data can improve upon this reduced form approach by terms of an instrumental variable strategy. The ethnic network variable constructed here is shown to have predictive power for bilateral trade flows and could thus be used as an instrument in future research. Alongside Eaton et al. (2004), Fafchamps (2003), Guiso et al. (2009) and Felbermayr & Toubal (2012) I argue that the main channel is through trust building measures and that networks erode fixed costs of exporting. However, since these estimates are based upon reported trade flows, the effect on the unreported trade flows between two villages at the border are potentially larger. Therewith, further research like Aker et al. (2014) using a spatial approach to identify study areas between ethnic groups can yield interesting results on the effect of ethnic boundaries on socio economic outcomes within a country and informal trade between countries. Understanding these networks in developing countries are of paramount importance since Dunlevy (2006) shows that networks are more important in more corrupt regimes and along with Bisin & Verdier (2000, 2001) cultural change and trust develop slowly implying entry barriers to foreign markets for years to come.

10 References

Aker, J. C., Klein, M. W., O'Connell, S. A. & Yang, M. (2014), 'Borders, ethnicity and trade', *Journal of Development Economics* **107**(1), 1–16.

Alesina, A., Easterly, W. & Matuszeski, J. (2011), 'Artificial states', *Journal of the European Economic Association* **25**, 246–277.

Anderson, J. E. (1979), 'A theoretical foundation for the gravity equation', *American Economic Review* **69**(1), 106–116.

Axtell, R. L. (2001), 'Zipf distribution of u.s. firm sizes', *Science* **293**(5536), 1818–1820.

Balnes-Cristóbal, J. (2008), 'Characteristics of immigrants and bilateral trade', *Revista de Economía Aplicada* **48**.

Bandyopadhyay, S., c. Coughlin, C. & Wall, H. J. (2008), 'Ethnic networks and us exports', *Review of International Economics* **16**, 199–213.

Bates, R. H. (2008), *When Things Fell Apart: State Failure in Late-Century Africa*, Cambridge University Press.

Bisin, A. & Verdier, T. (2000), ''beyond the melting pot': Cultural transmission, marriage and the evolution of ethnic and religious traits.', *Quarterly Journal of Economics* **115**(3), 955–988.

Bisin, A. & Verdier, T. (2001), 'The economics of cultural transmission and the dynamics of preferences', *Journal of Economic Theory* **97**(2), 298–319.

Burgess, R., Jedwab, R., Miguel, E., Morjaria, A. & Pardo i Miguel, G. (2013), 'The value of democracy: Evidence from road building in kenya', *Working Paper* .

Canavire, B., Javier, G. & Ehrlich, L. (2006), 'The impact of migration on foreign trade: A developing country approach', *Latin American Journal of Economic Development* **6**.

Chaney, T. (2008), 'Distorted gravity: The intensive and extensive margins of international trade', *American Economic Review* **98**(4), 1707–1721.

Combes, P.-P., Lafourcade, M. & Mayer, T. (2005), 'The trade-creating effects of business and social networks: evidence from france', *Journal of International Economics* **66**.

Dunlevy, J. A. (2006), 'The influence of corruption and language on the protrade effect of immigrants: Evidence from the american states', *Review of Economics and Statistics* **88**(1), 182–186.

Dunlevy, J. A. & Hutchinson, W. K. (1999), 'The impact of immigration on american import trade in the late nineteenth and ealry twentieth centuries', *Journal of Economic History* **59**, 1043–1062.

Eaton, J., Kortum, S. & Kramarz, F. (2004), 'Dissecting trade: Firms, industries, and export destinations', *American Economic Review* **94**(2), 150–154.

Eifert, B., Miguel, E. & Posner, D. N. (2010), 'Political competition and ethnic identification in africa', *American Journal of Political Science* **54**(2), 494–510.

Fafchamps, M. (2003), 'Ethnicity and networks in african trade', *Contributions to Economic Analysis and Policy* **2**(1).

Fafchamps, M. & Gubert, F. (2007), 'Risk sharing and network formation', *American Economic Review* **97**(2), 75–79.

Felbermayr, G. J., Jung, B. & Toubal, F. (2010), 'Ethnic networks, information, and international trade: Revisiting the evidence', *Annals of Economics and Statistics* **98**.

Felbermayr, G. J. & Toubal, F. (2012), 'Revisiting the trade-migration nexus: Evidence from new oecd data', *World Development* **40**(5), 928–937.

