Ethnic Remoteness Reduces the Peace Dividend from Trade Access*

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Abstract

This paper shows that ethnically remote locations do not reap the full peace dividend from increased market access. Exploiting the staggered implementation of the US-initiated Africa Growth and Opportunity Act (AGOA) and using high-resolution data on ethnic composition and violent conflict for sub-Saharan Africa, our analysis finds that in the wake of improved trade access conflict declines less in locations that are ethnically remote from the rest of the country. We hypothesize that ethnic remoteness acts as a barrier that hampers participation in the global economy. Consistent with this hypothesis, satellite-based luminosity data show that the income gains from trade are smaller in ethnically remote locations, and survey data indicate that ethnically more distant individuals do not benefit from the same positive income shocks when exposed to increased market access. These results underscore the importance of ethnic barriers when analyzing which locations and groups might be left behind by globalization.

Keywords: Trade Liberalization, Market Access, Conflict, Peace Dividend, Ethnic Remoteness, sub-Saharan Africa
JEL Codes: D74, F13, F6, O12, O55, R11, Z1

1 Introduction

The starting point of this paper are three observations. First, a positive terms of trade shock affects the likelihood of conflict in developing countries. If such a shock raises the opportunity cost of conflict, it may lead to a drop in violence: a peace dividend.[1] Second, the gains from trade are limited not just by tariffs and transport costs, but also by other frictions, such as ethnic and linguistic barriers.[2] Third, ethnic differences

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[1] Berman and Couttenier (2015) provide evidence of positive terms of trade shocks lowering conflict in sub-Saharan Africa, whereas Dix-Carneiro et al. (2018) show how negative terms of trade shocks increase crime in Brazil. Dube and Vargas (2013) present a more mixed picture, arguing that the benign effect of positive terms of trade shocks on conflict is limited to commodities that are labor-intensive.

[2] For evidence on ethnic and linguistic barriers to trade, see Isphording and Otten (2013), Melitz and Toubal (2014) and Aker et al. (2014).

are a fundamental driver of conflict around the world.[3] These observations raise the question of how a location's ethnic composition might affect the potential peace dividend from trade. Using high-resolution data for sub-Saharan Africa, this paper shows that after a positive trade access shock, there is an overall decline in conflict, but ethnically remote locations benefit less from this peace dividend. In addition, this paper provides evidence that ethnically remote locations and ethnically remote individuals are more likely to be left behind by the income gains of globalization.

Exploiting geographical and time variation in the access to trade in sub-Saharan Africa, we explore the role of a location's ethnic remoteness in mediating the impact of improved market access on conflict. The idea is that a location's ethnic remoteness acts as a barrier to accessing local trade networks and power structures that facilitate integration into the global market. Because in sub-Saharan Africa power tends to be assigned proportionally to the sizes of ethnic groups (Francois et al., 2015), we measure a location's ethnic remoteness as its population-weighted average ethnic distance to the rest of the country.[4] To get temporal and spatial variation in trade access, we rely on the Africa Growth and Opportunity Act (AGOA) that during the 2000s lowered U.S. trade barriers for most African countries (Frazer and Van Biesebroeck, 2010). Because not all African countries were part of AGOA, and because accession occurred in a staggered manner, there is cross-country and cross-time variation in trade access. By further interacting country-level exposure to AGOA with within-country geographic distances from the closest port, we also exploit within-country local variation in trade access. Combining the sub-national level trade access data with high-resolution geo-coded data on ethnic remoteness and conflict, we can analyze how the effect of trade liberalization on conflict depends on a location's ethnic remoteness.

Using a spatial resolution of $0.5° \times 0.5°$, we regress the intensity of conflict on local exposure to AGOA and on the interaction of this exposure with ethnic remoteness. Identification relies on including grid-cell fixed effects as well as country-specific time fixed effects in our empirical specification. These fixed effects purge estimates of time-invarying cell-level and time-varying country-level unobservable characteristics that might pose a threat to causality. For example, accession to AGOA depended partly on a country's democratic freedoms and its respect for private property rights, but these characteristics are also likely to affect conflict. Country-specific time fixed effects absorb any such impact. In addition to including fixed effects, we control for time-varying cell-level weather shock variables that have been found to be important for conflict (Burke et al., 2015), and for a wide range of potentially confounding cell-level variables interacted with local exposure to AGOA.

Our cell-level regressions establish two main results. First, locations that experience greater improvements in market access suffer less from violent conflict: accession to AGOA lowers conflict, and more so in locations that are closer to ports. There is thus a peace dividend from trade access. Second, being in an ethnically more remote location mitigates this positive effect. That is, the benefits of accession to AGOA on conflict are partly or wholly wiped out in locations that are ethnically distant from the rest of the country. This latter result is not driven by ethnically remote locations also being geographically remote.

In addition to ethnic remoteness, a location's ethnic composition might mediate the relation between market access and conflict in other ways. In particular, a location's ethnic diversity and its ethnic complementarity might matter too. A location's ethnic diversity measures to what extent its ethnic groups are fractionalized (Easterly and Levine, 1997; Alesina et al., 2003) or polarized (Esteban et al., 2012a; Montalvo

[3]Papers that have studied the link between ethnicity and conflict include Fearon and Laitin (2003), Collier and Hoeffler (2004), Montalvo and Reynal-Querol (2005), Esteban et al. (2012a) and Esteban et al. (2012b).

[4]As a robustness check, we also use an alternative measure, based on the population-weighted average ethnic distance to the country's largest ethnic group.

and Reynal-Querol, 2005). Ethnically diverse places typically find it harder to build consensus and reach agreements. When faced with an increase in contestable income in the wake of a positive trade shock, we might therefore expect ethnically diverse locations to resort to violence (Fearon and Laitin, 2003; Collier and Hoeffler, 2004; Montalvo and Reynal-Querol, 2005). Our paper finds no robust evidence of this mechanism. A location's ethnic complementarity, for its part, measures to what extent its ethnic groups depend on each other. Greater interdependence might facilitate sharing the gains from trade, so we might expect ethnic complementarity to reduce conflict (Jha, 2013). Our paper finds no empirical support for this mechanism either. Instead, only a location's ethnic remoteness affects the peace dividend from trade access. Controlling for additional measures of ethnic interdependence such as kinship tightness and segmentary lineage does not affect the results (Enke, 2019; Moscona et al., 2020).

Our main findings are consistent with improved trade access implying a greater opportunity cost to engage in conflict and with ethnic remoteness acting as a trade barrier that weakens this effect. Trade theory predicts that easier access to foreign markets through AGOA should imply income gains from trade. However, the relation between higher income and conflict is not without ambiguity. On the one hand, the opportunity cost effect emphasizes that positive income shocks make it more costly to engage in conflict. On the other hand, the rapacity effect emphasizes that positive income shocks increase contestable income, giving rise to more conflict (Dube and Vargas, 2013; Bazzi and Blattman, 2014; Berman et al., 2017; Blair et al., 2021).[5] Our finding of a peace dividend from AGOA is consistent with the opportunity cost effect, rather than with the rapacity effect. Of course, improved market access through AGOA does not do away with all trade costs. There continue to be trade frictions in the form of transport costs, linguistic barriers, and more generally, any other friction that limits effective integration into the world market. To the extent that ethnically remote locations face greater frictions to access the world market, we would expect them to benefit less from the positive effect of trade liberalization on conflict. This is consistent with our finding of a reduced peace dividend from AGOA in ethnically remote locations.

This particular interpretation of our results relies on AGOA having a positive income effect that is weakened by ethnic remoteness. However, so far we have not provided any evidence of the effect of AGOA on income. We therefore investigate whether cells that are more exposed to AGOA experience greater income gains as proxied by increases in nighttime luminosity, and whether cells that are ethnically more remote experience smaller gains. We use the exact same empirical specification as before, with the difference that we now look at the effect of the AGOA trade shock on luminosity rather than on conflict. Consistent with our interpretation, we find that accession to AGOA increases luminosity more in cells that are closer to a port, but this positive effect is smaller in cells that are ethnically more remote.

As further evidence for this income effect, we also use individual-level data from the different waves of the Afrobarometer. We find that individuals that are ethnically more distant from the rest of the country suffer negative income shocks when exposed to increased trade, compared to individuals that are ethnically less distant. When estimating this effect, we are able to control for a wide range of individual characteristics, such as age, gender, ethnicity and profession. Including profession purges estimates of possible effects coming from differences in specialization, and including ethnicity allows us to control for any effect of within-group genetic diversity (Arbatlı et al., 2020).

Our paper is related to a large literature on the effect of terms of trade shocks on conflict. Closest to our work is Berman and Couttenier (2015) who show that positive terms of trade shocks in sub-Saharan Africa lowers conflict, but less so in geographically more remote places. However, they do not explore the

[5] In contrast to our work, these empirical studies do not address the possible role of ethnic composition. For a theoretical analysis of these two effects, see Dal Bó and Dal Bó (2011).

relation between trade liberalization, ethnicity and conflict, which is the main focus of this paper. Other work that analyzes the relation between trade and conflict also ignores the ethnic dimension (Barbieri and Reuveny, 2005; Dix-Carneiro et al., 2018; Martin et al., 2008a,b, 2012).

Our interest in ethnic remoteness draws on the trade literature that has explored the role of linguistic and ethnic barriers as additional trade frictions (Isphording and Otten, 2013). These costs are not simply related to having a common language. Ethnic ties matter beyond their effect on the ease of communication (Melitz and Toubal, 2014). Trade frictions do not only exist between countries, they also exist within countries. For goods to be shipped overseas, they first need to successfully get to a port. This involves not just overcoming within-country geographic barriers but also within-country ethnic barriers. As an illustration, Aker et al. (2014) find within-country ethnic borders in Niger to be comparable to national borders in how they limit trade.

Ethnic, linguistic or genetic distances have also been shown to matter for other outcomes, such as human capital accumulation (Laitin and Ramachandran, 2016; Shastry, 2012), labor market outcomes of immigrants (Isphording, 2014), the diffusion of ideas (Spolaore and Wacziarg, 2009), market integration (Fenske and Kala, 2021), and the effectiveness of counterinsurgency policies (Armand et al., 2020). Recent work has taken a more micro approach, using high-resolution geographic data or individual-level data to study ethnic barriers. For instance, Gomes (2020) highlights how ethnic distance to neighbors impedes access to health information, leading to higher child mortality in sub-Saharan Africa.

Our paper speaks to the question which groups and locations are left behind by globalization. The differential impact of trade liberalization on skilled and unskilled workers is a well studied phenomenon (Goldberg and Pavcnik, 2007). More recent work has turned its focus to geography, comparing regions that are differentially affected by either lower import tariffs or improved market access. For example, Topalova (2010) finds smaller declines in poverty in Indian districts that experienced greater tariff reductions in the wake of India's 1991 trade liberalization, whereas McCaig (2011) finds faster declines in povery in Vietnamese provinces that benefited more from improved market access after the signing of the U.S-Vietnam Bilateral Trade Agreement in 2001. In developed countries, the so-called China trade shock has drawn much attention. Areas in the U.S. that were more exposed to Chinese import competition experienced deteriorating economic conditions (David et al., 2013; Autor et al., 2014, 2016). In these different studies of who might benefit and who might be left behind by globalization, the ethnic dimension has been ignored.[6] We find that both ethnically remote locations and ethnically remote individuals fail to reap the full benefits of improved trade access.

