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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 Africa Growth and Opportunity Act (AGOA) and using high-resolution data on ethnic composition, violent conflict, and sectoral specialization for sub-Saharan Africa, we find 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 equally from 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.

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1 Introduction

The starting point of this paper is three observations. First, positive terms of trade shocks affect the likelihood of conflict in developing countries. When such shocks increase the opportunity cost of conflict, they can potentially lead to a drop in violence, thereby resulting in 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 of whether a location's ethnic composition might affect the potential peace dividend from improved trade access. 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 geographic and temporal variation in trade access across 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), which 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

[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.

analyze how the effect of trade liberalization on conflict depends on a location's ethnic remoteness.

At a spatial resolution of $0.5° \times 0.5°$, we regress the intensity of conflict on local exposure to AGOA and on the interaction of this exposure with ethnic remoteness. Identification relies on including grid-cell fixed effects as well as country-time fixed effects in our empirical specification. These fixed effects purge estimates of time-invaryning 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. 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 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

[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).

exposed to the AGOA shock, though this positive effect is smaller in cells that are ethnically more remote.

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

An important contribution of our paper is the construction of a $0.5^\circ \times 0.5^\circ$ dataset for sub-Saharan Africa on production across all sectors of the economy. Existing research on trade shocks and conflict primarily relies on international price fluctuations as exogenous variation, limiting analysis to a narrow set of commodities with accessible price data (e.g., Armand et al., 2020; Berman et al., 2017; McGuirk and Burke, 2020; Dube and Vargas, 2013). In contrast, our method maps AGOA-eligible tariff lines to a comprehensive range of commodities, allowing us to move beyond specific crops or minerals and achieve a broader, more precise identification of trade shocks. Further, while existing studies often focus on either agriculture (e.g., Berman and Couttenier, 2015) or mining (e.g., Berman et al., 2017), our approach not only includes a highly granular set of crops, minerals, and oil fields but also expands to an additional 93 industries spanning manufacturing, textiles, and apparel. This enables us to construct a unique dataset with approximately 40,000 observations for these industries, geolocated across 7,142 sites in sub-Saharan Africa. Starting with NAICS-level industry data, we map each NAICS code to specific U.S. tariff lines, incorporating both AGOA and GSP provisions to enhance the dataset's granularity and utility. We expect this dataset to have value beyond the scope of our paper.

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 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, but 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. By linking ethnic remoteness to local conflict outcomes in the context of trade shocks, we add a new dimension to understanding how ethnic barriers shape the instability-inducing effects of globalization.

Our paper speaks to the question which groups and locations are left behind by globalization. The differential impact of trade liberalization on skilled and unskilled workers is a well-studied phenomenon (Goldberg and Pavcnik, 2007). More recent work has turned its focus to geography, comparing regions that are differentially affected by either lower import tariffs or improved market access. For example, Topalova (2010) finds smaller declines in poverty in Indian districts that experienced greater tariff reductions in the wake of India's 1991 trade liberalization, whereas McCaig (2011) finds faster declines in 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.

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

[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).

2 Data

Using a $0.5° \times 0.5°$ spatial grid (approximately 55 km by 55 km at the Equator), this paper empirically analyzes how ethnic remoteness mediates the effect of trade access on conflict.[8] We also consider how ethnic diversity and ethnic complementarity might act as separate channels affecting the relation between trade access and conflict. The time frame of our study goes from 1989 to 2017, and we focus on sub-Saharan Africa.

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. By using geo-coded data on conflict from UCDP and ACLED, we explore how ethnic remoteness affects the peace dividend from increased market access. Proxying local income by nighttime light intensity, we also analyze whether ethnic remoteness acts as a barrier that limits the income gains from trade. The rest of this section describes the data in more detail. Appendix A.1 provides a detailed list of data sources, and Appendix Tables B1 and B2 report summary statistics and cross-correlations of the main variables of interest.

2.1 Dependent Variable: Conflict or Income

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

As an alternative, we also use the Armed Conflict Location and Event Data (ACLED). This dataset takes a broader view of political violence by including civil and communal conflicts, violence against civilians, and rioting and protesting. One disadvantage of ACLED is that it starts in 1997, only three years before the enactment of ACLED. That makes the longer time span of UCDP somewhat more attractive for our purpose. However, we conduct extensive robustness analysis using the ACLED data.[9]

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

[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).