Francois, P., Rainer, I. & Trebbi, F. (2013), 'How is power shared in africa', *Working Paper* .

Gould, D. M. (1994), 'Immigrant links to the home country: Empirical implications for u.s. bilateral trade flows', *Review of Economics and Statistics* **76**, 302–316.

Grossman, G. M., Helpman, E. & Szeidl, A. (2006), 'Optimal integration strategies for the multinational firm', *Journal of International Economics* **70**(1), 216–238.

Guiso, L., Sapienza, P. & Zingales, L. (2009), 'Cultural biases in economic exchanges', *Quarterly Journal of Economics* **124**(3), 1095–1131.

Helpman, E., Melitz, M. & Rubinstein, Y. (2008), 'Estimating trade flows: Trading partners and trading volumes', *Quarterly Journal of Economics* **123**(2), 441–487.

Hensel, P. R. (2009), 'Icow colonial history data set, version 0.4', *http://www.icow.org/colhist.html* .

Herander, M. G. & Saavedra, L. A. (2005), 'Exports and the structure of immigrant-based networks: The role of geographic proximity', *Review of Economics and Statistics* **87**, 323–335.

Krautheim, S. (2012), 'Heterogenous firms, exporter networks and the effect of distance on international trade', *Journal of International Economics* **87**(1), 27–35.

Krueger, A. B. & Lindahl, M. (2001), 'Education for growth: Why and for whom?', *Journal of Economic Literature* **39**.

McKenzie, D. & Rapoport, H. (2007), 'Network effects and the dynamics of migration and inequality: theory and evidence from mexico', *Journal of development Economics* **84**(1), 1–24.

Melitz, M. J. (2003), 'the impact of trade on intra-industry reallocations and aggregate industry productivity', *Econometrica* **71**(6), 1695–1725.

Michalopoulos, S. & Papaioannou, E. (2013), 'Pre-colonial ethnic institutions and contemporary african development', *Econometrica* **81**(1), 113–152.

Michalopoulos, S. & Papaioannou, E. (2014), 'National institutions and subnational development in africa', *Quarterly Journal of Economics* **129**(1), 151–213.

Murdock, G. (1959), *Africa: Its Peoples and Their Culture History*, New York: McGraw-Hill.

Nunn, N. (2008), 'The long-term effects of africa's slave trades', *Quarterly Journals of Economics* **123**(1), 139–176.

Nunn, N. & Puga, D. (2012), 'Ruggedness: The blessing of bad geography in africa', *Review of Economics and Statistics* **94**(1), 20–36.

Nunn, N. & Wantchekon, L. (2011), 'The slave trade and the origins of mistrust in africa', *American Economic Review* **101**(7), 3221–3252.

Oezden, C., Parsons, C. R., Schiff, M. & Walmsley, T. L. (2012), 'Where on earth is everybody? the evolution of global bilateral migration 1960-2000', *World Bank Economic Review* **25**(1), 12–56.

Olken, B. & Barron, P. (2009), 'The simple economics of extortion: Evidence from trucking in aceh', *Journal of Political Economy* **117**(3), 417–452.

Page, J. & Soderbom, M. (2012), 'Is small beautiful? small enterprise, aid and employment in africa', *Working Paper* .

Partridge, J. & Furtan, H. (2008), 'Immigration wave effects on canada's trade flows', *Canadian Public Policy* **34**(2), 193–214.

Peri, G. & Requena-Silvente, F. (2010), 'The trade creation effect of immigrants: evidence from the remarkable case of spain', *Canadian Journal of Economics* **43**(4), 1433–1459.

Rauch, J. E. (1999), 'Networks versus markets in international trade', *Journal of International Economics* **48**.

Rauch, J. E. & Trindade, V. (2002), 'Ethnic chinese networks in international trade', *Review of Economics and Statistics* **84**(1), 116–130.

Santos-Silva, J. & Tenreyro, S. (2006), 'The log of gravity', *Review of Economics and Statistics* **88**(4), 641–658.

Santos-Silva, J. & Tenreyro, S. (2014), 'Estimating the extensive margin of trade', *Journal of International Economics* **93**(2), 67–75.

Soderbom, M. & Teal, F. (2003), 'Are manufacturing exports the key to economic success in africa', *Journal of African Economies* **12**, 1–29.

Svensson, J. (2003), 'Who must pay bribes and how much? evidence from a cross section of firms', *Quarterly Journal of Economics* **118**(1), 207–230.