2 Data

Using a $0.5° \times 0.5°$ spatial grid (approximately 55 km by 55 km at the Equator), this paper empirically analyzes how ethnic remoteness mediates the effect of trade access on conflict.[7] We also consider how ethnic diversity and ethnic complementarity might act as separate channels affecting the relation between trade access and conflict. By combining time-varying country-level accession to the Africa Growth and Opportunity Act (AGOA) with within-country geographic distances to the closest port, we construct a measure of trade access that varies across time and space. To measure ethnic remoteness at the cell level, we rely on high-

[6]This is a major omission as inequality between ethnic groups can have severe pernicious effects on both economic growth (Alesina et al., 2016) and violent conflict (Mitra and Ray, 2014).

[7]The $0.5° \times 0.5°$ spatial grid based on PRIO has been used extensively in the literature. See, for instance, McGuirk and Burke (2020), Berman and Couttenier (2015), and Berman et al. (2017). Cells that overlap the borders of two or more countries are split into smaller sub-cells pertaining to distinct countries.

resolution data on the location and size of ethnolinguistic groups. Our main data source for local-level conflict is UCDP. The time frame of our study goes from 1989 to 2017, and we focus on sub-Saharan Africa. We also use conflict data from ACLED, covering 1997 to 2017. To see whether ethnic remoteness acts as a barrier that limits the gains from trade, we analyze its impact on income, as proxied by nighttime lights, for which we use cell-level data starting in 1992. The rest of this section describes the data in more detail. Appendix A.1 provides a detailed list of data sources, and Appendix Tables B1 and B2 report summary statistics and cross-correlations of the main variables of interest.

2.1 Dependent Variable: Conflict or Income

Conflict. As main source for our geo-coded conflict data, we use the UCDP Georeferenced Event Dataset, covering all 48 sub-Saharan African countries in our study for the period 1989–2017. This dataset defines violence as the use of "armed force by an organized actor against another organized actor or against civilians" (Sundberg and Melander, 2013, p. 524). Organized actors include governments of independent states or non-governmental organized groups. For the purpose of our study, we aggregate the conflict data up to the $0.5° \times 0.5°$ grid-cell level.

As an alternative, we also use the Armed Conflict Location and Event Data (ACLED). This dataset takes a broader view of political violence by including civil and communal conflicts, violence against civilians, and rioting and protesting. One disadvantage of ACLED is that it starts in 1997, only three years before the enactment of ACLED. That makes the longer time span of UCDP somewhat more attractive for our purpose. However, we conduct extensive robustness analysis using the ACLED data.[8]

Income. Following the pioneering work by Henderson et al. (2012), a large number of papers have used nightlight as measured by satellites as a proxy for income.[9] For 1992–2013 we use the DMSP-OLS Nighttime Lights Time Series v.4, whereas for 2014–2017 we use the extension data generated by Ghosh et al. (2021). This gives us a cell-level panel dataset of luminosity for 1992–2017. Intensity of luminosity, coded at the grid-cell level, takes values ranging from 0 (no lights) to 63 (maximum luminosity).

2.2 Trade Access

To identify the effect of market access, we rely on the Africa Growth and Opportunity Act of 2000 that gave sub-Saharan African countries preferential trade access to the United States. Because not all countries became part of AGOA and because accession occurred in a staggered manner, there is cross-time and cross-country variation in trade access. More than 90% of international trade in Africa relies on maritime transport (Sebastian, 2014). We therefore rely on the proximity to major ports for within-country variation in trade access.[10] By multiplying country-level trade access by a measure that is increasing in proximity to the nearest port, we get a cell-level time-variant measure of trade access:

$$AGAccess_{ict} = AGOA_{ct} \times Proximity_{ic}. \tag{1}$$

where $AGAccess_{ict}$ denotes trade access in cell i of country c in year t, $AGOA_{ct}$ denotes whether or not country c has access to AGOA in the year t, and $Proximity_{ic}$ denotes the proximity of cell i of country c to

[8]For other papers that use UCDP and/or ACLED, see Berman and Couttenier (2015), McGuirk and Burke (2020), Armand et al. (2020), Cervellati et al. (2022), and Moscona et al. (2020).

[9]See Michalopoulos and Papaioannou (2018) for a review of this literature.

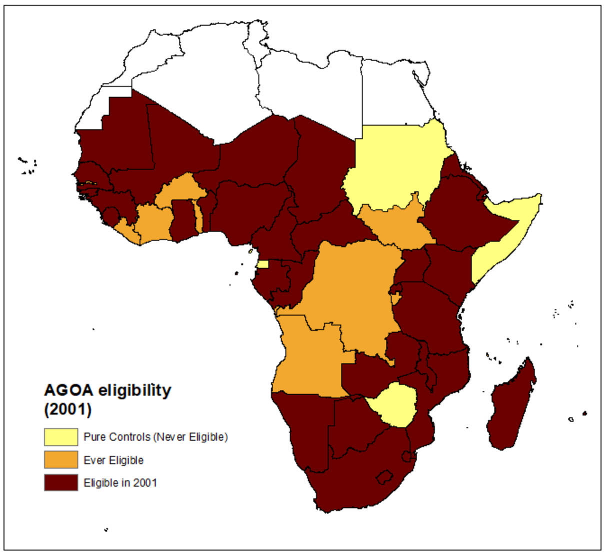
[10]See, for instance, Berman and Couttenier (2015) for a related approach.

the nearest major port. We compute $Proximity_{ic}$ by standardizing the number of hours required to travel to the nearest major port, and subtracting this standardized variable from its maximum. Figure 1a maps the cross-country variation in access to AGOA, whereas Figure 1b depicts the travel time to the nearest major port expressed in hours.

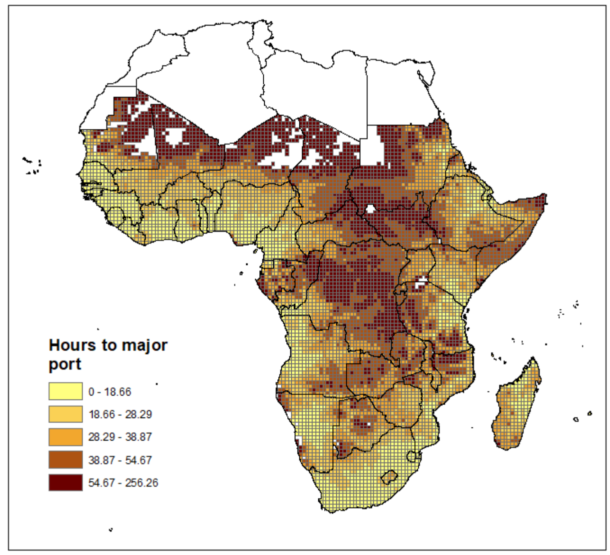
To use AGOA as a shock to trade access, ideally it needs to have a sufficiently large effect on exports. Focusing on the program's three key product categories (apparel, agriculture, and manufactures), Frazer and Van Biesebroeck (2010) estimate an AGOA-induced increase in exports of 34%. Looking more broadly at all non-oil exports, the effect was a more modest, but still not trivial, 8.0%.

Figure 1: Trade Access through AGOA

(a) AGOA membership



(b) Travel time to nearest port



Note: Panel (a) plots three types of countries i) countries that could have entered AGOA but never did (pure controls); ii) countries that entered AGOA for at least one year during the period of our study; iii) countries that were eligible for AGOA in 2001, i.e. the first year of its implementation. The North African countries in white were never part of AGOA and are not part of our sample. Panel b) plots the travel time to the nearest major port in hours for the year 2000 (i.e. pre-AGOA). Our measure of proximity to the port is based on this variable. A higher travel time to port represents a lower degree of trade openness, as approximately 90% of African trade is maritime. See Appendix A.1 for data sources and variable definitions.

Accession to AGOA depended mostly on countries having some basic level of private property rights, rule of law, democratic freedoms, and a market-based economy.[11] Differences in such rights, freedoms and institutions partly explain why some countries, such as Somalia, never became eligible, why other countries, such as Sierra Leone, were admitted late, and why a few countries, such as Eritrea, were removed. Appendix Table A1 lists the full list of countries that were ever eligible for AGOA along with years of eligibility.To the extent that accession criteria are related to conflict, we might face an endogeneity problem. We address this potential issue by including country $\times$ year fixed effects in all our regressions.

2.3 Ethnic Remoteness

In sub-Saharan Africa ethnicity and language largely overlap. Data on the population's ethnic composition at the $0.05° \times 0.05°$ grid-cell level come from the language database recently constructed by Desmet et al.

[11] See `https://agoa.info/about-agoa/country-eligibility.html`.

(2020). They combine three sources of information: data on the spatial distribution of population from Landscan, data on the linguistic composition of countries from Ethnologue (Lewis et al., 2014), and maps on the geographic distribution of 6,905 distinct languages from the World Language Mapping System (WLMS). Using this information, they then use an iterative proportional fitting algorithm to construct a comprehensive $0.05° \times 0.05°$ grid-cell level dataset on the ethnolinguistic composition of the population for the entire globe. Aggregating this information up to the $0.5° \times 0.5°$ grid-cell level, we can measure a cell's ethnic remoteness to the rest of the country.

Ethnic remoteness aims to proxy for the ethnic barriers that residents of a location face in accessing local trade networks and power structures that facilitate their integration into the global market. In the context of sub-Saharan Africa, Francois et al. (2015) find a high degree of proportionality in the assignment of power positions between ethnic groups. As main measure of a cell's ethnic remoteness, we therefore take the average ethnic distance between a random resident of the cell and a random resident of the country. To be more precise, consider a country partitioned into different grid-cells indexed by ℓ or k with a population belonging to different ethnic groups indexed by i or j. Denote by d_{ij} the ethnic distance between i and j, by s_i the share of the country's population pertaining to ethnic group i, and by $s_{\ell i}$ the share of the population of grid-cell ℓ pertaining to ethnic group i. We then define the ethnic remoteness of cell ℓ to the country as

$$ER_\ell = \sum_i \sum_j s_{\ell i} s_j d_{ij}. \tag{2}$$

Given that in Africa ethnicity tends to coincide with language, we measure d_{ij} as the linguistic distance between the language spoken by ethnic group i and the language spoken by ethnic group j (Gomes, 2020). Following a large literature, we use a linguistic distance measure that is based on the number of shared branches in a linguistic tree.[12] More specifically, we take the Ethnologue language tree, and denote by b_{ij} the number of shared branches between languages i and j, and by b_{max} the maximum number of shared branches between any two languages. We then define the linguistic distance between i and j as

$$d_{ij} = 1 - \left(\frac{b_{ij}}{b_{max}}\right)^\delta \tag{3}$$

where δ is a parameter that determines how fast the linguistic distance declines as the number of shared branches increases. We follow Desmet et al. (2009) and set $\delta = 0.05$.

Panel (a) of Figure 2 shows a grid-cell map of ethnic remoteness in sub-Saharan Africa. One relevant question is to what extent ethnic remoteness is distinct from geographic remoteness. The correlation between ethnic remoteness and travel time to the nearest port is only 0.255. This clarifies that ethnic remoteness captures a concept that is distinct from geographic remoteness.

