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 U.S.-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, satellite-based luminosity data show that income gains from improved trade access 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

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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 are a fundamental driver of conflict around the world.[3] Together, these observations raise the question whether 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 locations that are ethnically distant from the rest of the country benefit less from this peace dividend. In addition, such 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 how a location's ethnic remoteness mediates the impact of improved market access on conflict. Our premise is that a location's ethnic remoteness, defined as its population-weighted average ethnic distance to the rest of the country, acts as a barrier to accessing local trade networks and power structures that facilitate integration into the global market.[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. 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 variation in proximity to the closest port and in AGOA eligibility of local production, we also exploit within-country local variation in trade access. Combining the sub-national 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 re-

[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).

[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] In the baseline, we focus on the average distance when defining ethnic remoteness, because in sub-Saharan Africa power tends to be assigned proportionally to the sizes of ethnic groups (Francois et al., 2015). 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.

moteness.

At a spatial resolution of 0:5 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-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-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.

These findings are robust to alternative ways of measuring exposure to AGOA. In the baseline, we define a cell's exposure to AGOA as its proximity to the nearest port, conditional on the country being part of AGOA and on the cell producing AGOA-eligible goods in the pre-AGOA period. As a first alternative, we consider a broader definition of exposure that does not condition on a cell producing AGOA-eligible goods. In that case, within-country spatial variation in exposure comes only from differences in proximity to the nearest port. As a second alternative, we consider a narrower definition of exposure that conditions our baseline measure on a cell producing AGOA-eligible goods in which the country already had export capacity in the pre-AGOA period. As a last alternative, we condition exposure on the land suitability of cells for AGOA-eligible crops, rather than on the actual production of such crops. When using any of these alternative exposure measures, our results are unchanged.

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 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 these results (Enke, 2019; Moscona et al., 2020).

What mechanism might explain our findings? 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

[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).

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 lower conflict, but less so in geographically more remote places. However, they do not explore the 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.[6]

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 global-

[6] In related work, Boken et al. (2023) document that in West Bengal caste differences act as barriers to firm-to-firm trade.

ization. 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 poverty 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.[7] 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   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.[8] 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 variation in proximity to the closest port and in the production of AGOA-eligible goods, 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-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

[7] 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).

[8] The 0.5   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.

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 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.[9]

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.[10] 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.

Trade access through AGOA. 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. To get within-country variation in trade access, we rely on two

[9] 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).

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

sources of local variation: proximity to major ports,[11] and production of AGOA-eligible goods in the pre-AGOA period. The closer a location is to a major port, the more it gains market access when joining AGOA. However, market access only improves if the location already produced AGOA-eligible goods.

By multiplying country-level trade access by a cell-level measure of proximity to the nearest port and a cell-level binary measure of production of AGOA-eligible goods, we get a cell-level time-variant measure of trade access:

$$AGOAccess_{ict} = AGOA_{ct} \times Proximity_{ic} \times \max_{j \in J}\{Production_{icj}\} \tag{1}$$

where $AGOAccess_{ict}$ denotes trade access in cell i of country c in year t, $AGOA_{ct}$ denotes whether or not country c was part of AGOA in the year t, $Proximity_{ic}$ denotes the proximity of cell i of country c to the nearest major port in 2000, and $Production_{icj}$ denotes whether or not cell i of country c produced good j in the pre-AGOA period, where J is the set of AGOA-eligible products.

To get a measure of $Proximity_{ic}$, we standardize the number of hours required to travel to the nearest major port from IFPRI, and subtract this standardized variable from its maximum. Figure 1(a) maps the cross-country variation in access to AGOA, whereas Figure 1(b) depicts the travel time to the nearest major port expressed in hours. To measure $Production_{icj}$, we determine whether a cell produces AGOA-eligible product j. More specifically, we match the tariff lines of all products included in AGOA to geolocated data on the existence of oil fields and mines producing nine AGOA eligible minerals (from a list of 33), as well as on the production of 72 AGOA-eligible crops (from a list of 175) in the year 2000.[12] Figure 1(c) plots all the cells that produce AGOA eligible crops. Figure 1(d) plots all cells that have AGOA eligible mineral or oil production. All cells that produce either AGOA eligible crops, or minerals or oil are considered to be treated if the country is eligible for AGOA in the particular year (see Figure 2a).

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.[13] 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

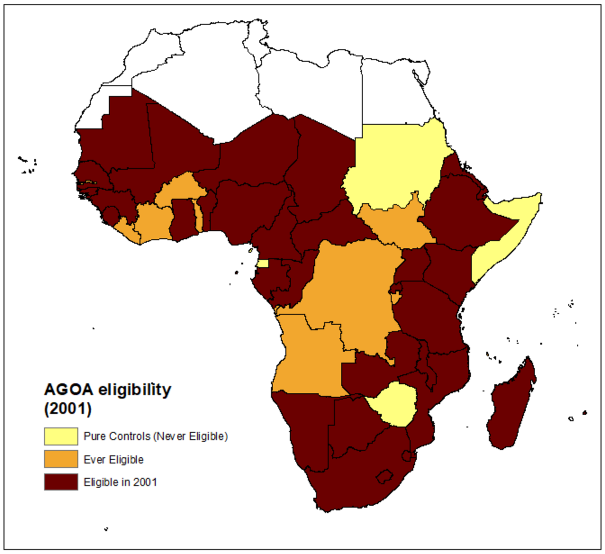
[11] Using proximity to a major port is reasonable, since more than 90% of international trade in Africa relies on maritime transport (Sebastian, 2014).

[12] The tariff lines are for the year 2000, and are based on publicly available data from the United States International Trade Commission (USITC). Mineral locations are based on the SNL Metals & Mining Database (S&P Global Marketplace) and the crop locations are based on Ramankutty et al. (2008) database. Locations of oil fields are based on the PETRODATA database. Please refer to Appendix A for further details.

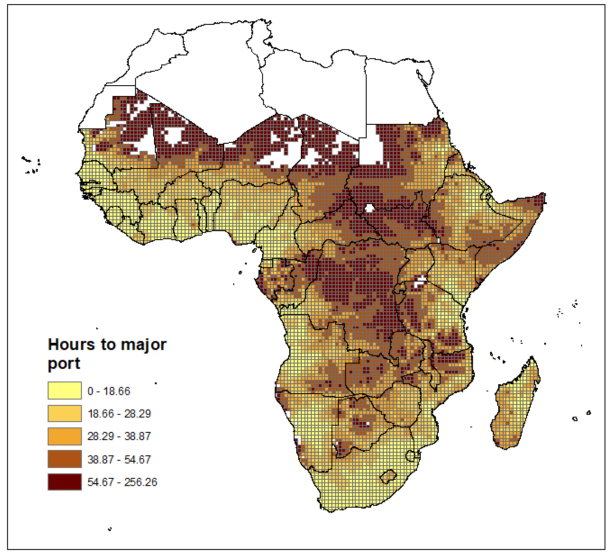
[13] See https://agoa.info/about-agoa/country-eligibility.html.

Figure 1: Trade Access through AGOA

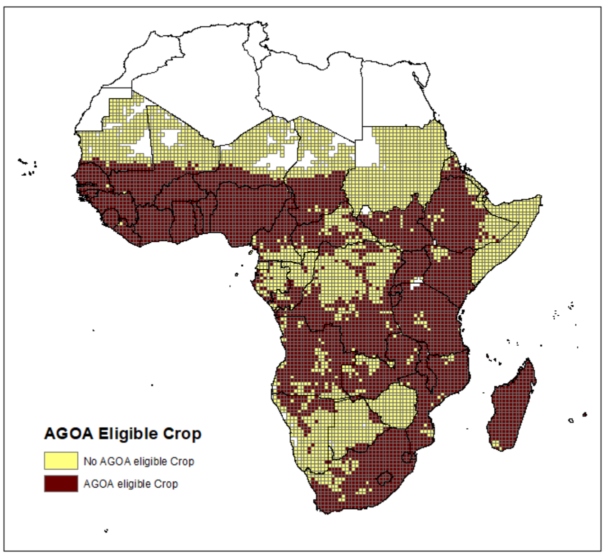
(a) AGOA membership



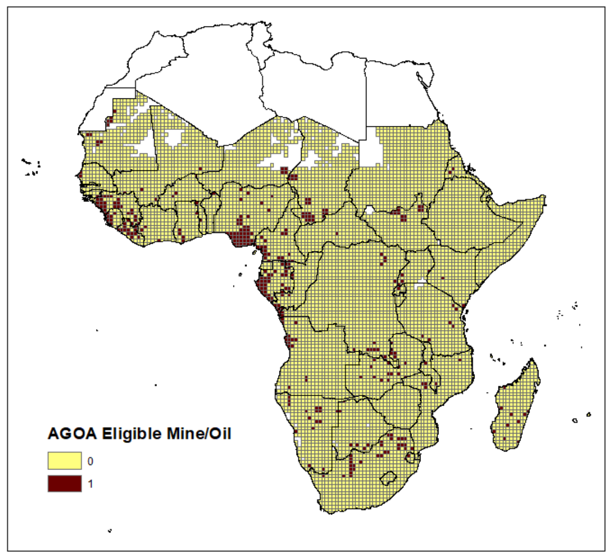
(b) Travel time to nearest port



(c) AGOA Eligible Crops



(d) AGOA Eligible Minerals and Oil



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. Panel (c) plots all cells that had an AGOA eligible crop. Panel (d) plots all cells that had an AGOA eligible mineral or oil. See Appendix A.1 for data sources and variable definitions.

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.

Of course, 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%.

Alternative measures of trade access through AGOA. For robustness, we consider three further measures of time-varying cell-level exposure to AGOA. A first alternative measure defines exposure to AGOA more broadly than our baseline measure (1):

$$AGOAGeo_{ict} = AGOA_{ct} \times Proximity_{ic} \tag{2}$$

In this case, a location's market access depends on proximity to the nearest port, but not on it producing AGOA-eligible goods in the pre-AGOA period. It aims to capture the possibility that locations may adjust their production in response to improved trade access to the US.