United Nations (2002), 'World urbanization prospects: The 2001 revision: Iv: Urbanization patterns and rural population growth at the country level', *UN* .

Weidmann, N. B., rod, J. K. & Cedermann, L.-E. (2010), 'Representic ethnic groups in space: A new dataset', *Journal of Peace Research* **47**(4).

White, R. (2007), 'Immigrant-trade links, transplanted home bias and network effects', *Applied Economics* **39**.

Wood, A. & Jordan, K. (2000), 'Why does zimbabwe export manufactures and uganda not? econometrics meets history', *Journal of Development Studies* **37**, 91–116.

Woodruff, C. & Zenteno, R. (2007), 'Migration networks and microenterprises in mexico', *Journal of Development Economics* **82**(2), 509 – 528.

Yoshino, Y. (2008), 'Domestic constraints, firm characteristics, and geographical diversification of firm-level manufacturing exports in africa', *World Bank Policy Research Working Paper* **4575**.

11 Appendix

Table 14: Summary Statistcs of outcome and control variables (GREG)

Variable	Mean	Std. Dev.	Min.	Max.	N
Exports	21606.27	113007.351	0	3361112.5	15961
Ethnic Connection	0.194	0.395	0	1	49446
log(Ethnic Network)	2.175	4.767	-1.076	19.402	49446
log(Ethnic Network, exp=0.5)	1.651	3.634	-1.117	15.135	49446
log(GDP)	22.252	1.518	18.542	26.619	49446
Common Border	0.083	0.275	0	1	49446
Part of the Border is a River	0.046	0.21	0	1	49446
Same Language	0.059	0.235	0	1	49446
log(Pop.)	8.918	1.317	5.893	11.981	49446
log(Distance)	7.909	0.954	-0.368	9.013	49402
Exporting Countries	48	0	48	48	49446
Importing Countries	48	0	48	48	49446
Number of ethnic connections	9.087	5.373	0	21	49446
Colonial Ties	0.24	0.427	0	1	49446
No. of ethnicities	10.578	7.456	1	33	49446
Area of Home Country	580107.806	583216.593	1862	2381741	49446
Ruggedness index	0.978	1.145	0.115	6.202	49446
% Tropical climate	50.735	42.831	0	100	49446
% Fertile soil	30.844	21.49	0	81.699	49446
% Desert	6.449	14.616	0	74.857	49446
No. of Conflicts in Destination	21.398	61.363	0	578	49446

Table 15: Results when the dependent variable is normalized by total exports

	(1)	(2)
Estimation Technique:	OLS	PPML
Dependent Variable:	Share of Total Exports	
log(Ethnic Network)	0.0006**	0.0445***
	(0.0003)	(0.0168)
log(Ethnic Network, exp=0.5)	0.0007*	0.0544**
	(0.0004)	(0.0225)
log(Ethnic Network, exp=0.2)	0.0007	0.0618**
	(0.0004)	(0.0276)
N	15945	15945

Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. The second and third row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). The first column uses an ordinary least squares estimator and the second the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). The dependent variable is exports to an importer divided by the total exports in that year by the exporter. Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Results with Disaggregated Data

	(1)	(2)	(3)
Estimation Technique:		PPML	
Dependent Variable:	Sector Exports	Total Exports	Sector Exports
Data Set:	Original Data	SIC 4-digit	
log(Ethnic Network)	0.0577***	0.0860***	0.0645***
	(0.0178)	(0.0203)	(0.0179)
log(Ethnic Network, exp=0.5)	0.0711***	0.1025***	0.0773***
	(0.0237)	(0.0269)	(0.0229)
log(Ethnic Network, exp=0.2)	0.0783***	0.1074***	0.0816***
	(0.0284)	(0.0329)	(0.0269)
N	160619	2203	116853
Sector Fixed Effects	Yes	No	Yes

Each entry is a separate regression of the dependent variable on the definition of ethnic networks, covariates and importer and exporter fixed effects. The second and third row depict an exponent of ν =0.5 and ν =0.2, respectively, in equation (12). The estimation technique is the poisson-pseudo-maximum-likelihood estimator as suggested by Santos-Silva & Tenreyro (2006). The first column uses the original data set and sectoral exports with sector fixed effects. The second and third columns use the SIC revision with 4 digit classification for the years 2007-2010. Standard errors are clustered within each importer-exporter pair and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.