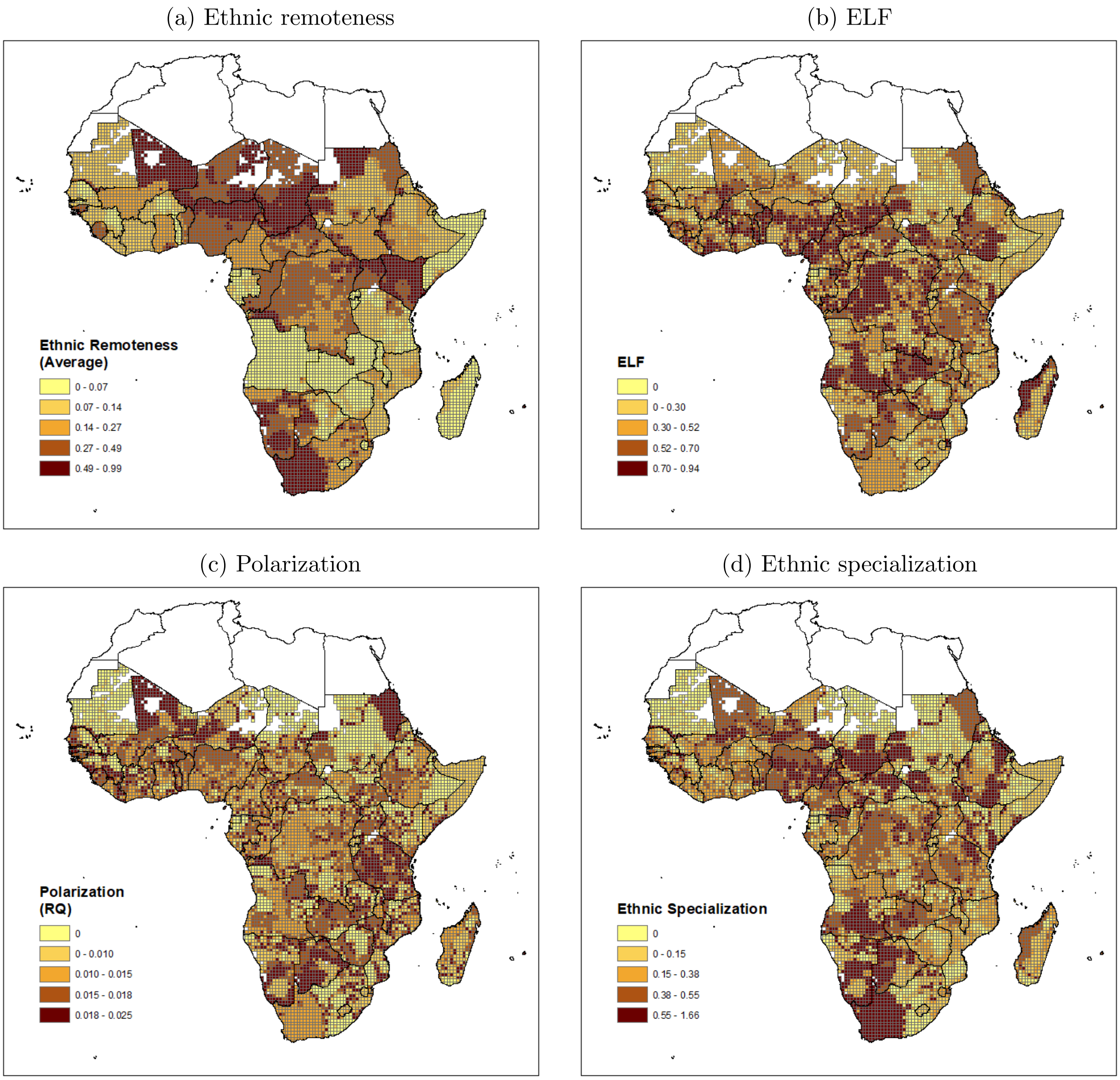
As an alternative measure to ethnic remoteness to the country average, we also consider the ethnic remoteness of a cell ℓ to the country's dominant group

$$ER_\ell^{dom} = \sum_i s_{\ell i} s_{dom} d_{i,dom}, \tag{4}$$

where s_{dom} is the share of the country's largest ethnic group.

[12]See, for instance, Fearon (2003), Desmet et al. (2009), Desmet et al. (2012), Esteban et al. (2012a), Esteban et al. (2012b), Laitin and Ramachandran (2016) and Gomes (2020) for a similar approach.

Figure 2: Ethnic Remoteness, Ethnic Diversity, and Ethnic Specialization



Notes: Panel a) plots ethnic remoteness, which measures the average ethnic distance between a random resident of the cell and a random resident of the country (equation (2)). Panel b) plots the ethnolinguistic fractionalization index, which measures the probability that two randomly drawn individuals of a cell pertain to different ethnic groups (equation (5)). Panel c) plots the ethnolinguistic polarization index, which measures how far the distribution of ethnic groups is from a bipolar distribution (equation (6)). Panel d) plots the ethnic specialization index, which measures measures the extent to which occupational specialization runs along ethnic lines (equation (7)). The distribution of ethnic groups is based on data from Desmet et al. (2020). See Appendix A.1 for further details on data sources and variable definitions.

2.4 Ethnic Diversity

Although our main focus is on ethnic remoteness, we also consider whether other aspects of a location's ethnic composition might mediate the relation between trade and conflict. It has been widely documented that ethnic diversity is a fundamental driver of conflict in sub-Saharan Africa (Collier and Hoeffler, 2004).

We consider two measures of a cell's ethnic diversity. One is the standard fractionalization index, which measures the probability that two randomly drawn individuals of cell ℓ pertain to different ethnic groups:

$$ELF_\ell = \sum_i \sum_j s_{\ell i} s_{\ell j}. \tag{5}$$

Another is the standard polarization index from Montalvo and Reynal-Querol (2005), which measures the distance of the distribution of the populations of ethnic groups in a cell from a bipolar distribution (i.e. a distribution with two ethnic groups each having a population of 50%):

$$POL_\ell = \sum_i s_{\ell i}^2 (1 - s_{\ell i}). \tag{6}$$

In the robustness checks, we will also consider other fractionalization and polarization indices that take into account distances between ethnic groups. Panels (b) and (c) of Figure 2 show ELF and POL at the grid-cell level. Visually, it is clear that the spatial variation in ELF and POL are quite different from the spatial variation in ethnic remoteness. In fact, the cell-level correlation between ethnic remoteness and ELF is only 0.09, and the corresponding correlation with POL is 0.13.

2.5 Ethnic Complementarity

One additional dimension of ethnicity that may matter for the relation between trade and conflict is ethnic complementarity. This concept aims to capture how much different ethnicities depend on each other and how likely they are to engage in productive cooperation. Stronger interethnic complementarities might lower the barriers to reaping the gains from trade, reducing the risk of conflict (Jha, 2013). On the other hand, the possibility to trade might disrupt and weaken the historic interdependence between ethnicities, increasing the risk of conflict. As measures of this interdependency, we use the concepts of ethnic specialization, kinship tightness, and segmentary lineage.

Ethnic specialization. Ethnic specialization measures the extent to which occupational specialization runs along ethnic lines. The idea is that if different ethnic groups specialize in different activities, they depend more on each other and they are more complementary to each other. To get a measure of ethnic specialization at the cell level, we combine information of occupational activity by ethnicity with the ethnic composition of grid cells. Denote by x_i^q be the share of ethnic group i traditionally employed in occupation q, where the data on occupational activity come from the Ethnographic Atlas (Murdock, 1967). Combining this with the ethnic composition of each grid-cell, we can then determine the share of cell ℓ traditionally employed in occupation q, $x_\ell^q = \sum_i s_{i\ell} x_i^q$.[13] Following Krugman (1991), we can define the specialization of ethnic group i as $\sum_q \mid x_i^q - x^q \mid$, where x^q is the share of the country's population traditionally employed in occupation q. The extent of ethnic specialization of cell ℓ is then

$$ES_\ell = \sum_i s_{\ell i} \sum_q \mid x_i^q - x^q \mid \tag{7}$$

[13]As mentioned before, we use ethnicities and languages interchangeably. However, since occupational composition is measured by ethnicity, and cell composition is measured by language, we need an explicit mapping between ethnicities and languages. For that mapping, we rely on the work of Giuliano and Nunn (2018).

The index is between 0 (no specialization along ethnic lines) and 2 (maximum specialization along ethnic lines). For ease of interpretation of the coefficients, we standardize ES_ℓ to have mean 0 and standard deviation 1. Panel (d) of Figure 2 shows a map of ethnic specialization at the local level.

Kinship tightness. As argued by Enke (2019), the looser the kinship links in a society, the easier it is to cooperate with distant strangers. In our view, ethnic groups are more complementary if they are able to reap the benefits from productive collaboration between them. Hence, the greater the kinship tightness of a cell, the lower the cell's ethnic complementarity. To measure a cell's kinship tightness, we use data on the kinship tightness by ethnicity from Enke (2019), and take the population-weighted average of the cell's different ethnic groups. Panel (a) of Appendix Figure A1 shows a cell-level map of kinship tightness. The correlation with ethnic remoteness is 0.11.

Segmentary lineage. Segmentary lineages are groups of people that trace their ancestry to a common founder. When an ethnic group is organized along segmentary lineages, it is less likely to form associations with other ethnicities, and it is more likely to engage in violent conflict (Moscona et al., 2020). As such, a cell populated by ethnicities that organize along segmentary lineages will experience a low level of ethnic complementarity. To measure a cell's segmentary lineage, we use ethnicity-level data on segmentary lineages from Moscona et al. (2020) and take its cell-level population-weighted average. Panel (b) of Appendix Figure A1 shows map of segmentary lineage. The correlation with ethnic remoteness is -0.24.

2.6 Other Control Variables

Since weather shocks have been shown to be an important predictor of conflict (Burke et al., 2015; Miguel et al., 2004; Ciccone, 2011), we control for both temperature and rainfall shocks. Following recent work, we use standardized deviations in rainfall and temperature (Hidalgo et al., 2010; Armand et al., 2020). The rainfall data are drawn from the CHIRPS dataset (Funk et al., 2014), while the temperature data come from the ERA reanalysis data (Muñoz-Sabater et al., 2021). Data on malaria suitability are drawn from Kiszewski et al. (2004), made available in raster format by McCord and Anttila-Hughes (2017). Data on crop suitability and Tse Tse fly suitability come from the FAO.

3 Ethnic Remoteness, Trade Access, and Conflict

Our primary objective is to explore the role of ethnic remoteness in mediating the relation between trade access and conflict. Ethnically more remote locations may face hurdles to fully participate in trading networks, possibly generating increased conflict in the wake of a trade agreement that improves access to foreign markets. In addition to ethnic remoteness, there may also be a role for ethnic diversity and ethnic complementarity. Ethnically more diverse locations may find it harder to share the benefits from a positive trade shock, leading to a greater risk of conflict. Ethnically more complementary locations may witness either more conflict (if improved trade access weakens ethnic interdependence) or less conflict (if ethnic interdependence facilitates collaboration in the wake of improved trade access).