A second alternative measure defines exposure to AGAO more narrowly:

$$AGOAExp_{ict} = AGOA_{ct} \times Proximity_{ic} \times \max_{j \in J} \{Export_{cj} | Production_{icj} = 1\} \tag{3}$$

where $Export_{cj}$ is a binary variable that indicates whether country c exported good j in the pre-AGOA period.[14] To measure export capacity, we use data from CEPII. Exposure measure (3) takes the view that if a location produces AGOA-eligible goods, but the country has no export capacity in those goods, then the cell will not experience an improvement in market access when the country joins AGOA.

A third alternative measure uses land suitability to define exposure to AGOA:

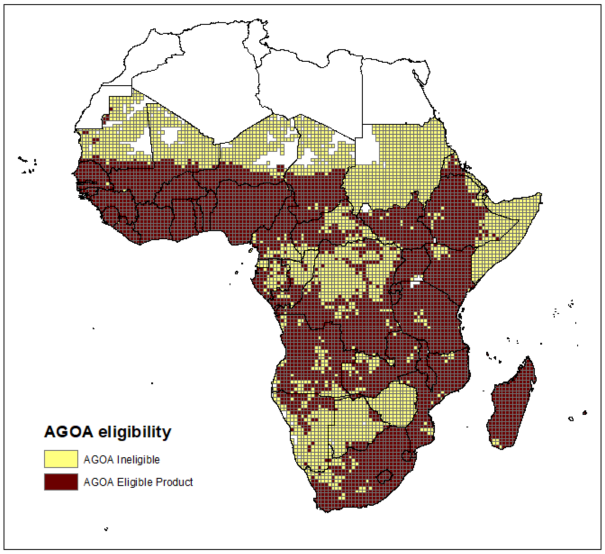
$$AGOASuit_{ict} = AGOA_{ct} \times Proximity_{ic} \times \max_{j \in J} \{Suitability_{icj}\} \tag{4}$$

where $Suitability_{icj}$ measures whether a location's land is suitable for AGOA-eligible crop j using data from the FAO's Global Agro-Ecological Zones (GAEZ) database. (For the case of minerals, we continue to use actual production.) It takes the view that as long as the and is suitable for the production of AGOA-eligible goods, the location experiences an improvement in market access when joining AGOA (see Figure 2b) .

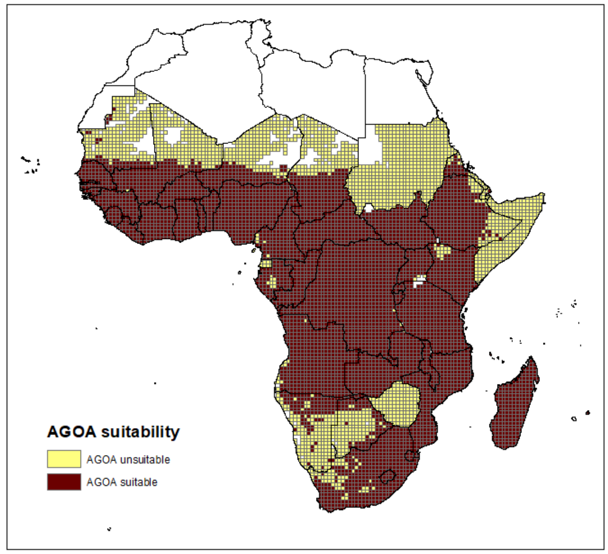
[14] We set two different bars for a country's export capacity in a certain good by requiring positive exports to either (i) anywhere in the world (see Figure 2c) or (ii) the US (see Figure 2d).

Figure 2: Trade Access through AGOA: Alternative definitions

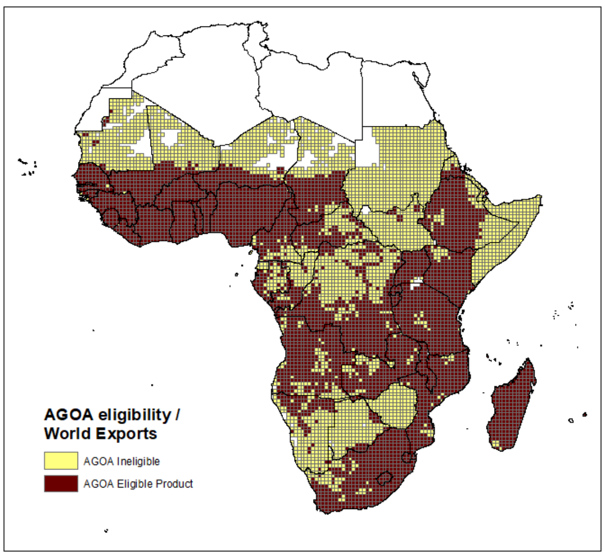
(a) Cells with AGOA eligible products



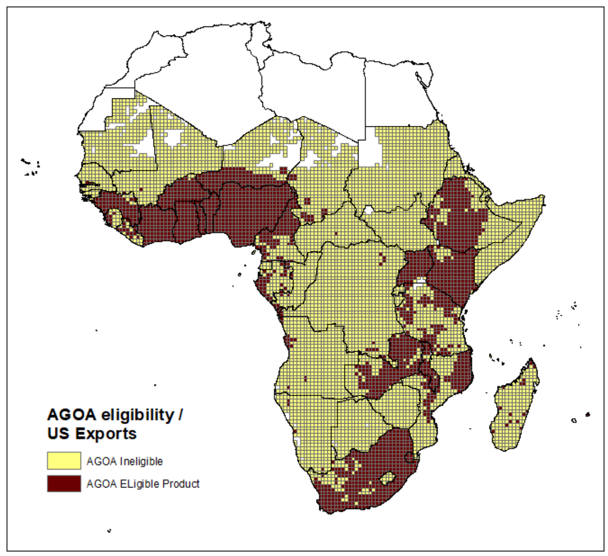
(b) Cells with AGOA product suitability



(c) World Exports



(d) USA Exports



Note: Panel (a) plots all cells that had an AGOA eligible product. Panel (b) plots all cells that had adequate conditions making them suitable for producing AGOA eligible products. Panel (c) plots all cells that had an AGOA eligible product conditional on the country exporting that product (to anywhere world) in the pre-AGOA period. Panel (d) plots all cells that had an AGOA eligible product conditional on the country exporting that product (to the U.S.A.) in the pre-AGOA period. See Appendix A.1 for data sources and variable. See Appendix A.1 for data sources and variable definitions.

2.3 Ethnic Remoteness

In sub-Saharan Africa ethnicity and language largely overlap. Data on the population's ethnic composition at the 0.05×0.05 grid-cell level come from the language database recently constructed by Desmet et al. (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 implement an iterative proportional fitting algorithm to construct a comprehensive 0.05×0.05 grid-cell level dataset on the ethnolinguistic composition of the population for the entire globe. We aggregate this information up to the 0.5×0.5 grid-cell level.

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. When measuring ethnic remoteness, we can either take remoteness to the country or remoteness to the dominant group. 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 n or m. Denote by d_{nm} the ethnic distance between n and m, by s_n the share of the country's population pertaining to ethnic group n, and by $s_{\ell n}$ the share of the population of grid-cell ℓ pertaining to ethnic group n. We then define the ethnic remoteness of cell ℓ to the country as

$$ER_\ell = \sum_n \sum_m s_{\ell n} s_m d_{nm}. \tag{5}$$

Given that in Africa ethnicity tends to coincide with language, we measure d_{nm} as the linguistic distance between the language spoken by ethnic group n and the language spoken by ethnic group m (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.[15] More specifically, we take the Ethnologue language tree, and denote by b_{nm} the number of shared branches between languages n and m, and by b_{max} the maximum number of shared branches between any two languages. We then define the linguistic distance between n and m as

$$d_{nm} = 1 - \left(\frac{b_{nm}}{b_{max}}\right)^{\lambda} \tag{6}$$

where λ is a parameter that determines how fast the linguistic distance declines as the number

[15] 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.

of shared branches increases. We follow Desmet et al. (2009) and set $= 0.05$.

Panel (a) of Figure 3 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

$$ER_{\ell}^{dom} = \sum_{n} s_{\ell n} s_{dom} d_{n,dom}, \tag{7}$$

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

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:

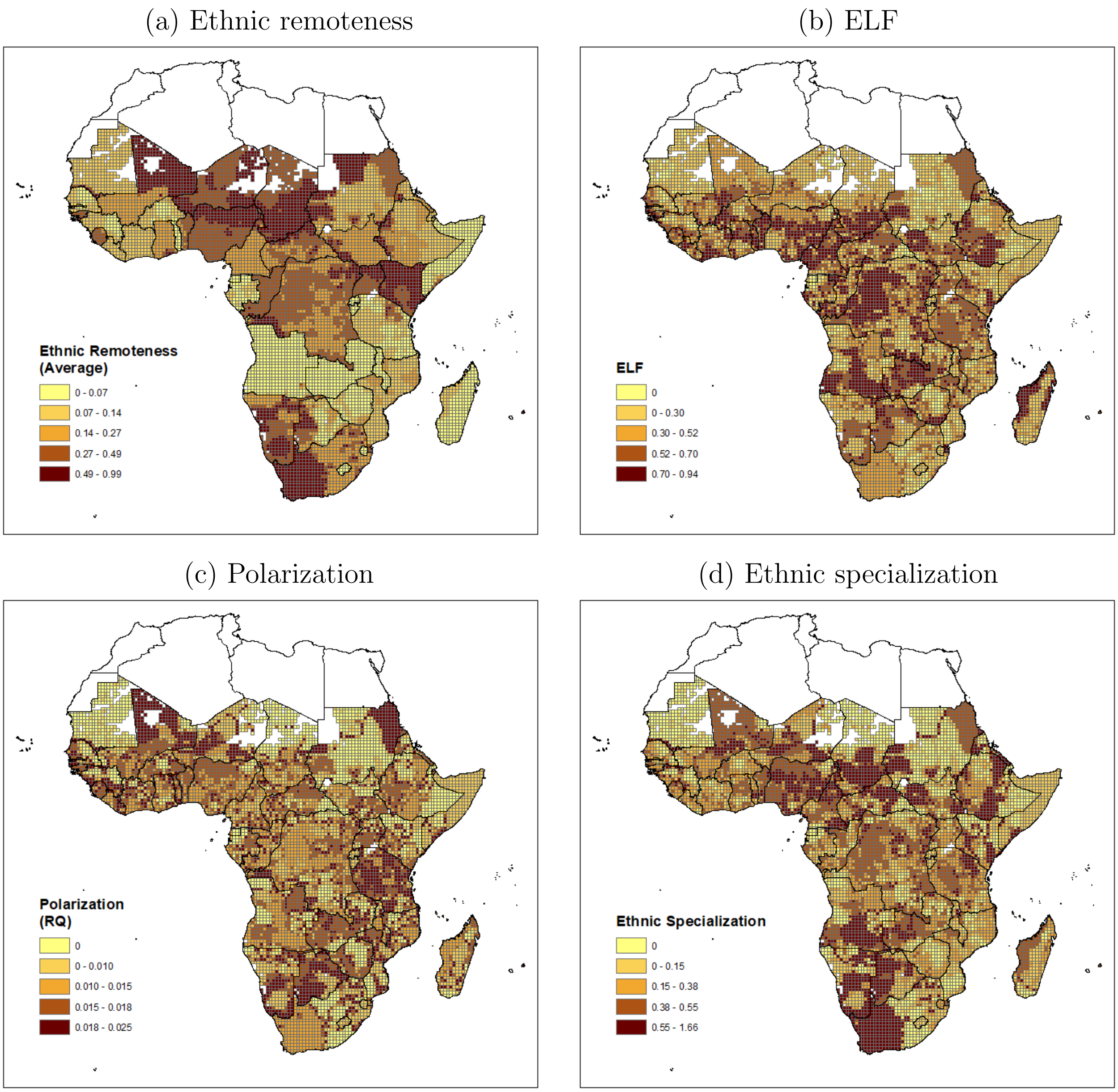
$$ELF_{\ell} = \sum_{n} \sum_{m} s_{\ell n} s_{\ell m}. \tag{8}$$

Another is the standard polarization index from Montalvo and Reynal-Querol (2005), which measures the proximity 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%):

$$POL_{\ell} = \sum_{n} s_{\ell n}^{2} (1 - s_{\ell n}). \tag{9}$$

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 3 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.

Figure 3: 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 (5)). Panel (b) plots the ethnolinguistic fractionalization index, which measures the probability that two randomly drawn individuals of a cell pertain to di erent ethnic groups (equation (8)). Panel (c) plots the ethnolinguistic polarization index (equation (9)). Panel (d) plots the ethnic specialization index, which measures the extent to which occupational specialization runs along ethnic lines (equation (10)). 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 de nitions.

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 traditionally ran 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 the traditional occupational activity by ethnicity with the ethnic composition of grid cells. Denote by x_n^q the share of ethnic group n 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 determine the share of cell ℓ traditionally employed in occupation q, $x_\ell^q = \sum_n s_{n\ell} x_n^q$.[16] Following Krugman (1991), we can define the specialization of ethnic group n as $\sum_q | x_n^q - x^q |$, 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

$$ES_\ell = \sum_n s_{\ell n} \sum_q | x_n^q - x^q | \qquad (10)$$

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 3 shows a map of ethnic specialization at the local level. The correlation between ethnic remoteness and ethnic remoteness is 0.26.

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

[16] 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).

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 a 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). The disease environment is also a predictor of conflict (Cervellati et al., 2022). 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 a relative increase in 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 relatively 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,

$$\log(y_{ict} + 1) = \quad AGOAccess_{ict} + AGOAccess_{ict}\mathbf{E}'_{ic} \quad + \mathbf{X}'_{ict} \quad + \quad _{ic} + \quad _{ct} + u_{ict} \tag{11}$$

where y_{ict} is the number of fatalities in cell i of country c at time t, $AGOAccess_{ict}$ is the degree of trade openness of cell i in country c at time t as defined in (1), $\mathbf{E}_{ic}$ 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), $_{ic}$ are cell fixed effects, $_{ct}$ 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).[17]

As pointed out by Roth et al. (2023), the single coefficient differences-in-differences (DiD) estimates and in (11) may be subject to potential biases that arise from heterogeneity in the dynamic treatment effects in staggered adoption designs. Recently developed estimators can potentially address these biases (de Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021). However, these estimators are applicable only to cases characterized by a 0–1 binary treatment variable, with treatment usually transitioning into an absorptive state with no reversals in treatment assignment. In our case, our primary treatment variable

[17] The correction of SEs for spatial and temporal correction is implemented using code from Fetzer (2020). 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.

is a composite of multiple continuous variables, represented by the term $AGOAccess_{ict}\mathbf{E}'_{ic}$, where $AGOAccess_{ict} = AGOA_{ct} \times Proximity_{ic} \times \max_{j \in J}\{Production_{icj}\}$. Among these, only the country-level variable $AGOA_{ct}$ is binary. The other three variables are continuous, precluding the application of existing econometric methods designed for a binary treatment DiD framework. Furthermore, the flips in treatment caused by the entry and exit of some countries in AGOA across different years, further impedes the use of these estimators.

3.2 Ethnic Remoteness Weakens the Peace Dividend from Trade

Ethnic diversity, ethnic remoteness, and ethnic complementarity. Table 1 reports results from estimating equation (11) 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. These additional interaction are statistically insignificant. Columns (5) through (7) add interaction terms between trade openness and different measures of ethnic complementarity. Here as well, none of these additional interaction terms are statistically significant. 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 5.4%. The corresponding number when going from the ethnically least remote cell to the ethnically most remote cell is a predicted increase in fatalities by 20.4%.

Robustness to alternative measures of exposure to AGOA. Table 2 shows robustness to alternative measures of exposure to AGOA. First, columns (1) and (2) report results for a broader definition of AGOA as defined in equation (2). This definition measures a cell's exposure as proximity to the closest major port, without taking into account whether the cell produces any AGOA eligible products. Next, columns (3), (4), (5) and (6) report results for a narrower definition of AGOA as defined in equation (3). In addition to requiring a cell to produce an AGOA eligible product, it makes exposure conditional on the country exporting that good to either the world or the U.S. in the pre-AGOA period. Finally, columns (7)

Table 1: AGOA and Conflict: Ethnic Remoteness

		Intensity of Conflict from UCDP						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGOAccess		-0.047	-0.109	-0.103	-0.098	-0.107	-0.117	-0.109
		(0.009)	(0.018)	(0.017)	(0.017)	(0.016)	(0.031)	(0.021)
AGOAccess	ER		0.206	0.210	0.214	0.211	0.205	0.206
			(0.048)	(0.050)	(0.051)	(0.055)	(0.047)	(0.049)
AGOAccess	ELF			-0.017				
				(0.022)				
AGOAccess	POL				-0.112			
					(0.081)			
AGOAccess	Specialization					-0.018		
						(0.044)		
AGOAccess	Kinship						0.020	
							(0.055)	
AGOAccess	Segmented							-0.000
								(0.015)
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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

and (8) follow equation (4) by defining exposure based on whether a cell has the adequate suitability conditions to produce an AGOA eligible product. As can be seen, when using any of these alternative measures of exposure to AGOA, our results remain unchanged.

Effect of crops versus mines and oil. In Appendix Section B.2.2, we investigate whether there are differences in the effect of AGAO exposure between cells that produce AGOA eligible crops and cells that produce AGOA eligible minerals or oil. Work by Dube and Vargas (2013) argues that the peace dividend from a positive income shock is limited to labor-intensive sectors, such as agriculture. In the context of Colombia, they find a decline in conflict in coffee-growing areas when the coffee price increases, whereas there is no such peace dividend in oil-producing areas when the oil price rises. Consistent with this, our results are primarily driven by cells that produce AGOA eligible crops, rather than by cells producing AGOA eligible minerals or oil. Of course, we cannot discard the possibility that the absence of statistically significant results in the case of minerals and oil is due to the small number of cells that fall in this category.

Table 2: AGOA and Conflict: Alternative Definitions of AGOA Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOAGeo	-0.144	-0.176						
	(0.031)	(0.033)						
AGOAGeo ER		0.145						
		(0.039)						
AGOAExp (World)			-0.049	-0.116				
			(0.009)	(0.018)				
AGOAExp (World) ER				0.216				
				(0.049)				
AGOAExp (U.S.)					-0.041	-0.106		
					(0.011)	(0.022)		
AGOAExp (U.S.) ER						0.250		
						(0.071)		
AGOASuit							-0.039	-0.108
							(0.009)	(0.020)
AGAO Suitability ER								0.195
								(0.049)
Observations	269497	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. Columns (1) and (2) use the broad definition of AGOA exposure without requiring the production of AGOA eligible goods as defined in equation (2). Columns (3), (4), (5), and (6) use a narrow definition of AGOA that takes into account if the country has export capacity in eligible AGOA goods to either the rest of the world or the U.S. as defined in equation (3). Columns (7) and (8) measure make AGOA exposure conditional on a location's land being suitable for AGOA-eligible crops as defined in equation (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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

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 in Appendix Section B.2.4. 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 B13 uses the exact same specifications as Table 1, with the exception of the dependent variable. Our main result is unchanged: openness reduces conflict, but this benign effect is smaller in cells that are more ethnically remote from the rest of the country.

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 result does not change: the effect of ethnic remoteness, interacted with trade openness, is still positive, statistically significant at the 1% level, and of a similar magnitude.

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.[18] Columns (3) and (4) of Table 3 report results when controlling for interactions with malaria and tsetse fly suitability. As expected, cells with higher malaria incidence get a smaller reduction in conflict after the AGOA trade shock. In contrast, cells with higher tsetse fly suitability show no difference. Again, our main finding is unchanged: ethnic remoteness weakens the peace dividend from trade liberalization.