3.1 Cell-Level Regression Specification

Our main specification regresses cell-level conflict severity in time t on the cell's degree of trade openness at time t and on the interaction of that trade openness with different measures related to the cell's ethnic makeup, controlling for cell and country-time fixed effects as well as for time-varying cell characteristics that may affect conflict. More specifically,

$$\log(y_{ict}+1) = \alpha AGAccess_{ict} + AGAccess_{ict}\mathbf{E'}_{ic}\beta + \mathbf{X'}_{ict}\gamma + \delta_{ic} + \eta_{ct} + u_{ict} \tag{8}$$

where y_{ict} is the number of fatalities in cell i of country c at time t, $AGAccess_{ict}$ is the degree of trade openness of cell i in country c at time t, $\mathbf{E}_{ic}$ is a vector of time-invariant cell-level variables related to ethnicity (ethnic remoteness, ethnic diversity, ethnic complementarity) which we interact with the cell's degree of trade openness at time t, $\mathbf{X}_{ict}$ is a vector of cell-level time-varying characteristics (weather shocks), δ_{ic} are cell fixed effects, η_{ct} are country-time fixed effects, and u_{ict} is an idiosyncratic error term. By using cell and country-time fixed effects, we address a number of concerns. Cell fixed effects absorb all time-invarying cell characteristics that might affect conflict. Country-time fixed effects absorb all characteristics that vary across countries and time, such as time-varying country characteristics that determine selection into the AGOA program. We always correct standard errors for spatial correlation within a 500 km radius and for infinite serial correlation following Conley (1999) and Hsiang (2010).[14]

3.2 Ethnic Remoteness Weakens the Peace Dividend from Trade

Ethnic diversity, ethnic remoteness, and ethnic complementarity. Table 1 reports results from estimating (8) using conflict data from UCDP. Column (1) shows that a higher degree of trade openness is associated with lower levels of conflict. Column (2) adds an interaction of trade openness with ethnic remoteness, measured as the linguistic distance between a random individual of the cell and a random individual of the country. As can be seen, ethnic remoteness diminishes the benign effect of trade openness on conflict. That is, ethnically remote cells reap a smaller peace dividend from trade openness. Columns (3) and (4) add interaction terms between trade openness and the cell's ethnic diversity, measured as either ethnic fractionalization or ethnic polarization. The negative coefficients suggest that more diverse cells benefit even more from trade openness. However, the coefficient in coloumn (3) is not significant, and as we will see, neither result is robust to the use of alternative conflict data from ACLED. Columns (5) through (7) add interaction terms between trade openness and different measures of ethnic complementarity. None of these additional interaction terms are statistically significant. Reassuringly, columns (3) to (7) do not affect our main coefficient of interest: the interaction of trade openness with ethnic remoteness continues to yield a positive and statistically significant coefficient at the 1% level, with a magnitude that is stable. The magnitude of the impact of ethnic remoteness on conflict is meaningful. Taking column (2) as our preferred specification, a one standard deviation increase in ethnic remoteness in a cell that is fully open to trade lowers the fatalities from conflict by 3.8%. The corresponding number when comparing the ethnically least remote cell to the ethnically most remote cell increase to 14.3%.

Robustness to ACLED conflict data. As an alternative to the UCDP conflict data, we re-run the same regressions using conflict data based on ACLED. As a reminder, the ACLED dataset is based on a broader definition of conflict, as it includes civil and communal conflicts, violence against civilians, and rioting and protesting. However, it only includes three years of pre-AGOA data. Table 2 uses the exact same specifications as Table 1, with the exception of the dependent variable. Our main result is unchanged:

[14]The correction of SEs for spatial and temporal correction is implemented using code from Fetzer (2014). The recent literature has usually allowed a spatial correlation of SEs within the distance of 100 km (see e.g. Armand et al. (2020)) to 500 km (see e.g. Berman et al. (2017) and McGuirk and Burke (2020)). We choose the more demanding 500 km cutoff.

Table 1: AGOA and Conflict: Ethnic Remoteness

	Intensity of Conflict from UCDP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGAccess	-0.144***	-0.176***	-0.161***	-0.156***	-0.170***	-0.176***	-0.180***
	(0.031)	(0.033)	(0.033)	(0.033)	(0.033)	(0.036)	(0.034)
AGAccess × ER		0.145***	0.151***	0.156***	0.152***	0.144***	0.146***
		(0.039)	(0.040)	(0.041)	(0.044)	(0.038)	(0.039)
AGAccess × ELF			-0.027				
			(0.018)				
AGAccess × Pol^{rq}				-0.139**			
				(0.065)			
AGAccess × Specialization					-0.028		
					(0.031)		
AGAccess × Kinship						0.001	
						(0.043)	
AGAccess × Segmented							0.006
							(0.013)
Observations	269497	269497	269497	269497	269497	269497	269497

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (fatalities + 1), where fatalities is based on data from UCDP. The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include a constant, rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1989–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

openness reduces conflict, but this benign effect is smaller in cells that are more ethnically remote from the rest of the country. One difference with our previous results is that ethnic fractionalization and ethnic polarization no longer affect the size of the peace dividend of trade liberalization.

Robustness to environmental variables. Some variables may affect both a cell's ethnic remoteness and the degree of conflict it suffers. Because we include cell fixed effects, this is only an issue if these factors affect not just the level of conflict but also the change in conflict following accession to AGOA. One example would be if ethnically remote groups reside on marginal land, forcing them to rely on subsistence activity that does not lend itself to taking advantage of trade openness. Consistent with this, column (2) of Table 3 shows that cells that are unsuitable for crops benefit from a smaller peace dividend from AGOA. However, our main coefficient of interest does not change: the effect of ethnic remoteness, interacted with trade openness, is still positive and statistically significant at the 1% level.

Another example would be if areas with high incidence of malaria and other infectious diseases have more remote ethnic groups, because the disease environment incentivizes groups to isolate themselves. If a higher disease incidence also limits the gains from trade, then we should control for the interaction of the disease environment with AGOA.[15] Columns (3) and (4) of Table 3 report results when controlling for interactions with malaria and tsetse fly suitability. We find contrasting results: cells with higher malaria incidence get a smaller reduction in conflict after the AGOA trade shock, but the opposite holds for cells with higher tsetse fly suitability. Our main finding is unchanged though: ethnic remoteness weakens the peace dividend from trade liberalization.

[15]See Cervellati et al. (2022) for evidence on the effect of malaria suitability on conflict in Africa.

Table 2: AGOA and Conflict: Ethnic Remoteness – ACLED data

	Intensity of Conflict from ACLED						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGAccess	-0.086**	-0.111**	-0.120***	-0.113**	-0.107**	-0.108**	-0.108**
	(0.041)	(0.044)	(0.046)	(0.046)	(0.044)	(0.047)	(0.043)
AGAccess × ER		0.110**	0.105**	0.109**	0.115**	0.111**	0.110**
		(0.043)	(0.045)	(0.046)	(0.048)	(0.045)	(0.043)
AGAccess × ELF			0.019				
			(0.023)				
AGAccess × Pol^{rq}				0.016			
				(0.084)			
AGAccess × Specialization					-0.018		
					(0.040)		
AGAccess × Kinship						-0.007	
						(0.054)	
AGAccess × Segmented							-0.004
							(0.015)
Observations	195153	195153	195153	195153	195153	195153	195153

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (fatalities + 1), where fatalities is based on data from ACLED. The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include a constant, rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1997–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Robustness to different measures of ethnic diversity. When exploring the interaction between a cell's openness and its ethnic diversity in Table 1, we relied on standard measures of fractionalization and polarization. Table B5 considers a number of alternative measures of diversity.

First, in column (1) we use the Greenberg index, a generalization of the fractionalization index that takes into account the linguistic distances between the different ethnic groups (Greenberg, 1956; Desmet et al., 2009):

$$GI_\ell = \sum_i \sum_j s_{\ell i} s_{\ell j} d_{ij}. \tag{9}$$

This index measures the average linguistic distance between two randomly drawn individuals of cell ℓ. Second, in columns (2) and (3) we use the standard fractionalization index, but now define languages at different levels of coarseness. Take the example of Chad: at the finest level, the country has 135 ethnic groups, corresponding to its 135 languages, whereas at the coarsest level, there are two ethnic groups, corresponding to the Nilo-Saharan and the Afro-Asiatic language family. Generalizing this example, Desmet et al. (2012) define ethnic groups at 15 different levels of coarseness, yielding 15 corresponding fractionalization indices, $ELF_\ell^{15}, \ldots, ELF_\ell^1$. Columns (2) and (3) use ELF_ℓ^2 (more coarse) and ELF_ℓ^9 (less coarse). Third, in column (4) we use a generalization of the polarization index that takes into account linguistic distance between the different groups Esteban and Ray (1994):

$$POL_\ell^{er} = \sum_i \sum_j s_{\ell i}^2 s_{\ell j} d_{ij}. \tag{10}$$

The interaction of these alternative measures of diversity with AGOA yield negative coefficients, indi-

Table 3: AGOA and Conflict: Robustness to Environmental Variables

	Intensity of Conflict from UCDP			
	(1)	(2)	(3)	(4)
AGAccess	-0.176***	-0.201***	-0.255***	-0.163***
	(0.033)	(0.034)	(0.043)	(0.033)
AGAccess × ER	0.145***	0.129***	0.158***	0.136***
	(0.039)	(0.039)	(0.039)	(0.037)
AGAccess × Crop Unsuitability		0.011***		
		(0.003)		
AGAccess × Malaria Suitability			0.028***	
			(0.007)	
AGAccess × Tsetse Suitability				-0.010
				(0.007)
Observations	269497	269497	269497	269497

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (fatalities + 1), where fatalities is based on data from UCDP. The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include a constant, rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1989–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

cating that cells that are more diverse benefit from a larger peace dividend. However, here again, the results are not robust to using the ACLED conflict data (Table B6). More importantly, in both Tables B5 and B6 the main coefficient of interest on the interaction between AGOA openness and ethnic remoteness continues to be negative and statistically highly significant. The weaker peace dividend from AGOA in ethnically remote cells is a robust finding.

Robustness to specialization. Another concern might be that ethnic remoteness correlates with specialization in non-tradable or import-competing sectors. This would limit, or even overturn, the gains from trade, and hence the peace dividend. For want of cell-level data on sectoral composition we cannot run this robustness check here. However, in the Section 4.2, where we show results from individual-level regressions of income shocks on ethnic remoteness, we are able to control for an individual's profession. As we will see, doing so does not affect our key finding.

Ethnic remoteness from the dominant group. Rather than considering ethnic remoteness from the rest of the country, we consider ethnic remoteness from the country's dominant group for the same baseline specifications of Table 1. The results, reported in Table 4, confirm our previous conclusions. Hence, whether we measure ethnic remoteness as distance to the rest of the country or to the dominant group, it lowers the peace dividend from trade openness.

Robustness to alternative transformations of the dependent variable. In order not to lose locations with no conflict, in our baseline analysis we use $\log(y_{ict} + 1)$ as the dependent variable, where y_{ict} is the number of fatalities in cell i of country c in year t. In Appendix Table B7 we explore alternative ways to transform the conflict data. One such alternative is to use the inverse hyperbolic sine transformation,

Table 4: AGOA and Conflict: Ethnic Remoteness from Dominant Group

	Intensity of Conflict from UCDP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGAccess	-0.144***	-0.152***	-0.139***	-0.133***	-0.148***	-0.150***	-0.156***
	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)	(0.035)	(0.032)
AGAccess × $\mathrm{ER}^{\mathrm{dom}}$		0.100***	0.101***	0.104***	0.101***	0.100***	0.100***
		(0.025)	(0.025)	(0.026)	(0.027)	(0.026)	(0.025)
AGAccess × ELF			-0.022				
			(0.017)				
AGAccess × $\mathrm{Pol}^{\mathrm{rq}}$				-0.125**			
				(0.063)			
AGAccess × Specialization					-0.017		
					(0.029)		
AGAccess × Kinship						-0.005	
						(0.046)	
AGAccess × Segmented							0.005
							(0.013)
Observations	269497	269497	269497	269497	269497	269497	269497

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (fatalities + 1), where fatalities is based on data from UCDP. The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include a constant, and controls for rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1989–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$\log(y + \sqrt{y^2+1})$ and another is to use $\log(y_{ict} + 0.5)$. As can be seen, our findings do not change. We could also ignore the intensive margin by defining conflict as a binary variable that takes the value of 1 if the number of fatalities is greater than 0. Doing so does not change the results.

4 Ethnic Remoteness, Trade, and Income

Our findings so far are consistent with an opportunity cost view of conflict. Indeed, if AGOA leads to gains from trade, then the ensuing higher income increases the opportunity cost of engaging in conflict. In addition, if ethnic remoteness acts as a barrier to reaping the full income benefits from trade liberalization, then the peace dividend should be weaker in ethnically more remote locations.

This opportunity cost interpretation assumes that the AGOA trade shock increases income, but less so in ethnically more remote locations. To see whether this income channel is consistent with the data, we start by using the exact same cell-level regression specification as before, with the difference that we look at the effect of AGOA on income (as proxied by luminosity), rather than on conflict. We then use individual-level data from different waves of the Afrobarometer to see whether the ethnic barrier interpretation also holds at the individual level. We explore whether ethnically more remote individuals suffer negative income shocks when exposed to trade, compared to individuals that are ethnically less distant.

4.1 Ethnic Remoteness Weakens the Income Gains from Trade

In this section we examine the effects of AGOA and its interaction with ethnic remoteness on income, as proxied by luminosity. While sub-national statistical data on income are scarce, especially in the context of developing countries, a large number of papers pioneered by Henderson et al. (2012) have shown nightlight measured by satellites to provide a good proxy income.[16]

Table 5: AGOA and Luminosity: Ethnic Remoteness

	Income proxied by Luminosity						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGAccess	0.110***	0.118***	0.125***	0.126***	0.127***	0.103***	0.104***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
AGAccess × ER		-0.037***	-0.034***	-0.033***	-0.027***	-0.044***	-0.034***
		(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
AGAccess × ELF			-0.014***				
			(0.005)				
AGAccess × Pol^{rq}				-0.057***			
				(0.020)			
AGAccess × Specialization					-0.041***		
					(0.009)		
AGAccess × Kinship						0.041***	
						(0.012)	
AGAccess × Segmented							0.022***
							(0.004)
Observations	241618	241618	241618	241618	241618	241618	241618

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (nighttime light + 1). The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include controls for rainfall deviation and temperature deviation. The sample includes 8,670 grid-cells spread across 48 sub-Saharan African countries for the period of 1992–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We take the same estimating equation (8) as before, but replace y_{ict} by luminosity. Table 5 reports our main results. We find what we expect: in all columns, the AGOA trade shock increases income, but less so in ethnically remote locations. When looking at some of the other interaction terms, we find that AGOA has a smaller effect on income in ethnically diverse locations, and a larger effect on income in cells where ethnic complementarity is smaller. While some of these effects differ from what we found in the case of conflict, our main result is unchanged: ethnically remote cells benefit less from the gains from trade.

Table 6 controls for the interaction of AGOA openness with different environmental variables. If cells that are ethnically remote have land that is unproductive, that may limit their capacity to reap the gains from trade. Consistent with this, column (2) shows that cells that are more unsuitable for crop production experience smaller income gains from AGOA openness. Cells that have a worse disease environment may also be in a disadvantaged position to benefit from trade. Consistent with this, columns (3) and (4) indicate that locations with a higher incidence of either malaria or the tsetse fly experience smaller income gains from trade openness. Reassuringly, none of these additional interaction terms affect the main finding: the income gains from trade are smaller in ethnically remote locations.

As further robustness checks, Appendix Table B8 includes alternative measures of fractionalization and polarization, and Appendix Table B9 considers alternative transformations of our dependent variable. These additional exercises have no qualitative impact on our main coefficient of interest.

[16]See Michalopoulos and Papaioannou (2018) for a review of the literature that has used luminosity data as a proxy for economic development.

Table 6: AGOA, Luminosity and Remoteness: Controlling for Environmental Variables

	Income proxied by Nighlight			
	(1)	(2)	(3)	(4)
AGAccess	0.118***	0.131***	0.129***	0.125***
	(0.011)	(0.012)	(0.013)	(0.011)
AGAccess × ER	-0.037***	-0.029***	-0.039***	-0.042***
	(0.009)	(0.009)	(0.009)	(0.008)
AGAccess × Crop Unsuitability		-0.006***		
		(0.001)		
AGAccess × Malaria Suitability			-0.004*	
			(0.002)	
AGAccess × Tsetse Suitability				-0.006**
				(0.003)
Observations	241618	241618	241618	241618

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (nighttime light + 1). The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include controls for rainfall deviation and temperature deviation. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1992–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Individual-Level Evidence

If ethnic remoteness acts as a barrier to reaping the income gains from trade, we would expect to find evidence for this mechanism not just at the cell level, but also at the individual level. In this section, we use data from the Afrobarometer to explore how the effect of the AGOA trade shock on income depends on an individual's ethnic remoteness.

Empirical specification. We regress measures of an individual's income on the trade openness of the cell where she resides and on the interaction of that openness with the individual's ethnic remoteness from either the rest of the country or from the country's dominant group. More specifically,

$$I_{jeict} = \alpha AGAccess_{ict} + AGAccess_{ict}\mathbf{E'}_{jec}\beta_1 + AGAccess_{ict}\mathbf{E'}_{ic}\beta_2 + \mathbf{X'}_{ict}\gamma + \delta_{ic} + \eta_{ct} + \theta_e + u_{jeict} \quad (11)$$

where I_{jeict} is a measure of the income of individual j of ethnicity e residing in cell i of country c at time t, $AGAccess_{ict}$ is the degree of trade openness of cell i in country c at time t, $\mathbf{E'}_{jec}$ is a vector of individual-level variables related to ethnicity which we interact with the cell's degree of trade openness at time t, $\mathbf{E'}_{ic}$ is a vector of cell-level variables related to ethnicity which we also interact with the degree of openness, $\mathbf{X}_{ict}$ is a vector of cell-level time-varying characteristics, δ_{ic} are cell fixed effects, η_{ct} are country-time fixed effects, θ_e are ethnicity fixed effects, and u_{jeict} is an idiosyncratic error term.

Individual data. We use individual-level data from the 12 countries that were included in all six rounds of the Afrobarometer surveys conducted between 1999–2015. This includes the first round that was conducted between 1999 and 2001, before the entry into AGOA for most countries.[17] As proxies for income, we use two

[17]Table A2 lists the countries for which we have individual-level survey responses prior to the entry to AGOA. Apart from Mali and Tanzania, which were surveyed in the same year as their entry into AGOA, all the other 10 countries were surveyed before entry into AGOA. This includes Zimbabwe, which was never part of AGOA.

measures: food poverty and income poverty. These measures correspond to the questions: “Over the past year, how often, if ever, have you or your family gone without: enough food to eat / cash income?”. We recode the responses to these questions as binary variables, that take the value 1 if individuals answer “just once or twice”, “several times”, “many times” or “always”, and the value 0 if individuals answer “never”.

When estimating whether the income shock of trade has a differential effect on individuals that are ethnically remote, we need to know where the individual resides and which ethnicity she belongs to. An individual’s location determines the size of the trade liberalization shock, and an individual’s ethnicity determines her remoteness to either the country’s average or the country’s largest group. The Afrobarometer provides an individual’s GPS location and her language (which, as before, we use as a proxy for ethnicity).[18]

Ethnically remote individuals and food poverty. In developing countries, food poverty is often a more reliable measure of economic well-being than income (Meyer and Sullivan, 2003). Table 7 reports results for regressions of individual-level food poverty on trade openness, using specification (11). All our individual-level regressions include ethnic group fixed effects, which among other things purge any possible effects of within-group genetic diversity (Arbatlı et al., 2020). Column (1) shows that individuals that are ethnically remote experience more food poverty in the wake of trade liberalization. Column (2) indicates that individuals that reside in ethnically remote cells also suffer from more food poverty when trade is liberalized. Column (3) includes interactions of both individual-level and cell-level ethnic remoteness with trade liberalization. The results suggest that the ethnic remoteness of the individual drives the increased food poverty effect of trade liberalization. In terms of magnitudes, taking column (3) as our preferred specification, a one standard deviation increase in an individual’s ethnic remoteness in a cell that is fully open to trade increases food poverty by 5.5 percent. Overall, this provides support to the hypothesis that an individual’s ethnic remoteness makes it more difficult to take advantage of trade liberalization.

Profession and other individual controls. One concern is that ethnically remote individuals might work in professions that benefit less from trade liberalization. Another concern is that ethnically remote individuals might have other specific characteristics that affect their capacity to take advantage of a positive trade shock. In columns 4–6 of Table 7 we control for an individual’s profession, age and gender, as well as for whether she resides in a rural location. The results are unchanged: individuals that either are ethnically remote or reside in an ethnically remote location are more likely to suffer from food poverty in the wake of a positive trade shock.[19]

Robustness. Appendix Table B10 uses distance from the dominant group rather than distance from the average group. As before, greater individual’s ethnic remoteness to the dominant group increases the probability of going without food. Appendix Table B11 introduces additional cell-level interactions of ethnic diversity and ethnic complementarity with trade openness. The coefficient of interest is quantitatively unchanged: a one standard deviation increase in an individual’s ethnic remoteness in a cell that is fully open to trade raises the chance of food poverty by 5.5 percent. Appendix Table B12 instead adds cell-level interactions with environmental variables. Our main result is robust to introducing those variables.

[18] Table B3 provides the summary statistics of the individual-level data. Table B4 provides the correlation between individual- and cell-level measures of ethnic remoteness.

[19] We use the following professional categories “Agriculture / farming / fishing / forestry”, “Artisan or skilled manual worker”, “Clerical or secretarial”, “Don’t know”, “Housewife / home-maker”, “Missing”, “Never had a job”, “Other”, “Professional”, “Retail / Shop”, “Security services”, “Student”, “Supervisor / Foreman / Senior Manager”, “Trader / hawker / vendor”, and “Unskilled manual worker.” Waves 4 and 5 do not include information on occupational categories, at least for the 12 countries in our sample. Hence results in columns 4–6 of Table 7 are based on waves 1, 2, 3 and 6.