Table 3: AGOA and Conflict: Robustness to Environmental Variables

		Intensity of Conflict from UCDP			
		(1)	(2)	(3)	(4)
AGOAccess		-0.109	-0.187	-0.116	-0.100
		(0.018)	(0.028)	(0.018)	(0.018)
AGOAccess	ER	0.206	0.190	0.195	0.199
		(0.048)	(0.048)	(0.049)	(0.047)
AGOAccess	Crop Unsuitability		0.016		
			(0.004)		
AGOAccess	Malaria Suitability			0.023	
				(0.008)	
AGOAccess	Tsetse Suitability				-0.008
					(0.006)
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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

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

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

(Greenberg, 1956; Desmet et al., 2009):

$$GI_{\ell} = \sum_{n} \sum_{m} s_{\ell n} s_{\ell m} d_{nm}. \tag{12}$$

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):

$$POL_{\ell}^{er} = \sum_{n} \sum_{m} s_{\ell n}^{2} s_{\ell m} d_{nm}. \tag{13}$$

The interaction of these alternative measures of diversity with AGOA yield negative coefficients, indicating that cells that are more diverse benefit from a larger peace dividend. However, these results are not robust to using the ACLED conflict data (Table B14). More importantly, in both Tables B5 and B14 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 is that ethnic remoteness might correlate positively with specialization in non-tradable or import-competing sectors. If so, 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 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. Whether we measure ethnic remoteness as distance

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

		Intensity of Conflict from UCDP						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGOAccess		-0.047	-0.081	-0.075	-0.070	-0.081	-0.085	-0.079
		(0.009)	(0.012)	(0.013)	(0.013)	(0.012)	(0.026)	(0.014)
AGOAccess	ER^{dom}		0.125	0.127	0.129	0.126	0.125	0.125
			(0.030)	(0.031)	(0.032)	(0.033)	(0.030)	(0.030)
AGOAccess	ELF			-0.015				
				(0.022)				
AGOAccess	POL				-0.103			
					(0.081)			
AGOAccess	Specialization					-0.002		
						(0.041)		
AGOAccess	Kinship						0.009	
							(0.057)	
AGOAccess	Segmented							-0.003
								(0.014)
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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

to 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 B6 we explore alternative ways to transform the conflict data. One such alternative is to use the inverse hyperbolic sine transformation, $\log(y + \sqrt{y^2 + 1})$ 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. However, so far, we have not shown any results based on income. 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.[19]

We take the same estimating equation (11) 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, none of them are statistically significant.

Table 6 considers alternative definitions of exposure to AGOA. Columns (1) and (2) define exposure based on proximity to a major port, without taking into account product eligibility. Columns (3) through (6) make exposure conditional not just on product eligibility, but also on the country's export capacity of the product. Columns (7) and (8) define exposure in terms of suitability to produce AGOA eligible products, rather than on actual production. Our findings are robust to these alternative ways of defining exposure.

Table 7 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. Though columns (3) and (4) show negative impacts of the

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

Table 5: AGOA and Luminosity: Ethnic Remoteness

		Income Proxied by Luminosity						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGOAccess		0.355	0.395	0.407	0.418	0.412	0.315	0.382
		(0.029)	(0.034)	(0.041)	(0.042)	(0.038)	(0.063)	(0.041)
AGOAccess	ER		-0.148	-0.144	-0.139	-0.136	-0.159	-0.145
			(0.057)	(0.057)	(0.057)	(0.058)	(0.058)	(0.057)
AGOAccess	ELF			-0.029				
				(0.056)				
AGOAccess	POL				-0.212			
					(0.215)			
AGOAccess	Specialization					-0.100		
						(0.099)		
AGOAccess	Kinship						0.194	
							(0.132)	
AGOAccess	Segmented							0.024
								(0.042)
Observations		241072	241072	241072	241072	241072	241072	241072

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 control for rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. The sample includes 8,670 grid-cells spread across 48 sub-Saharan African countries for the period of 1992–2017. $p < 0.10$, $p < 0.05$, $p < 0.01$.

incidence of either malaria or the tsetse fly, the effects are not statistically significant. 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 B7 includes alternative measures of fractionalization and polarization, and Appendix Table B8 considers alternative transformations of our dependent variable. These additional exercises have no qualitative impact on our main coefficients of interest.

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 access shock on income depends on an individual's ethnic remoteness.

Table 6: AGOA and Luminosity: Alternative Definitions of AGOA Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOAGeo	1.518	1.592						
	(0.107)	(0.108)						
AGOAGeo ER		-0.338						
		(0.075)						
AGOAExp (World)			0.357	0.450				
			(0.030)	(0.043)				
AGOAExp (World) ER				-0.303				
				(0.089)				
AGOAExp (U.S.)					0.255	0.311		
					(0.044)	(0.056)		
AGOAExp (U.S.) ER						-0.216		
						(0.116)		
AGOASuit							0.404	0.531
							(0.037)	(0.050)
AGAOSuit ER								-0.358
								(0.083)
Observations	241072	241072	241072	241072	241072	241072	241072	241072

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). Columns (1) and (2) use the broad definition of AGOA exposure without requiring the production of AGOA eligible goods as defined in equation (2). Columns (3), (4), (5), and (6) use a narrow definition of AGOA that takes into account if the country has export capacity in eligible AGOA goods to either the rest of the world or the U.S. as defined in equation (3). Columns (7) and (8) measure make AGOA exposure conditional on a location's land being suitable for AGOA-eligible crops as defined in equation (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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table 7: AGOA, Luminosity and Remoteness: Controlling for Environmental Variables

	Income Proxied by Nighlight			
	(1)	(2)	(3)	(4)
AGOAccess	0.444	0.599	0.451	0.451
	(0.042)	(0.079)	(0.043)	(0.046)
AGOAccess ER	-0.294	-0.263	-0.283	-0.299
	(0.086)	(0.086)	(0.087)	(0.087)
AGOAccess Crop Unsuitability		-0.033		
		(0.013)		
AGOAccess Malaria Suitability			-0.024	
			(0.023)	
AGOAccess Tsetse Suitability				-0.006
				(0.018)
Observations	241072	241072	241072	241072

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 control 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 1992–2017. $p < 0.10$, $p < 0.05$, $p < 0.01$.

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,

$$I_{jeict} = \quad AGOAccess_{ict} + AGOAccess_{ict}\mathbf{E}'_{jec} \;{}_{1} + AGOAccess_{ict}\mathbf{E}'_{ic} \;{}_{2} + \mathbf{X}'_{ict} \;+\; {}_{ic} + \;{}_{ct} + \;{}_{e} + u_{jeict} \tag{14}$$

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, $AGOAccess_{ict}$ 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, ${}_{ic}$ are cell fixed effects, ${}_{ct}$ are country-time fixed effects, ${}_{e}$ 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.[20] As proxies for income, we use two 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).[21]

[20] 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.

[21] 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.

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 8 reports results for regressions of individual-level food poverty on trade openness, using specification (14). 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. Columns (2) and (3) suggest that ethnic remoteness of the individual, rather than ethnic remoteness of the location, 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 3.6 percent. Overall, this provides support to the hypothesis that an individual's ethnic remoteness makes it more difficult to take advantage of trade liberalization.

Table 8: AGOA and Food Poverty

		Individual Food Poverty					
		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		-0.047	-0.041	-0.048	-0.087	-0.085	-0.095
		(0.046)	(0.045)	(0.047)	(0.048)	(0.048)	(0.049)
AGOAccess	Indiv ER	0.146		0.143	0.187		0.165
		(0.047)		(0.051)	(0.045)		(0.052)
AGOAccess	Cell ER		0.100	0.012		0.174	0.075
			(0.063)	(0.078)		(0.060)	(0.080)
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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

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 8 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 are more likely to suffer from food poverty in the wake of a positive trade shock.[22]

Table 9: AGOA and Income Poverty

		Individual Income Poverty					
		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		-0.015	-0.033	-0.039	-0.029	-0.044	-0.054
		(0.045)	(0.046)	(0.047)	(0.052)	(0.054)	(0.054)
AGOAccess	Indiv ER	0.148		0.119	0.189		0.159
		(0.060)		(0.063)	(0.054)		(0.059)
AGOAccess	Cell ER		0.284	0.191		0.300	0.179
			(0.093)	(0.104)		(0.127)	(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 9 replicates the above table but uses income poverty as an alternative measure 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

[22]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 8 are based on waves 1, 2, 3 and 6.

poverty in the wake of trade liberalization. Controlling for individual characteristics, such as profession and age, does not change these findings (columns (4) to (6)). Focusing on column (6), 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 4.0 percent. Appendix Tables B31–B33 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.

Robustness. Appendix Table B27 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 B28 introduces additional cell-level interactions of ethnic diversity and ethnic complementarity with trade openness. Appendix Table B29 instead adds cell-level interactions with environmental variables. Our main result is robust to introducing those variables.

5 Conclusion

This paper explored how ethnicity affects the relation between trade liberalization and conflict. Exploiting the staggered implementation of the Africa Growth and Opportunity Act (AGOA), we found that improved trade access generates a peace dividend, but less so in locations that are ethnically remote from the rest of the country. Our findings are consistent with an opportunity cost view of participating in 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 less from a 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 poverty data from Afrobarometer, we found evidence in support of these predictions. Overall, we conclude that ethnic remoteness acts as a barrier to participating in the global economy. In addition to geographic remoteness and sectoral specialization, ethnic remoteness should be a key concern when analyzing which locations and groups might be left behind by globalization.

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Online 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®.
Con ict intensity (ACLED, UCDP)	We measure con ict using fatalities in each cell for a speci c year. Data are obtained from two event-based databases: The Uppsala Con ict Data Program (UCDP) (Sundberg and Melander, 2013) for 1989{2017 and the Armed Con ict 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 tting algorithm to construct a comprehensive 0:05 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).

(continued on next page)

Variable (Source)	Description
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 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 rst 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.
Tse Tse y 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.
AGOA Eligibile Crops (FAO, USITC,M3)	We combine the following 3 data sources: *Cell-level crop location* { We identify the cell-level location of 175 crops from the M3 crops data (Ramankutty et al., 2008) available at the 5 minute 5 minute grid of the world for the year 2000 (average during the period 1997{2003). *US tari ine data* { Data on US tari s at the eight-digit level come from the US International Trade Commission (USITC) for the year 2000 (https://dataweb.usitc.gov/tariff). *Crop description* { Description of the crops are from the FAO available at https://uses.plantnet-project.org/en/FAO,_product_nomenclature. We combine the 175 identi able crops from Ramankutty et al. (2008), with the USITC tari data for the year 2000 using the FAO crop descriptions. From the 175 crops we keep 72 crops which appear as the main product of at least one tari line. The 72 eligible crops are: alfalfa, almond, apple, apricot, artichoke, asparagus, avocado, bambara, barley, bean, blueberry, broadbean, cabbage, carrots, cauli ower, cerealnes, cherry, chicory, citrusnes, clover, cotton, cowpea, cucumberetc, currant, date, g, grape, grapefruit, greenbean, greenbroadbean, greencorn, groundnut, hazelnut, hop, lemonlime, linseed, melonetc, millet, mushrooms, mustard, nutnes, oilseednes, olive, onion, orange, papaya, peachetc, pear, pineapple, plum, potato, quince, rapseed, raspberry, rice, rootnes, rye, ryefor, sa ower, soybean, spinach, strawberry, stringbean, sugarbeet, sun ower, tangetc, tobacco, tomato, vegetablenes, walnut, watermelon, wheat.

(continued on next page)

Variable (Source)	Description
AGOA Eligibile Minerals (SNL, USITC)	Data on mines come from S & P Global - SNL Metals and Mining (https://www.marketplace.spglobal.com/en/datasets/snl-metals-mining-(19)). The database covers 33 minerals along with information on the geo-location of the mines. For large-scale mines, it also covers if the active is active, their production capacity, the volume of production, and the year production started. From the 33 minerals, we select those ones which are present in at least one tariff lines in USITC as the main product, following the same procedure as with the crops (explained above). The AGOA eligible minerals include the following: bauxite (aluminum), iron, silver, zinc, cobalt, manganese (ferromanganese), niobium, tungsten, and vanadium. Taking the geolocation of the mines, we use GIS software to construct dummies equal to 1 if a cell contains at least one mine of some of the eligible minerals.
AGOA Eligibile Oil (PETRODATA)	Data on oil are based on the PETRODATA dataset (Lujala et al., 2007) which contains information of oil and gas fields throughout the world. It covers 884 records for onshore and 378 for offshore of natural gas and crude oil during the period 1946–2003. It includes a shapefile of polygons representing petroleum fields. For each cell, we compute the fraction area covered by these polygons using GIS software. Next, we construct dummies equal to 1 if a cell contains a positive fraction of an oil field.
AGOA suitability (FAO GAEZ)	We obtain crop-specific suitability data from the FAO's Global Agro-Ecological Zones (GAEZv4 database https://gaez.fao.org/). They produce estimates on crop suitability for individual crops at 5 arc-minutes resolution for historical, current, and future conditions. In particular, we use the suitability index, which takes values from 0–10000 depending on how suitable each cell is (variable name is "Suitability index range (0 – 10000); all land in grid cell"). We download the data selecting the following options: rain-fed (water supply is "rainfed"), high input intensity (input level is "high"), and without CO2 fertilization (CO2 fertilization is "Without CO2 Fertilization"). The measure is calculated for the period 1971-2000 (time period is "1971–2000"). Following Nunn and Qian (2011) we define a cell as suitable if it is classified in the database as being either "very suitable", "suitable", or "moderately suitable". In other words, a cell is suitable if it has a value greater or equal than 4000 in the suitability index. From the selection of crops available from GAEZ, we choose those which are present in at least one of the tariff lines eligible under AGOA as the main product of the tariff. These crops are the following: Alfalfa, Barley, Phaseolus Bean, Cabbage, Carrot, Citrus, Cotton, Cowpea, Groundnut, Foxtail Millet, Pearl Millet, Olive, Onion, White Potato, Rapeseed, Dryland Rice, Wetland Rice, Rye, Soybean, Sugarbeet, Sunflower, Tobacco, Tomato, and Wheat.
Pre-AGOA Exports (CEPII)	The CEPII-BACI dataset gives us the 6-digit product identifier and bilateral country-level trade from 1995–2021 (Gaulier and Zignago, 2010). These were downloaded from http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37 on June 19, 2023. We use the version 202301 last updated on February 1st, 2023. The exact downloading option chosen was called: HS92 (1995–2021).

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. (2023). 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

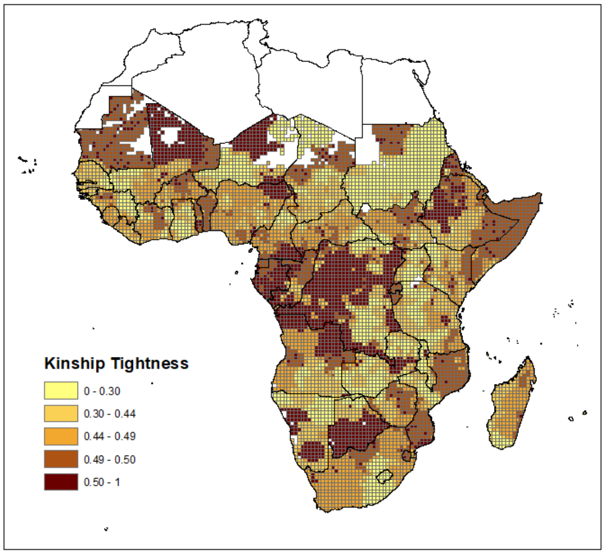
Country	AGOA entry	Survey Year
Botswana	2001	1999
Ghana	2001	1999
Lesotho	2001	2000
Malawi	2001	1999
Mali	2001	2001
Namibia	2001	1999
Nigeria	2001	2000
South Africa	2001	2000
Tanzania	2001	2001
Uganda	2001	2000
Zambia	2001	1999
Zimbabwe	NA	1999

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.

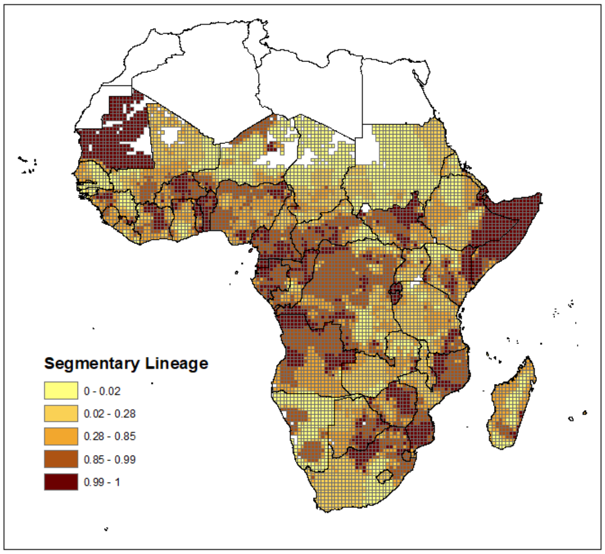
A.4 Data Maps

Figure A1: Kinship Tightness and Segmentary Lineage

(a) Kinship Tightness



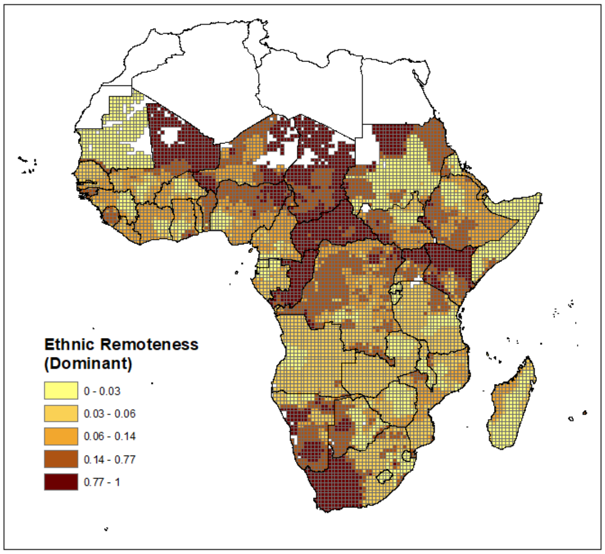
(b) Segmentary Lineage



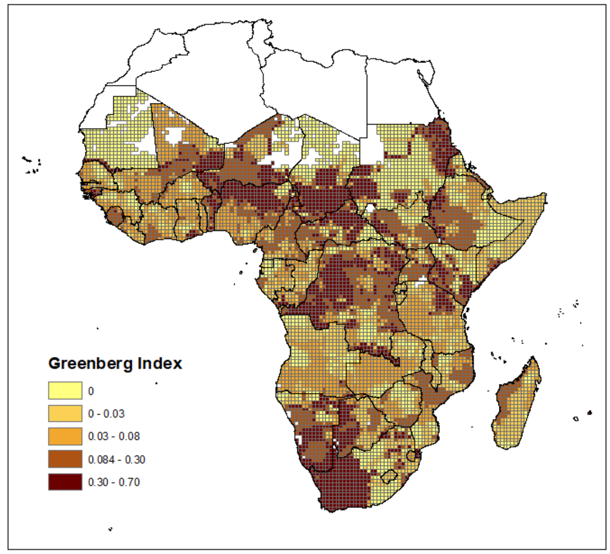
Notes: Panel a) plots the average kinship tightness in a cell (Enke, 2019). Panel b) plots the average segmentary lineage in a cell (Moscona et al., 2020). The distribution of ethnic groups is based on data from Desmet et al. (2020). See Appendix A.1 for further details on data sources and variable de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

Figure A2: Alternative Ethnic Remoteness and Ethnic Diversity

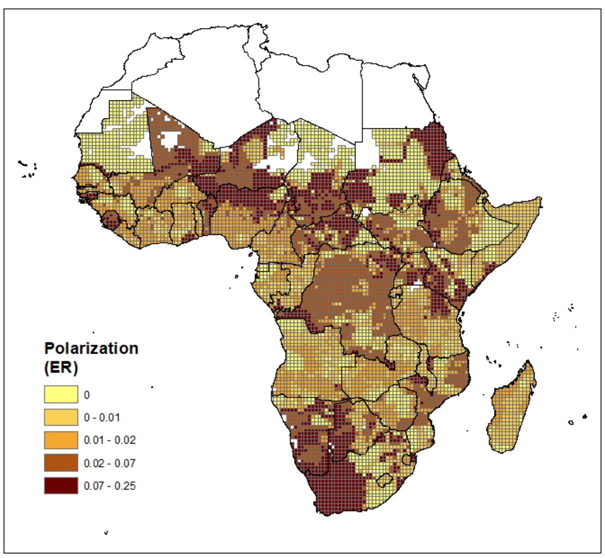
(a) Ethnic remoteness from the dominant group