Table 7: AGOA and Food Poverty

	Individual Food Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGAccess	-0.145	-0.305	-0.142	-0.079	-0.295	-0.093
	(0.418)	(0.397)	(0.419)	(0.478)	(0.461)	(0.473)
AGAccess × Indiv ER	0.214***		0.217***	0.246***		0.231***
	(0.047)		(0.052)	(0.044)		(0.051)
AGAccess × Cell ER		0.122**	-0.010		0.185***	0.050
		(0.061)	(0.083)		(0.060)	(0.085)
Observations	114176	114176	114176	72112	72112	72112

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: Enough food to eat?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The unit of observation is the individual. The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 17k and 22k individual per round spread across 12 countries (see Appendix A.3 for full list of countries). Cell-level ethnic remoteness is for the cell which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguisitic group FE. Additional Individual controls include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: AGOA and Income Poverty

	Individual Income Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGAccess	0.061	-0.016	-0.153	0.182	0.110	-0.026
	(0.401)	(0.404)	(0.416)	(0.498)	(0.475)	(0.479)
AGAccess × Indiv ER	0.227***		0.205***	0.229***		0.209***
	(0.063)		(0.066)	(0.059)		(0.062)
AGAccess × Cell ER		0.301***	0.154		0.282**	0.139
		(0.097)	(0.107)		(0.129)	(0.137)
Observations	108463	108463	108463	66500	66500	66500

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: A cash income?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The unit of observation is the individual. The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 13k and 22k individuals per round spread across 12 countries (see Appendix A.3 for full list of countries). Cell-level ethnic remoteness is for the cell which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguisitic group FE. Additional Individual controls include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Income poverty. Table 8 replicates the above table but uses income poverty as an alternative measures of an individual's well-being. Focusing on column (3), we see that individuals that are ethnically remote from the country average experience a smaller decrease in income poverty in the wake of trade liberalization. A one standard deviation increase in an individual's ethnic remoteness in a cell that is fully open to trade increases the chance of income poverty by 5.2 percent. Controlling for individual characteristics, such as profession and age, does not change these findings (Columns (4) to (6)). Appendix Tables B13–B15 show that these results are robust to measuring remoteness as distance to the dominant group and to including additional cell-level controls. From these different exercises, we conclude that it is more difficult for ethnically remote individuals to reap the gains from trade. This is consistent with an interpretation that ethnic distance acts as a barrier that limits the benefits from trade openness.

5 Conclusion

This paper explored how ethnicity affects the relation between trade liberalization and conflict. On the one hand, ethnically more remote locations and individuals may face additional frictions that preclude them from fully taking advantage of a positive trade shock. Left behind, such locations may not be able to reap the peace dividend from trade. On the other hand, ethnically more diverse locations may find it harder to peacefully share the spoils of trade liberalization. Using high-resolution data from sub-Saharan Africa, we found evidence for the former mechanism: ethnic remoteness, rather than ethnic diversity, mediates the effect of trade liberalization on conflict. Faced with the same positive trade shock, ethnically remote locations reap a smaller peace dividend, whereas ethnically more diverse locations do not suffer this negative effect.

Our findings are consistent with an opportunity cost view of conflict. As the gains from trade raise the standard of living, it becomes more costly to engage in conflict. For this mechanism to be a potential explanation of our main result, we would expect more remote locations to benefit from a smaller positive income shock in the wake of AGOA. We would also expect ethnically more remote individuals to face higher barriers to reap the income gains from trade. Using high-resolution luminosity data as well as individual-level income data from Afrobarometer, we found evidence in support of this mechanism.

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Appendix

A Data

A.1 Data Sources for Cell-Level Regressions

Variable (Source)	Description
Basemaps (GMI)	Basemaps used in the paper are based on the Semaless Digital Chart of the World (Version 10.0), which accompanied the World Geodatasets data from Global Mapping International. The maps were created by the authors using ArcGIS® software by Esri®.
Conflict intensity (ACLED, UCDP)	We measure conflict using fatalities in each cell for a specific year. Data are obtained from two event-based databases: The Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013) for 1989–2017 and the Armed Conflict Location & Event Data Project (ACLED) (Raleigh et al., 2010) for 1997–2017.
Travel time to nearest port (IFPRI)	Travel time to nearest major port in hours in the year 2000. Source: HarvestChoice/International Food Policy Research Center (IFPRI), 2011. Citation: HarvestChoice, 2015. "Travel time to nearest port (hours, 2000)", International Food Policy Research Institute, Washington, DC., and University of Minnesota, St. Paul, MN.
Linguistic composition of cells (Desmet et al., 2020)	Distribution of language groups at the resolution of 5 km × 5 km from Desmet et al. (2020). They construct the data combining three sources of information: data on the spatial distribution of population from Landscan (Source: `http://web.ornl.gov/sci/landscan/`), data on the linguistic composition of countries from Ethnologue Version 17 (Lewis et al., 2014), and maps on the geographic distribution of 6,905 distinct languages from the World Language Mapping System (Version 17) produced by Global Mapping International (Source: `https://worldgeodatasets.com/language/`. Using this information, they then use an iterative proportional fitting algorithm to construct a comprehensive $0.05° \times 0.05°$ grid-cell level dataset on the ethnolinguistic composition of the population for the entire globe.
Poverty (Afrobarometer)	The sample is based on individual level data from six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 13k and 22k individuals per round spread across 12 countries (see Appendix A.3 for full list of countries). Food poverty: Based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: A cash income?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015. Income poverty: based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: A cash income?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). .
Nightlight (DMSP-OLS)	Average nighttime light emission (measured by sq. km) for 1992–2013 from the DMSP-OLS Nighttime Lights Time Series v.4 (National Oceanic and Atmospheric Administration, 2014) were downloaded from `https://eogdata.mines.edu/products/dmsp`. For 2014–2017 we use the extension data generated by Ghosh et al. (2021).
Precipitation (CHIRPS)	Average amount of daily precipitations (in mm) in the cell, based on daily precipitations data provided by the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) database (Funk et al., 2014). CHIRPS provides $0.05° \times 0.05°$ resolution satellite imagery supplemented with in-situ monitoring station data. To ensure comparability of the measure across cells, we use double-standardized rainfall deviations (Hidalgo et al., 2010). We first account for seasonal patterns by standardizing monthly rain totals by cell and month for the period 1989–2020. For each cell, these indicators are then summed up by year and standardized over the same period.
Crop Suitability (FAO)	Crop suitability index (class) for low input level rain-fed cereals based on the average climate of baseline period 1961–1990. Source: FAO/IIASA, 2011-2012. Global Agro-ecological Zones (GAEZ v3.0). FAO Rome, Italy and IIASA, Laxenburg, Austria.

(continued on next page)

Variable (Source)	Description
Tse Tse fly suitability (FAO)	These data were downloaded from `http://www.fao.org/geonetwork/srv/en/main.home?uuid=f8a4e330-88fd-11da-a88f-000d939bc5d8`. We use the median number of species, which lies between 0 and 10, in a grid cell as a measure of Tse Tse suitability.
Malaria suitability (Kiszewski et al., 2004)	Data on malaria suitability are drawn from Kiszewski et al. (2004), made available in raster format by McCord and Anttila-Hughes (2017).
Temperature (ERA)	Yearly mean temperature (in degrees Celsius) in the cell, based on monthly meteorological statistics from ERA Reanalysis dataset (Muñoz-Sabater et al., 2021). Data are available for the period 1948–2020. To ensure comparability of the measure across cells, we use standardized temperature deviations, by restricting the standardization to the year level.

Notes. For time-varying variables, missing values are linearly interpolated.

A.2 AGOA Membership

Table A1: Years of access to AGOA

Country	AGOA years	No. of years
Angola	2004 – 2017	14
Benin	2001 – 2017	17
Botswana	2001 – 2017	17
Burkina Faso	2005 – 2017	13
Burundi	2006 – 2015	10
Cameroon	2001 – 2017	17
Cape Verde	2001 – 2017	17
Central African Republic	2001 – 2003; 2017	4
Chad	2001 – 2017	17
Comoros	2008 – 2017	10
DRC	2003 – 2010	8
Congo (ROC)	2001 – 2017	17
Cote d'Ivoire	2002 – 2004; 2011 – 2017	10
Djibouti	2001 – 2017	17
Eritria	2001 – 2003	3
Ethiopia	2001 – 2017	17
Gabon	2001 – 2017	17
Gambia	2003 – 2014	12
Ghana	2001 – 2017	17
Guinea	2001 – 2009; 2011 – 2017	16
Guinea-Bissau	2001 – 2012; 2015 – 2017	15
Kenya	2001 – 2017	17
Lesotho	2001 – 2017	17
Liberia	2007 – 2017	11
Madagascar	2001 – 2009; 2014 – 2017	13
Malawi	2001 – 2017	17
Mali	2001 – 2012; 2014 – 2017	16
Mauritania	2001 – 2005; 2007 – 2008; 2010 – 2017	15
Mauritius	2001 – 2017	17
Mozambique	2001 – 2017	17
Namibia	2001 – 2017	17
Niger	2001 – 2009; 2014 – 2017	16
Nigeria	2001 – 2017	17
Rwanda	2001 – 2017	17
Sao Tome & Principe	2001 – 2017	17
Senegal	2001 – 2017	17
Seychelles	2001 – 2016	16
Sierra Leone	2001 – 2017	17
South Africa	2001 – 2017	17
South Sudan	2013 – 2014	2
Swaziland	2001 – 2014	14
Tanzania	2001 – 2017	17
Togo	2008 – 2017	10
Uganda	2001 – 2017	17
Zambia	2001 – 2017	17

Notes: This table reports the years in which the different sub-Saharan African countries enjoyed access to free trade with the U.S. under AGOA. Data are based on Appendix A of Fernandes et al. (2019). Equatorial Guinea, Somalia, Sudan and Zimbabwe were never part of AGOA. Our data stops in the year 2017, though AGOA might have continued to subsequent years.

A.3 Afrobarometer Data

We use the 12 countries that were included in all 6 Afrobarometer rounds. This includes the first round of the Afrobarometer surveys conducted between 1999 and 2001, which for the vast majority of countries was before the entry into AGOA in the year 2001. Table A2 provides the information on the countries for which we have individual-level survey responses prior to the entry to AGOA. Apart from Mali and Tanzania, which were surveyed in the same year as AGOA entry, all the other 10 countries were surveyed before entry into AGOA. This includes Zimbabwe, which was never part of AGOA.

Table A2: Afrobarometer Round 1 and year of entry to AGOA

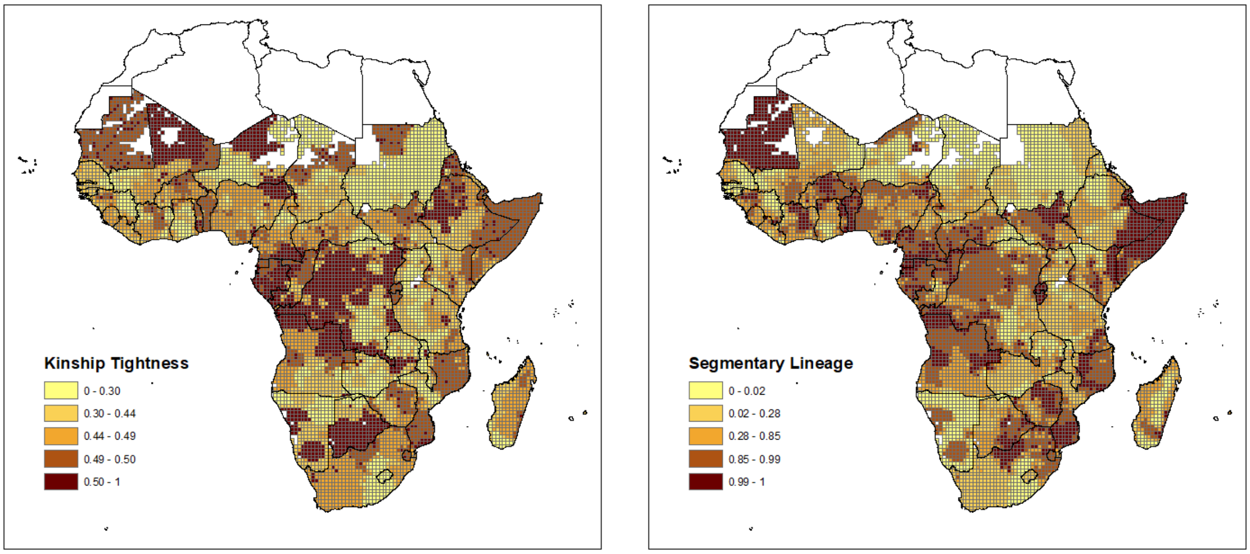
Country	AGOA entry	Survey Year
Botswana	2001	1999
Ghana	2001	1999
Lesotho	2001	2000
Malawi	2001	1999
Mali	2001	2001
Namibia	2001	1999
Nigeria	2001	2000
South Africa	2001	2000
Tanzania	2001	2001
Uganda	2001	2000
Zambia	2001	1999
Zimbabwe	NA	1999

Notes: This table provides the information on the countries for which we have individual-level survey responses prior to the entry to AGOA. Apart from Mali and Tanzania, which were surveyed in the same year as AGOA entry, all the other 10 countries were surveyed before entry into AGOA. This includes Zimbabwe, which was never part of AGOA.

A.4 Data Maps

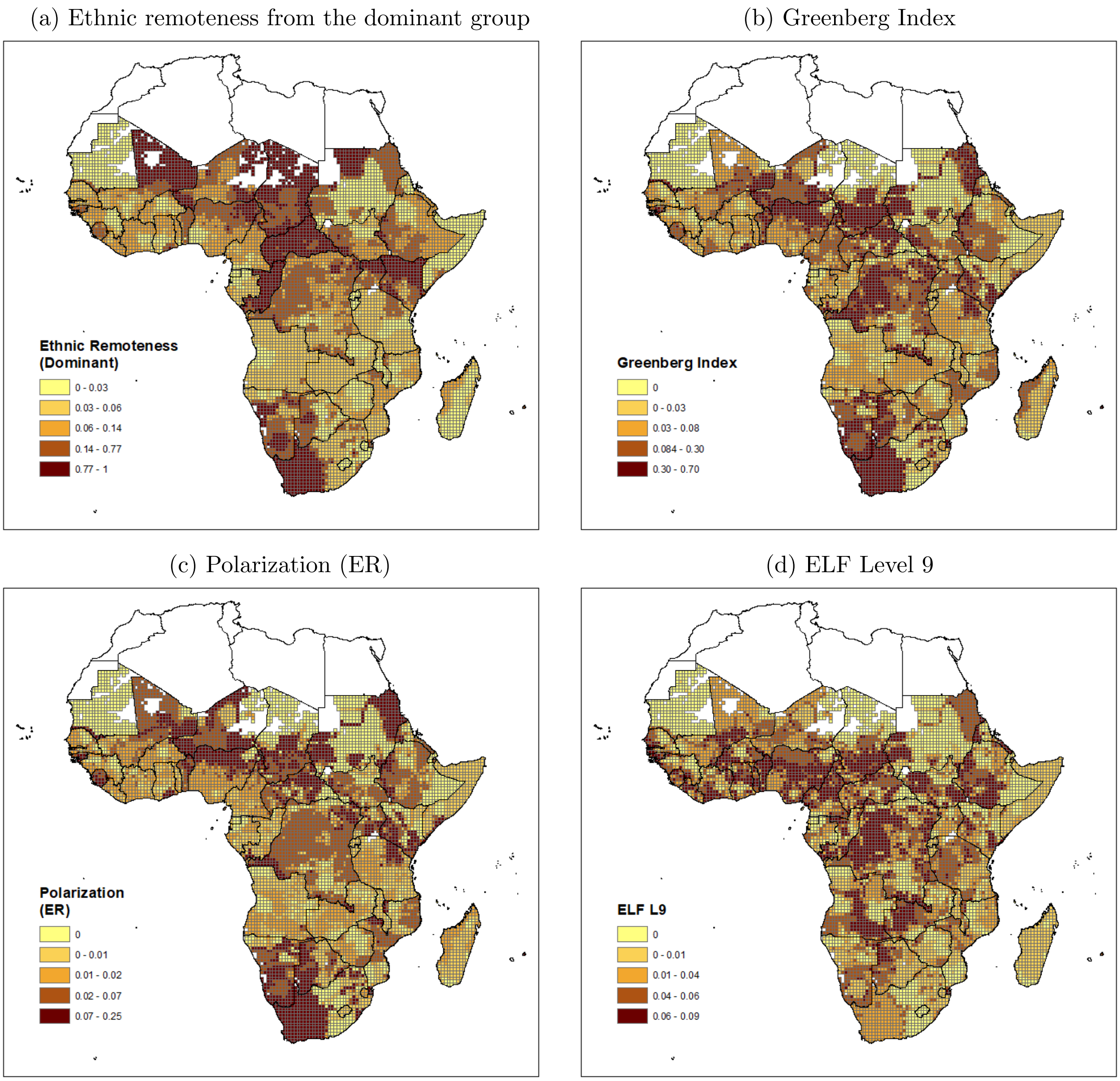
Figure A1: Kinship Tightness and Segmentary Lineage

(a) Kinship Tightness (b) Segmentary Lineage



Notes: Panel a) plots the average kinship tightness in a cell (Enke, 2019). Panel b) plots the average segmentary lineage in a cell (Moscona et al., 2020). The distribution of ethnic groups is based on data from Desmet et al. (2020). See Appendix A.1 for further details on data sources and variable definitions.

Figure A2: Alternative Ethnic Remoteness and Ethnic Diversity



Notes: Panel a) plots ethnic remoteness from the dominant group, which measures the average ethnic distance between a random resident of the cell and a random member of the most populous ethnic group in the country (equation (4)). Panel b) plots the Greenberg index, which measures the expected ethnic distance between any two random resident of the cell (equation (9)). Panel c) plots the the Polarization index (equation (10)), *à la* Esteban and Ray (1994) . Panel d) plots the fractionalization index at aggregation level 9 *à la* Desmet et al. (2012). The distribution of ethnic groups is based on data from Desmet et al. (2020). See Appendix A.1 for further details on data sources and variable definitions.

B Additional Tables

B.1 Summary Statistics

Table B1: Cell-level summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Log (Fatalities + 1) UCDP	0.08	0.54	0	12.7	269497
Log (Fatalities + 1) ACLED	0.13	0.64	0	11.08	195153
Log (Luminosity + 1)	0.1	0.35	0	4.11	241618
Openness	0.86	0.1	0.09	1	269497
AGAccess	0.38	0.44	0	1	269497
ER	0.29	0.26	0	0.99	269497
$\mathrm{ER}^{\mathrm{dom}}$	0.27	0.36	0	1	269497
Specialization	0.18	0.18	0	1	269497
Kinship Tightness	0.43	0.13	0	1	269497
Segmentary Lineage	0.53	0.42	0	1	269497
Greenberg	0.13	0.17	0	0.70	269497
ELF2	0.16	0.2	0	0.82	269497
ELF9	0.3	0.28	0	0.92	269497
ELF15	0.38	0.31	0	0.94	269497
$\mathrm{POL}^{\mathrm{rq}}$	0.11	0.08	0	0.25	269497
Greenberg	0.13	0.17	0	0.70	269497
$\mathrm{POL}^{\mathrm{er}}$	0.04	0.05	0	0.25	269497
Crop Unsuitability	5.41	1.55	1	9	269497
Malaria Suitability	0.28	0.98	-0.94	2.98	269497
TseTse Suitability	0.85	1.27	0	6	269497

Notes: The sample includes 9,293 country-specific grid-cells (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator) spread across 48 sub-Saharan African countries for the period of 1989–2017 for the UCDP data, 1997–2017 for the ACLED data and 1992–2017 for the luminosity data. See Section 2 and Appendix A.1 for further details on data sources and variable definitions.

Table B2: Cell-level cross-correlation table

Variables	ER	ER^{Dom}
ER^{Dom}	0.85	-
Specialization	0.26	0.17
Kinship Tightness	0.11	0.13
Segmentary Lineage	-0.24	-0.20
ELF_2	0.46	0.33
ELF_9	0.22	0.15
ELF_{15}	0.09	0.05
POL^{rq}	0.13	0.09
Greenberg	0.49	0.36
POL^{er}	0.54	0.41
Crop Unsuitability	0.24	0.21
Malaria Suitability	-0.01	-0.03
TseTse Suitability	-0.11	-0.06
Log (Fatalities + 1) UCDP	0.01	0.01
Log (Fatalities + 1) ACLED	0.02	0.01
Log (Luminosity + 1)	-0.01	-0.07
AGAccess	-0.00	-0.04
Openness	-0.26	-0.29

Notes: The sample includes 9,293 country-specific grid-cells (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator) spread across 48 sub-Saharan African countries for the period of 1989–2017 for the UCDP data, 1997–2017 for the ACLED data and 1992–2017 for the luminosity data. See Section 2 and Appendix A.1 for further details on data sources and variable definitions.

Table B3: Individual-level summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
		Panel A			
Food Poverty	0.51	0.5	0	1	114176
Openness	0.92	0.04	0.44	1	114176
AGAccess	0.74	0.37	0	1	114176
Cell ER	0.25	0.22	0.01	0.97	114176
Indiv ER	0.24	0.25	0	1	114176
Cell ER^{Dom}	0.17	0.28	0	1	114176
Indiv ER^{Dom}	0.16	0.34	0	1	114176
Female	0.5	0.5	0	1	114070
Rural	0.6	0.49	0	1	113846
Age	36.78	14.83	15	115	112896
		Panel B			
Income Poverty	0.76	0.42	0	1	108463
Openness	0.92	0.04	0.44	1	108463
AGAccess	0.78	0.34	0	1	108463
Cell ER	0.24	0.22	0.01	0.97	108463
Indiv ER	0.23	0.25	0	1	108463
Cell ER^{Dom}	0.16	0.27	0	1	108463
Indiv ER^{Dom}	0.16	0.34	0	1	108463
Female	0.5	0.5	0	1	108358
Rural	0.61	0.49	0	1	108121
Age	36.93	14.88	15	115	107194

Notes: Summary statistics for the individual-level data from six rounds of the Afrobarometer surveys. Panel A (Panel B) summarizes the sample for which the food poverty (income poverty) variable is available. These surveys were conducted between 1999–2015 comprising approximately between 17k and 22k individuals (Panel A) and 13k and 22k individuals (Panel B) per round spread across 12 countries (see Appendix A.3 for full list of countries). The regressions in the paper use a gender dummy, which we display as a female dummy here. The regressions in the paper control for age categories rather than the age variable summarized here. See Section 2 and Appendix A.1 for further details on data sources and variable definitions.

Table B4: Individual-level cross-correlation table

Variables	Indiv ER	Indiv ER^{Dom}
Indiv ER^{Dom}	0.89	-
Cell ER	0.80	0.60
Cell ER^{Dom}	0.66	0.67

Notes: The sample includes 116,183 individual-level observations from six rounds of the Afrobarometer surveys conducted between 1999–2015 spread across 12 countries (see Appendix A.3 for full list of countries). See Section 2 and Appendix A.1 for further details on data sources and variable definitions.