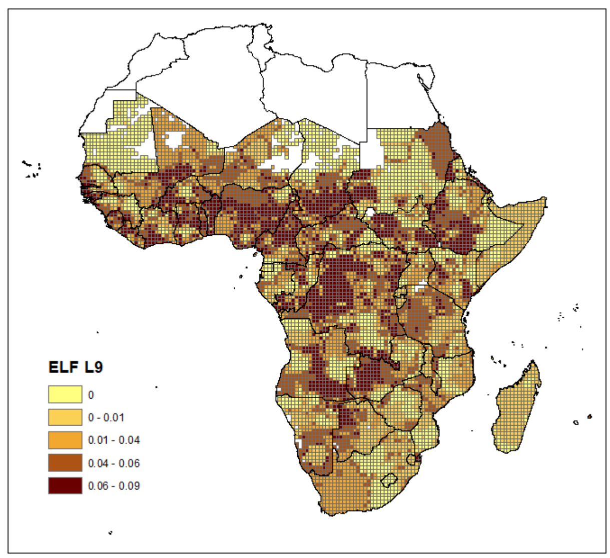
(b) Greenberg Index



(c) Polarization (ER)



(d) ELF Level 9



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 (7)). Panel b) plots the Greenberg index, which measures the expected ethnic distance between any two random resident of the cell (equation (12)). Panel c) plots the the Polarization index (equation (13)), *a la* Esteban and Ray (1994) . Panel d) plots the fractionalization index at aggregation level 9 *a 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: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Log (Fatalities + 1) UCDP	0.079	0.54	0	12.7	269497
Log (Fatalities + 1) ACLED	0.13	0.637	0	11.079	195153
Log (Luminosity + 1)	0.1	0.347	0	4.107	241618
Openness	0.863	0.102	0.095	1	269497
AGOAOpen	0.382	0.438	0	1	269497
AGOAccess	0.238	0.426	0	1	269497
AGOAExp World	0.575	0.494	0	1	269497
AGOAExp USA	0.305	0.46	0	1	269497
AGOASuit	0.729	0.445	0	1	269497
ER	0.295	0.26	0	0.989	269497
ER Dom	0.274	0.358	0	1	269497
Specialization	0.181	0.177	0	1	269497
Kinship Tightness	0.431	0.128	0	1	269497
Segmentary Lineage	0.533	0.417	0	1	269497
Greenberg	0.129	0.166	0	0.700	269497
ELF2	0.16	0.199	0	0.824	269497
ELF9	0.299	0.277	0	0.915	269497
ELF15	0.381	0.305	0	0.941	269497
ELP rq	0.11	0.08	0	0.25	269497
ELP er	0.037	0.051	0	0.25	269497
Crop Unsuitability	5.411	1.548	1	9	269497
Malaria Suitability	0.28	0.98	-0.942	2.975	269497
TseTse Suitability	0.851	1.265	0	6	269497

Table B2: Cell-Level Cross-Correlations

Variables	ER	ER Dom
ER	1.00	
ER Dom	0.85	1.00
Log (Fatalities + 1) UCDP	0.01	0.01
Log (Fatalities + 1) ACLED	0.02	0.01
Log (Luminosity + 1)	-0.01	-0.07
Openness	-0.26	-0.29
AGOAOpen	0.02	-0.00
AGOAcces	0.14	0.05
AGOAExp World	-0.11	-0.13
AGOAExp USA	0.03	-0.04
AGOASuit	-0.16	-0.13
Specialization	0.26	0.17
Kinship Tightness	0.11	0.13
Segmentary Lineage	-0.24	-0.20
Greenberg	0.49	0.36
ELF2	0.46	0.33
ELF9	0.22	0.15
ELF15	0.09	0.05
ELP rq	0.13	0.09
ELP er	0.54	0.41
Crop Unsuitability	0.24	0.22
Malaria Suitability	-0.01	-0.03
TseTse Suitability	-0.11	-0.06

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
AGOAAccess (Geo)	0.74	0.37	0	1	114176
AGOAccess	0.51	0.5	0	1	114176
AGOAccess / World Exports	0.85	0.35	0	1	114176
AGOAExp / U.S. Exports	0.61	0.49	0	1	114176
AGOASuit	0.89	0.31	0	1	114176
Cell ER	0.25	0.22	0.01	0.97	114176
Indiv ER	0.24	0.25	0	1	114176
Cell ERdom	0.17	0.28	0	1	114176
Indiv ERdom	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
AGOAOpen	0.78	0.34	0	1	108463
AGOAccess	0.48	0.5	0	1	108463
AGOAExp World	0.85	0.36	0	1	108463
AGOAExp USA	0.59	0.49	0	1	108463
AGOASuit	0.89	0.32	0	1	108463
Cell ER	0.24	0.22	0.01	0.97	108463
Indiv ER	0.23	0.25	0	1	108463
Cell ERdom	0.16	0.27	0	1	108463
Indiv ERdom	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-Correlations

Variables	Indiv ER	Indiv ER$^{\mathsf{Dom}}$
Indiv ER$^{\mathsf{dom}}$	0.89	-
Cell ER	0.80	0.60
Cell ER$^{\mathsf{dom}}$	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

B.2.1 Baseline definition of AGOA

Table B5: AGOA and Conflict: Different Diversity Measures

		(1)	(2)	(3)	(4)
AGOAccess		-0.110	-0.106	-0.102	-0.118
		(0.018)	(0.017)	(0.016)	(0.019)
AGOAccess	ER	0.292	0.252	0.217	0.346
		(0.069)	(0.060)	(0.053)	(0.075)
AGOAccess	Greenberg	-0.165			
		(0.063)			
AGOAccess	ELF2		-0.088		
			(0.044)		
AGOAccess	ELF9			-0.032	
				(0.027)	
AGOAccess	POL^{er}				-0.773
					(0.214)
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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B6: AGOA and Conflict: Alternative Transformations of Dependent Variable

	Intensity of Conflict from UCDP			
	Log (y+1)	IH	Log (y+0.5)	0-1
AGOAccess	-0.109	-0.113	-0.129	-0.031
	(0.018)	(0.018)	(0.021)	(0.005)
AGOAccess ER	0.206	0.214	0.243	0.059
	(0.048)	(0.050)	(0.056)	(0.013)
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) 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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B7: AGOA and Luminosity: Different Diversity Measures

	(1)	(2)	(3)	(4)
AGOAccess	0.445	0.438	0.443	0.452
	(0.042)	(0.042)	(0.045)	(0.042)
AGOAccess ER	-0.392	-0.385	-0.296	-0.421
	(0.096)	(0.092)	(0.087)	(0.103)
AGOAccess Greenberg	0.187			
	(0.115)			
AGOAccess ELF2		0.174		
		(0.093)		
AGOAccess ELF9			0.006	
			(0.063)	
AGOAccess POL^{er}				0.698
				(0.385)
Observations	241072	241072	241072	241072

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 control 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 1992–2017. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B8: AGOA and Luminosity: Alternative Transformations of Dependent Variable

	Income Proxied by Nighlight			
	Log (y+1)	IH	Log (y+0.5)	0-1
AGOAccess	0.444	0.447	0.487	0.125
	(0.042)	(0.042)	(0.047)	(0.010)
AGOAccess ER	-0.294	-0.295	-0.315	-0.073
	(0.086)	(0.087)	(0.097)	(0.020)
Observations	241072	241072	241072	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 control for rainfall deviation, temperature deviation, cell FEs, and country specific year FEs. 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.2.2 Split by Crops and Minerals or Oil

Table B9: AGOA and Conflict: Crops vs. Minerals & Oil

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOAccess (Crops)	-0.047	-0.107						
	(0.009)	(0.018)						
AGOAccess (Oil)	-0.046	-0.038					-0.048	-0.047
	(0.021)	(0.028)					(0.021)	(0.028)
AGOAcess (Crops) ER		0.198						
		(0.049)						
AGOAcess (Oil) ER		-0.003						0.008
		(0.089)						(0.089)
AGOAExp (World, Crops)			-0.051	-0.116				
			(0.009)	(0.018)				
AGOAExp (World, Oil)			-0.056	-0.034				
			(0.022)	(0.030)				
AGOAExp (World, Crops) ER				0.211				
				(0.050)				
AGOAExp (World, Oil) ER				-0.057				
				(0.100)				
AGOAExp (U.S., Crops)					-0.027	-0.096		
					(0.011)	(0.023)		
AGOAExp (U.S., Oil)					-0.072	-0.051		
					(0.027)	(0.037)		
AGOAExp (U.S., Crops) ER						0.259		
						(0.075)		
AGOAExp (U.S., Oil) ER						-0.041		
						(0.105)		
AGOASuit (Crops)							-0.023	-0.058
							(0.011)	(0.018)
AGOASuit (Crops) ER								0.114
								(0.052)
Observations	269497	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. Column 1 and 2 use our main definition of AGOAccess used in equation (1) splitting the *Production* between crops and oil and mines (MO). Columns 3, 4, 5, and 6 use a definition of AGOAccess taking into account if the country has export capacity in eligible AGOA goods as defined in equation (3) to the US and to the rest of the world, splitting the *Production* between crops and oil and mines (MO). Columns 7 and 8 measure AGOAccess considering if a location's land is suitable for AGOA-eligible crop as defined in equation (4), splitting the *Production* between crops and oil and mines (MO). The unit of observation is the PRIO GRID cell (resolution 0.5 0.5 decimal degrees, approximately 55km 55km at the equator). All specifications control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B10: AGOA and Luminosity : Crops vs. Minerals & Oil

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOAccess (Crops)	0.312	0.383						
	(0.029)	(0.043)						
AGOAccess (Oil)	0.190	0.291						
	(0.073)	(0.109)						
AGOAccess (Crops) ER		-0.234						
		(0.088)						
AGOAccess (Oil) ER		-0.448						
		(0.362)						
AGOAExp (World, Crops)			0.317	0.392				
			(0.030)	(0.044)				
AGOAExp (World, Oil)			0.207	0.262				
			(0.078)	(0.116)				
AGOAExp (World, Crops) ER				-0.244				
				(0.090)				
AGOAExp (World, Oil) ER				-0.274				
				(0.418)				
AGOAExp (U.S., Crops)					0.206	0.252		
					(0.044)	(0.058)		
AGOAExp (U.S., Oil)					0.203	0.299		
					(0.090)	(0.142)		
AGOAExp (U.S., Crops) ER						-0.175		
						(0.115)		
AGOAExp (U.S., Oil) ER						-0.385		
						(0.460)		
AGOASuit (Crops)							0.209	0.308
							(0.032)	(0.045)
AGOASuit (Oil)							0.202	0.307
							(0.072)	(0.107)
AGOASuit (Crops) ER								-0.324
								(0.091)
AGOASuit (Oil) ER								-0.460
								(0.357)
Observations	241072	241072	241072	241072	241072	241072	241072	241072

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). Column 1 and 2 use our main definition of AGOAccess used in equation (1) splitting the *Production* between crops and oil and mines (MO). Columns 3, 4, 5, and 6 use a definition of AGOAccess taking into account if the country has export capacity in eligible AGOA goods as defined in equation (3) to the US and to the rest of the world, splitting the *Production* between crops and oil and mines (MO). Columns 7 and 8 measure AGOAccess considering if a location's land is suitable for AGOA-eligible crop as defined in equation (4), splitting the *Production* between crops and oil and mines (MO). The unit of observation is the PRIO GRID cell (resolution 0.5 0.5 decimal degrees, approximately 55km 55km at the equator). All specifications control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

B.2.3 GSP vs. AGOA

Table B11: AGOA vs. GSP and Conflict

	(1)	(2)	(3)	(4)	(5)
AGOAccess	-0.043		-0.125		-0.125
	(0.011)		(0.030)		(0.030)
GSPAccess		-0.006		-0.023	-0.021
		(0.014)		(0.021)	(0.021)
AGOAccess ER			0.250		0.249
			(0.087)		(0.087)
GSPAccess ER				0.060	0.055
				(0.049)	(0.049)
Observations	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 shock is split between those countries that were benefited in 1997 of being least developed countries (LDC) receiving the shock in 1997, GSPAcess, and those which received the shock in 2000, AGOAccess. The unit of observation is the PRIO GRID cell (resolution 0.5 0.5 decimal degrees, approximately 55km 55km at the equator). All specifications control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B12: AGOA vs. GSP and Luminosity

	(1)	(2)	(3)	(4)	(5)
AGOAccess	0.256		0.383		0.380
	(0.050)		(0.066)		(0.066)
GSPAccess		0.433		0.441	0.438
		(0.037)		(0.058)	(0.058)
AGOAccess ER			-0.389		-0.394
			(0.123)		(0.123)
GSPAccess ER				-0.028	-0.025
				(0.128)	(0.128)
Observations	241072	241072	241072	241072	241072

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), where fatalities is based on data from UCDP. The shock is split between those countries that were benefited in 1997 of being least developed countries (LDC) receiving the shock in 1997, GSPAcess, and those which received the shock in 2000, AGOAccess. The unit of observation is the PRIO GRID cell (resolution 0.5 0.5 decimal degrees, approximately 55km 55km at the equator). All specifications control 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.
$p < 0.10$, $p < 0.05$, $p < 0.01$.

B.2.4 ACLED Definition of Conflict

Table B13: AGOA and Conflict: Ethnic Remoteness (ACLED)

	Intensity of Conflict from ACLED						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGOAccess	-0.031	-0.093	-0.103	-0.101	-0.092	-0.088	-0.081
	(0.012)	(0.021)	(0.023)	(0.022)	(0.021)	(0.034)	(0.022)
AGOAccess ER		0.206	0.199	0.200	0.208	0.207	0.202
		(0.055)	(0.056)	(0.057)	(0.060)	(0.054)	(0.055)
AGOAccess ELF			0.029				
			(0.027)				
AGOAccess POL				0.088			
				(0.101)			
AGOAccess Specialization					-0.006		
					(0.054)		
AGOAccess Kinship						-0.013	
						(0.062)	
AGOAccess Segmented							-0.019
							(0.017)
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 control 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 1997–2017. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B14: AGOA and Conflict: Different Diversity Measures (ACLED)

		(1)	(2)	(3)	(4)
AGOAccess		-0.093	-0.093	-0.094	-0.095
		(0.021)	(0.021)	(0.021)	(0.022)
AGOAccess	ER	0.209	0.208	0.204	0.237
		(0.075)	(0.066)	(0.058)	(0.081)
AGOAccess	Greenberg	-0.006			
		(0.066)			
AGOAccess	ELF2		-0.003		
			(0.047)		
AGOAccess	ELF9			0.006	
				(0.031)	
AGOAccess	POL^{er}				-0.169
					(0.216)
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 control 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 1997–2017. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B15: AGOA and Conflict: Environmental Variables (ACLED)

	(1)	(2)	(3)	(4)
AGOAccess	-0.093	-0.159	-0.102	-0.064
	(0.021)	(0.036)	(0.022)	(0.022)
AGOAccess ER	0.206	0.194	0.190	0.188
	(0.055)	(0.055)	(0.055)	(0.053)
AGOAccess Crop Unsuitability		0.014		
		(0.006)		
AGOAccess Malaria Suitability			0.032	
			(0.011)	
AGOAccess Tsetse Suitability				-0.023
				(0.008)
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 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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B16: AGOA and Conflict: Alternative Transformations of Dependent Variable (ACLED)

	(1)	(2)	(3)	(4)
AGOAccess	-0.093	-0.093	-0.104	0.013
	(0.021)	(0.022)	(0.025)	(0.005)
AGOAccess ER	0.206	0.210	0.236	0.012
	(0.055)	(0.056)	(0.063)	(0.013)
Observations	195153	195153	195153	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) 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 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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B17: AGOA and Conflict: Alternative Definitions of AGOA Exposure (ACLED)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOAGeo	-0.086	-0.111						
	(0.041)	(0.044)						
AGOAGeo ER		0.110						
		(0.043)						
AGOAExp (World)			-0.038	-0.109				
			(0.012)	(0.022)				
AGOAExp (World) ER				0.235				
				(0.055)				
AGOAExp (U.S.)					-0.017	-0.074		
					(0.013)	(0.025)		
AGOAExp (U.S.) ER						0.218		
						(0.082)		
AGOASuit							-0.019	-0.072
							(0.013)	(0.024)
AGAOSuit ER								0.150
								(0.055)
Observations	195153	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. Columns (1) and (2) use the broad definition of AGOA exposure without requiring the production of AGOA eligible goods as defined in equation (2). Columns (3), (4), (5), and (6) use a narrow definition of AGOA that takes into account if the country has export capacity in eligible AGOA goods to either the rest of the world or the U.S. as defined in equation (3). Columns (7) and (8) measure make AGOA exposure conditional on a location's land being suitable for AGOA-eligible crops as defined in equation (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 control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B18: The Effect of AGOA on Conflict: ACLED data : Crops vs. Minerals & Oil

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOAccess (Crops)	-0.028	-0.088						
	(0.012)	(0.021)						
AGOAccess (Oil)	-0.049	-0.054						
	(0.030)	(0.047)						
AGOAcess (Crops) ER		0.201						
		(0.055)						
AGOAcess (Oil) ER		0.051						
		(0.126)						
AGOAExp (World, Crops)			-0.038	-0.109				
			(0.012)	(0.022)				
AGOAExp (World, Oil)			-0.062	-0.066				
			(0.033)	(0.052)				
AGOAExp (World, Crops) ER				0.234				
				(0.055)				
AGOAExp (World, Oil) ER				0.057				
				(0.146)				
AGOAExp (U.S., Crops)					0.002	-0.053		
					(0.012)	(0.025)		
AGOAExp (U.S., Oil)					-0.090	-0.113		
					(0.037)	(0.062)		
AGOAExp (U.S., Crops) ER						0.207		
						(0.086)		
AGOAExp (U.S., Oil) ER						0.116		
						(0.158)		
AGOASuit (Crops)							0.011	-0.019
							(0.015)	(0.024)
AGOASuit (Crops) ER								0.101
								(0.062)
AGOASuit (Oil)							-0.051	-0.063
							(0.030)	(0.047)
AGOASuit (Oil) ER								0.060
								(0.127)
Observations	195153	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. Column 1 and 2 use our main definition of AGOAccess used in equation (1) splitting the *Production* between crops and oil and mines (MO). Columns 3, 4, 5, and 6 use a definition of AGOAccess taking into account if the country has export capacity in eligible AGOA goods as defined in equation (3) to the US and to the rest of the world, splitting the *Production* between crops and oil and mines (MO). Columns 7 and 8 measure AGOAccess considering if a location's land is suitable for AGOA-eligible crop as defined in equation (4), splitting the *Production* between crops and oil and mines (MO). The unit of observation is the PRIO GRID cell (resolution 0.5 0.5 decimal degrees, approximately 55km 55km at the equator). All specifications control 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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

B.3 Robustness: Individual Level Data

B.3.1 Food Poverty: Baseline Definition of AGOA

Table B19: AGOA and Food Poverty – Remoteness from the Dominant Group

	(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess	-0.031	-0.030	-0.031	-0.066	-0.065	-0.068
	(0.043)	(0.043)	(0.043)	(0.045)	(0.045)	(0.045)
AGOAccess Indiv ER^{dom}	0.078		0.076	0.109		0.098
	(0.028)		(0.031)	(0.027)		(0.032)
AGOAccess Cell ER^{dom}		0.057	0.007		0.098	0.036
		(0.037)	(0.045)		(0.036)	(0.049)
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 B20: AGOA and Food Poverty: Additional Cell Controls