B.2 Robustness: Cell-Level Regressions

Table B5: AGOA and Conflict: Robustness to Alternative Ethnic Diversity Measures

	Intensity of Conflict from UCDP			
	(1)	(2)	(3)	(4)
AGAccess	-0.158***	-0.158***	-0.162***	-0.153***
	(0.032)	(0.033)	(0.033)	(0.032)
AGAccess × ER	0.185***	0.174***	0.156***	0.212***
	(0.050)	(0.046)	(0.042)	(0.054)
AGAccess × Greenberg	-0.086**			
	(0.042)			
AGAccess × ELF2		-0.063*		
		(0.033)		
AGAccess × ELF9			-0.034	
			(0.022)	
AGAccess × Pol^{er}				-0.403***
				(0.146)
Observations	269497	269497	269497	269497

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (fatalities + 1), where fatalities is based on data from UCDP. The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include a constant, rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1989–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: AGOA and Conflict: Robustness to Alternative Ethnic Diversity Measures – ACLED

	Intensity of Conflict from ACLED			
	(1)	(2)	(3)	(4)
AGAccess	-0.118***	-0.113**	-0.114**	-0.112***
	(0.044)	(0.044)	(0.045)	(0.044)
AGAccess × ER	0.093*	0.107**	0.108**	0.106*
	(0.053)	(0.049)	(0.047)	(0.058)
AGAccess × Greenberg	0.036			
	(0.045)			
AGAccess × ELF2		0.008		
		(0.036)		
AGAccess × ELF9			0.007	
			(0.026)	
AGAccess × Pol^{er}				0.024
				(0.146)
Observations	195153	195153	195153	195153

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (fatalities + 1), where fatalities is based on data from ACLED. The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include a constant, rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1997–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B7: AGOA and Conflict (UCDP) – Robustness to Alternative Transformations of Dependent Variable

	Intensity of Conflict from UCDP			
	Log (y+1)	IH	Log (y+0.5)	0-1
AGAccess	-0.176***	-0.182***	-0.208***	-0.050***
	(0.033)	(0.034)	(0.039)	(0.010)
AGAccess × ER	0.145***	0.151***	0.172***	0.045***
	(0.039)	(0.040)	(0.045)	(0.011)
Observations	269497	269497	269497	269497
r2	0.269	0.272	0.273	0.264

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log(fatalities +1) in column (1), the inverse hyperbolic sine transformation in column (2), log(fatalities +0.5) in column (3), and a binary variable that takes the value of 1 if the number of fatalities > 0 in column (4), where fatalities is based on data from UCDP. The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include a constant, rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1989–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B8: AGOA and Luminosity: Robustness to Alternative Ethnic Diversity Measures

	Income proxied by Nightlight			
	(1)	(2)	(3)	(4)
AGAccess	0.118***	0.117***	0.125***	0.119***
	(0.011)	(0.011)	(0.012)	(0.011)
AGAccess × ER	-0.038***	-0.039***	-0.031***	-0.036***
	(0.007)	(0.008)	(0.008)	(0.007)
AGAccess × Greenberg	0.002			
	(0.010)			
AGAccess × ELF2		0.003		
		(0.007)		
AGAccess × ELF9			-0.017***	
			(0.006)	
AGAccess × Pol^{er}				-0.006
				(0.035)
Observations	241618	241618	241618	241618

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log (nighttime light + 1). The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include controls for rainfall deviation and temperature deviation. The sample includes 9,293 grid-cells spread across 48 sub-Saharan African countries for the period of 1992–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B9: AGOA and Luminosity: Robustness to Alternative Transformations of Dependent Variable

	Income proxied by Nighlight			
	Log (y+1)	IH	Log (y+0.5)	0-1
AGAccess	0.118***	0.140***	0.171***	0.507***
	(0.011)	(0.013)	(0.015)	(0.027)
AGAccess × ER	-0.037***	-0.048***	-0.059***	-0.091***
	(0.009)	(0.009)	(0.011)	(0.019)
Observations	241618	241618	241618	269497

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is log(nighttime light + 1) in column (1), the inverse hyperbolic sine transformation in column (2), log(nighttime light +0.5) in column (3), and a binary variable that takes the value of 1 if nighttime light > 0 in column (4). The unit of observation is the PRIO GRID cell (resolution 0.5 × 0.5 decimal degrees, approximately 55km × 55km at the equator). All specifications include controls for rainfall deviation and temperature deviation. The sample includes 8,670 grid-cells spread across 48 sub-Saharan African countries for the period of 1992–2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Robustness: Individual Level Data

Table B10: AGOA and Food Poverty – Remoteness from the Dominant Group

	Individual Food Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGAccess	-0.089	-0.270	-0.088	0.006	-0.241	0.001
	(0.410)	(0.396)	(0.410)	(0.477)	(0.463)	(0.474)
AGAccess × Indiv ER^{dom}	0.104***		0.107***	0.134***		0.127***
	(0.028)		(0.031)	(0.026)		(0.031)
AGAccess × Cell ER^{dom}		0.062*	-0.008		0.099***	0.019
		(0.037)	(0.048)		(0.036)	(0.051)
Observations	114176	114176	114176	72112	72112	72112

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: Enough food to eat?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The unit of observation is the individual. The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 17k and 22k individual per round spread across 12 countries (see Appendix A.3 for full list of countries). Cell-level ethnic remoteness is for the cell which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguisitic group FE. Additional Individual controls include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B11: AGOA and Food Poverty: Additional Cell Controls

	Individual Food Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGAccess	-0.142	-0.138	-0.144	-0.124	-0.145	-0.132
	(0.419)	(0.419)	(0.420)	(0.416)	(0.418)	(0.419)
AGAccess × Indiv ER	0.217***	0.217***	0.217***	0.217***	0.218***	0.218***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
AGAccess × Cell ER	-0.010	-0.007	-0.012	0.001	-0.012	-0.000
	(0.083)	(0.083)	(0.081)	(0.085)	(0.079)	(0.083)
AGAccess × ELF		-0.007				
		(0.037)				
AGAccess × Pol^{rq}			0.012			
			(0.128)			
AGAccess × Specialization				-0.038		
				(0.066)		
AGAccess × Kinship					-0.034	
					(0.103)	
AGAccess × Segmented						0.032
						(0.033)
Observations	114176	114176	114176	114176	114176	114176

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: Enough food to eat?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The unit of observation is the individual. The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 17k and 22k individual per round spread across 12 countries (see Appendix A.3 for full list of countries). Cell-level ethnic remoteness is for the cell which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguisitic group FE. Additional Individual controls include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B12: AGOA and Food Poverty: Environmental Controls

	Individual Food Poverty			
	(1)	(2)	(3)	(4)
AGAccess	-0.142	-0.177	-0.264	-0.053
	(0.419)	(0.427)	(0.405)	(0.412)
AGAccess × Indiv ER	0.217***	0.215***	0.235***	0.213***
	(0.052)	(0.052)	(0.052)	(0.052)
AGAccess × Cell ER	-0.010	-0.002	0.005	-0.025
	(0.083)	(0.084)	(0.072)	(0.088)
AGAccess × Crop Unsuitability		-0.015*		
		(0.009)		
AGAccess × Malaria Suitability			0.048	
			(0.033)	
AGAccess × Tsetse Suitability				-0.007
				(0.015)
Observations	114176	114176	114176	114176

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: Enough food to eat?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The unit of observation is the individual. The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 17k and 22k individual per round spread across 12 countries (see Appendix A.3 for full list of countries). Cell-level ethnic remoteness is for the cell which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguisitic group FE. Additional Individual controls include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3.1 Income Poverty

Table B13: AGOA and Income Poverty – Remoteness from the Dominant Group

	Individual Income Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGAccess	0.111	0.006	-0.112	0.211	0.144	0.019
	(0.399)	(0.405)	(0.415)	(0.497)	(0.481)	(0.483)
AGAccess $\times$ Indiv ER$^{\text{dom}}$	0.122***		0.105***	0.129***		0.115***
	(0.038)		(0.040)	(0.034)		(0.037)
AGAccess $\times$ Cell ER$^{\text{dom}}$		0.171***	0.099		0.155**	0.078
		(0.055)	(0.061)		(0.072)	(0.076)
Observations	108463	108463	108463	66500	66500	66500

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: A cash income?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The unit of observation is the individual. The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 13k and 22k individuals per round spread across 12 countries (see Appendix A.3 for full list of countries). Cell-level ethnic remoteness is for the cell which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguisitic group FE. Additional Individual controls include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B14: AGOA and Income Poverty: Additional Cell Controls

	Individual Income Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGAccess	-0.153	-0.164	-0.216	-0.151	-0.154	-0.151
	(0.416)	(0.427)	(0.432)	(0.402)	(0.432)	(0.428)
AGAccess × Indiv ER	0.205***	0.204***	0.203***	0.205***	0.205***	0.205***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)
AGAccess × Cell ER	0.154	0.192	0.213*	0.150	0.154	0.155
	(0.107)	(0.119)	(0.116)	(0.139)	(0.120)	(0.107)
AGAccess × ELF		-0.033				
		(0.053)				
AGAccess × Pol^{rq}			-0.166			
			(0.153)			
AGAccess × Specialization				0.004		
				(0.103)		
AGAccess × Kinship					-0.001	
					(0.146)	
AGAccess × Segmented						0.003
						(0.043)
Observations	108463	108463	108463	108463	108463	108463

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: A cash income?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The unit of observation is the individual. The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 13k and 22k individuals per round spread across 12 countries (see Appendix A.3 for full list of countries). Cell-level ethnic remoteness is for the cell which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguisitic group FE. Additional Individual controls include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B15: AGOA and Income Poverty: Environmental Controls

	Individual Income Poverty			
	(1)	(2)	(3)	(4)
AGAccess	-0.153	-0.043	-0.097	-0.155
	(0.416)	(0.453)	(0.440)	(0.418)
AGAccess × Indiv ER	0.205***	0.203***	0.207***	0.205***
	(0.066)	(0.067)	(0.066)	(0.066)
AGAccess × Cell ER	0.154	0.137	0.155	0.154
	(0.107)	(0.109)	(0.109)	(0.107)
AGAccess × Crop Unsuitability		0.007		
		(0.007)		
AGAccess × Malaria Suitability			0.029	
			(0.041)	
AGAccess × Tsetse Suitability				-0.009
				(0.056)
Observations	108463	108463	108463	108463
r2	0.021	0.021	0.021	0.021

Notes: Standard errors in parentheses corrected for spatial correlation within a 500 km radius and for infinite serial correlation (Conley, 1999; Hsiang, 2010). The dependent variable is based on the answer to the question: "Over the past year, how often, if ever, have you or your family gone without: A cash income?". It is coded as 0 (if answer is never) or 1 (if answer is sometimes/several times/frequently/many times/always). The unit of observation is the individual. The sample is based on six rounds of the Afrobarometer surveys conducted between 1999–2015 comprising approximately between 13k and 22k individuals per round spread across 12 countries (see Appendix A.3 for full list of countries). Cell-level ethnic remoteness is for the cell which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguisitic group FE. Additional Individual controls include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.