		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		-0.048	-0.047	-0.050	-0.044	-0.052	-0.085
		(0.047)	(0.047)	(0.049)	(0.047)	(0.064)	(0.050)
AGOAccess	Indiv ER	0.143	0.143	0.143	0.143	0.142	0.145
		(0.051)	(0.051)	(0.051)	(0.051)	(0.052)	(0.051)
AGOAccess	Cell ER	0.012	0.014	0.009	0.025	0.013	0.030
		(0.078)	(0.078)	(0.078)	(0.081)	(0.077)	(0.077)
AGOAccess	ELF		-0.006				
			(0.039)				
AGOAccess	Pol^{rq}			0.019			
				(0.133)			
AGOAccess	Specialization				-0.041		
					(0.070)		
AGOAccess	Kinship					0.008	
						(0.103)	
AGOAccess	Segmented						0.046
							(0.032)
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 B21: AGOA and Food Poverty: Alternative Diversity controls

		(1)	(2)	(3)	(4)	(5)
AGOAccess		-0.048	-0.052	-0.053	-0.047	-0.055
		(0.047)	(0.047)	(0.047)	(0.046)	(0.047)
AGOAccess	Indiv ER	0.143	0.144	0.144	0.143	0.140
		(0.051)	(0.050)	(0.050)	(0.051)	(0.051)
AGOAccess	Cell ER	0.012	0.113	0.118	0.027	0.141
		(0.078)	(0.077)	(0.077)	(0.077)	(0.070)
AGOAccess	Greenberg		-0.134			
			(0.069)			
AGOAccess	ELF2			-0.137		
				(0.070)		
AGOAccess	ELF9				-0.034	
					(0.046)	
AGOAccess	Pol^{er}					-0.427
						(0.197)
Observations		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 B22: AGOA and Food Poverty: Environmental Controls

		(1)	(2)	(3)	(4)
AGOAccess		-0.048	0.043	-0.038	-0.041
		(0.047)	(0.063)	(0.048)	(0.046)
AGOAccess	Indiv ER	0.143	0.143	0.157	0.136
		(0.051)	(0.051)	(0.051)	(0.051)
AGOAccess	Cell ER	0.012	0.020	0.025	-0.015
		(0.078)	(0.078)	(0.069)	(0.086)
AGOAccess	Crop Unsuitability		-0.019		
			(0.009)		
AGOAccess	Malaria Suitability			0.039	
				(0.031)	
AGOAccess	Tsetse Suitability				-0.013
					(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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table B23: AGOA and Income Poverty: Additional Cell Controls (Dominant)

		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		-0.031	-0.030	-0.033	-0.026	-0.035	-0.063
		(0.043)	(0.044)	(0.045)	(0.043)	(0.063)	(0.046)
AGOAccess	Indiv ER$^{\mathsf{dom}}$	0.076	0.076	0.076	0.076	0.075	0.077
		(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
AGOAccess	Cell ER$^{\mathsf{dom}}$	0.007	0.008	0.005	0.014	0.007	0.016
		(0.045)	(0.046)	(0.046)	(0.048)	(0.045)	(0.046)
AGOAccess	ELF		-0.007				
			(0.039)				
AGOAccess	Pol^{rq}			0.018			
				(0.134)			
AGOAccess	Specialization				-0.039		
					(0.071)		
AGOAccess	Kinship					0.008	
						(0.105)	
AGOAccess	Segmented						0.044
							(0.032)
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: 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 B24: AGOA and Food Poverty: Alternative Diversity Indices (Dominant)

		(1)	(2)	(3)	(4)	(5)
AGOAccess		-0.031	-0.023	-0.024	-0.028	-0.024
		(0.043)	(0.042)	(0.042)	(0.042)	(0.042)
AGOAccess	Indiv ER^{dom}	0.076	0.076	0.076	0.076	0.073
		(0.031)	(0.030)	(0.030)	(0.031)	(0.030)
AGOAccess	Cell ER^{dom}	0.007	0.073	0.077	0.016	0.095
		(0.045)	(0.050)	(0.050)	(0.046)	(0.046)
AGOAccess	Greenberg		-0.149			
			(0.074)			
AGOAccess	ELF2			-0.154		
				(0.074)		
AGOAccess	ELF9				-0.034	
					(0.047)	
AGOAccess	Pol^{er}					-0.494
						(0.217)
Observations		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. $p < 0.10$, $p < 0.05$, $p < 0.01$.

B.3.2 Food Poverty: Alternative Definition of AGOA

Table B25: AGOA and Food Poverty: Alternative definitions of AGOA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOAccess (Geo)	-0.291	-0.093						
	(0.491)	(0.473)						
AGOAcess (Geo) Indiv ER		0.231						
		(0.051)						
AGOAcess (Geo) Cell ER		0.050						
		(0.085)						
AGOAccess/WExports			-0.059	-0.095				
			(0.044)	(0.048)				
AGOAccess/WExports Indiv ER				0.160				
				(0.044)				
AGOAccess/WExports Cell ER				0.078				
				(0.069)				
AGOAccess/USExports					0.038	0.032		
					(0.043)	(0.045)		
AGOAccess/USExports Indiv ER						0.162		
						(0.056)		
AGOAccess/USExports Cell ER						0.078		
						(0.082)		
AGOA Suitability							-0.124	-0.197
							(0.064)	(0.065)
AGAO Suitability Indiv ER								0.182
								(0.042)
AGAO Suitability Cell ER								0.073
								(0.071)
Observations	72112	72112	72112	72087	72112	72112	72112	72087

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.3.3 Food Poverty: Broad Definition of AGOA

Table B26: AGOA and Food Poverty

		Individual Food Poverty					
		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		-0.145	-0.305	-0.142	-0.079	-0.295	-0.093
		(0.418)	(0.397)	(0.419)	(0.478)	(0.461)	(0.473)
AGOAccess	Indiv ER	0.214		0.217	0.246		0.231
		(0.047)		(0.052)	(0.044)		(0.051)
AGOAccess	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). This table uses the broad definition of AGOAccess as defined in equation (2). 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 B27: AGOA and Food Poverty – Remoteness from the Dominant Group

	Individual Food Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess	-0.089	-0.270	-0.088	0.006	-0.241	0.001
	(0.410)	(0.396)	(0.410)	(0.477)	(0.463)	(0.474)
AGOAccess Indiv ER^{dom}	0.104		0.107	0.134		0.127
	(0.028)		(0.031)	(0.026)		(0.031)
AGOAccess 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 B28: AGOA and Food Poverty: Additional Cell Controls

		Individual Food Poverty					
		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		-0.142	-0.138	-0.144	-0.124	-0.145	-0.132
		(0.419)	(0.419)	(0.420)	(0.416)	(0.418)	(0.419)
AGOAccess	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)
AGOAccess	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)
AGOAccess	ELF		-0.007				
			(0.037)				
AGOAccess	Pol^{rq}			0.012			
				(0.128)			
AGOAccess	Specialization				-0.038		
					(0.066)		
AGOAccess	Kinship					-0.034	
						(0.103)	
AGOAccess	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 B29: AGOA and Food Poverty: Environmental Controls

		Individual Food Poverty			
		(1)	(2)	(3)	(4)
AGOAccess		-0.142	-0.177	-0.264	-0.053
		(0.419)	(0.427)	(0.405)	(0.412)
AGOAccess	Indiv ER	0.217	0.215	0.235	0.213
		(0.052)	(0.052)	(0.052)	(0.052)
AGOAccess	Cell ER	-0.010	-0.002	0.005	-0.025
		(0.083)	(0.084)	(0.072)	(0.088)
AGOAccess	Crop Unsuitability		-0.015		
			(0.009)		
AGOAccess	Malaria Suitability			0.048	
				(0.033)	
AGOAccess	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.3.4 Income Poverty

Table B30: AGOA and Income Poverty

		Individual Income Poverty					
		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		0.061	-0.016	-0.153	0.182	0.110	-0.026
		(0.401)	(0.404)	(0.416)	(0.498)	(0.475)	(0.479)
AGOAccess	Indiv ER	0.227		0.205	0.229		0.209
		(0.063)		(0.066)	(0.059)		(0.062)
AGOAccess	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). This table uses the broad definition of AGOAccess as defined in equation (2). 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 B31: AGOA and Income Poverty – Remoteness from the Dominant Group

		Individual Income Poverty					
		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		0.111	0.006	-0.112	0.211	0.144	0.019
		(0.399)	(0.405)	(0.415)	(0.497)	(0.481)	(0.483)
AGOAccess	Indiv ER^{dom}	0.122		0.105	0.129		0.115
		(0.038)		(0.040)	(0.034)		(0.037)
AGOAccess	Cell ER^{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 B32: AGOA and Income Poverty: Additional Cell Controls

		Individual Income Poverty					
		(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess		-0.153	-0.164	-0.216	-0.151	-0.154	-0.151
		(0.416)	(0.427)	(0.432)	(0.402)	(0.432)	(0.428)
AGOAccess	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)
AGOAccess	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)
AGOAccess	ELF		-0.033				
			(0.053)				
AGOAccess	Pol^{rq}			-0.166			
				(0.153)			
AGOAccess	Specialization				0.004		
					(0.103)		
AGOAccess	Kinship					-0.001	
						(0.146)	
AGOAccess	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 B33: AGOA and Income Poverty: Environmental Controls

		Individual Income Poverty			
		(1)	(2)	(3)	(4)
AGOAccess		-0.153	-0.043	-0.097	-0.155
		(0.416)	(0.453)	(0.440)	(0.418)
AGOAccess	Indiv ER	0.205	0.203	0.207	0.205
		(0.066)	(0.067)	(0.066)	(0.066)
AGOAccess	Cell ER	0.154	0.137	0.155	0.154
		(0.107)	(0.109)	(0.109)	(0.107)
AGOAccess	Crop Unsuitability		0.007		
			(0.007)		
AGOAccess	Malaria Suitability			0.029	
				(0.041)	
AGOAccess	Tsetse Suitability				-0.009
					(0.056)
Observations		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. $p < 0.10$, $p < 0.05$, $p < 0.01$.