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 2013–2017 we use the DMSP-like Nighttime Lights Derived from VNL, an extend series of annual nighttime lights using VIRSS data developed by Nechaev 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 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

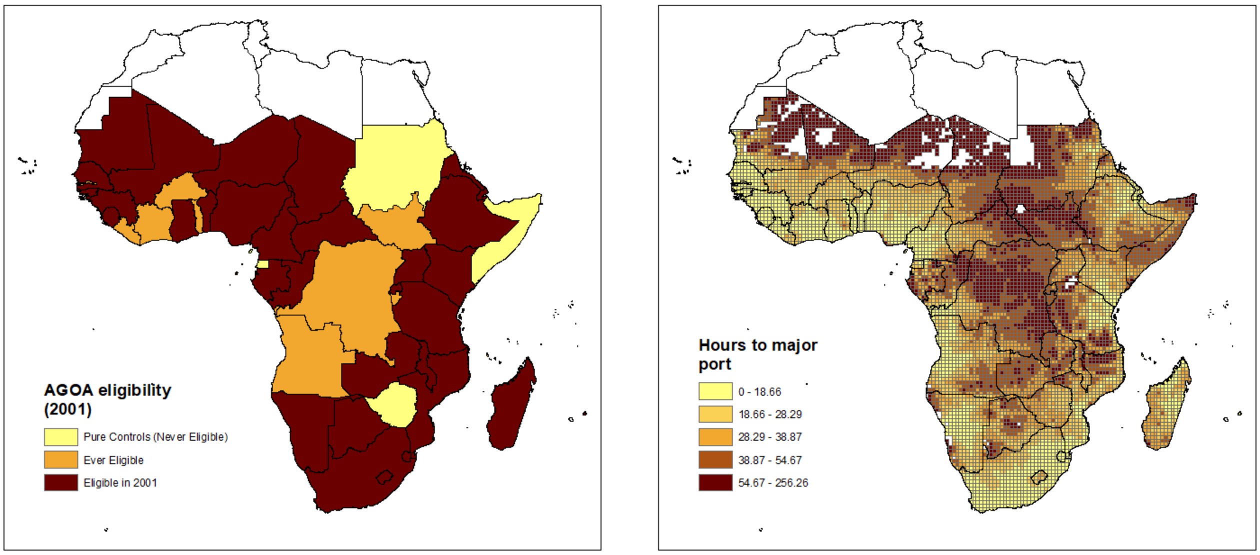
[10] See Michalopoulos and Papaioannou (2018) for a review of this literature.

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

1(b) depicts the travel time to the nearest major port expressed in hours.

Figure 1: Trade Access through AGOA

(a) AGOA Membership (b) Travel Time to Nearest Port



Notes: 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.

To measure $Production_{icj}$, we determine whether a cell i in country c produces AGOA-eligible product j. Constructing this high-resolution sectoral database for sub-Saharan Africa is a key contribution of this paper. More specifically, we match the tariff lines of all products included in AGOA to geolocated data on the production of oil and 19 AGOA-eligible minerals (from a list of 33), 72 AGOA-eligible crops (from a list of 175), and 93 AGOA-eligible textile, apparel, agricultural and other manufacturing industries. The tariff lines are for the year 2000, and are based on publicly available data from the United States International Trade Commission (USITC).[12] Locations of oil fields and mines come from PETRODATA and SNL Metals & Mining dataset (S&P Global Marketplace); crop locations are based on Ramankutty et al. (2008); and locations of textile, apparel and other manufacturing sectors at the 4-digit NAICS level are from Dunn & Bradstreet. Appendices A and C provide further details on the construction of these data.

[12]In the specific case of apparel, textiles, and other manufacturing sectors, each 4-digit NAICS industry tends to match to many different tariff lines. In that case, we consider a sector to be treated by AGOA if at least 25% of the tariff lines are AGOA-eligible.

Figure 2 plots the cells that produce different categories of AGOA-eligible products. We consider a cell as treated if it produces AGOA-eligible crops, minerals, or oil, or if it houses manufacturing units producing AGOA-eligible products, provided the country is eligible for AGOA in the particular year. Additionally, we also consider a cell as treated if it hosts textile or apparel production units, provided the country is eligible for apparel or textile provisions under AGOA in that particular year.[13] Using this definition, Figure 3a depicts all cells that were treated in at least one year.

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.[14] Differences in such rights, freedoms, and institutions partly explain why some countries, such as Somalia, never became eligible, why other countries, such as Sierra Leone, were admitted late, and why a few countries, such as Eritrea, were removed. Appendix Table A1 lists the full list of countries that were ever eligible for AGOA along with years of eligibility, and Appendix Table A2 does the same for the textile and apparel sectors. To the extent that accession criteria are related to conflict, we might face an endogeneity problem. We address this potential issue by including country × 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):

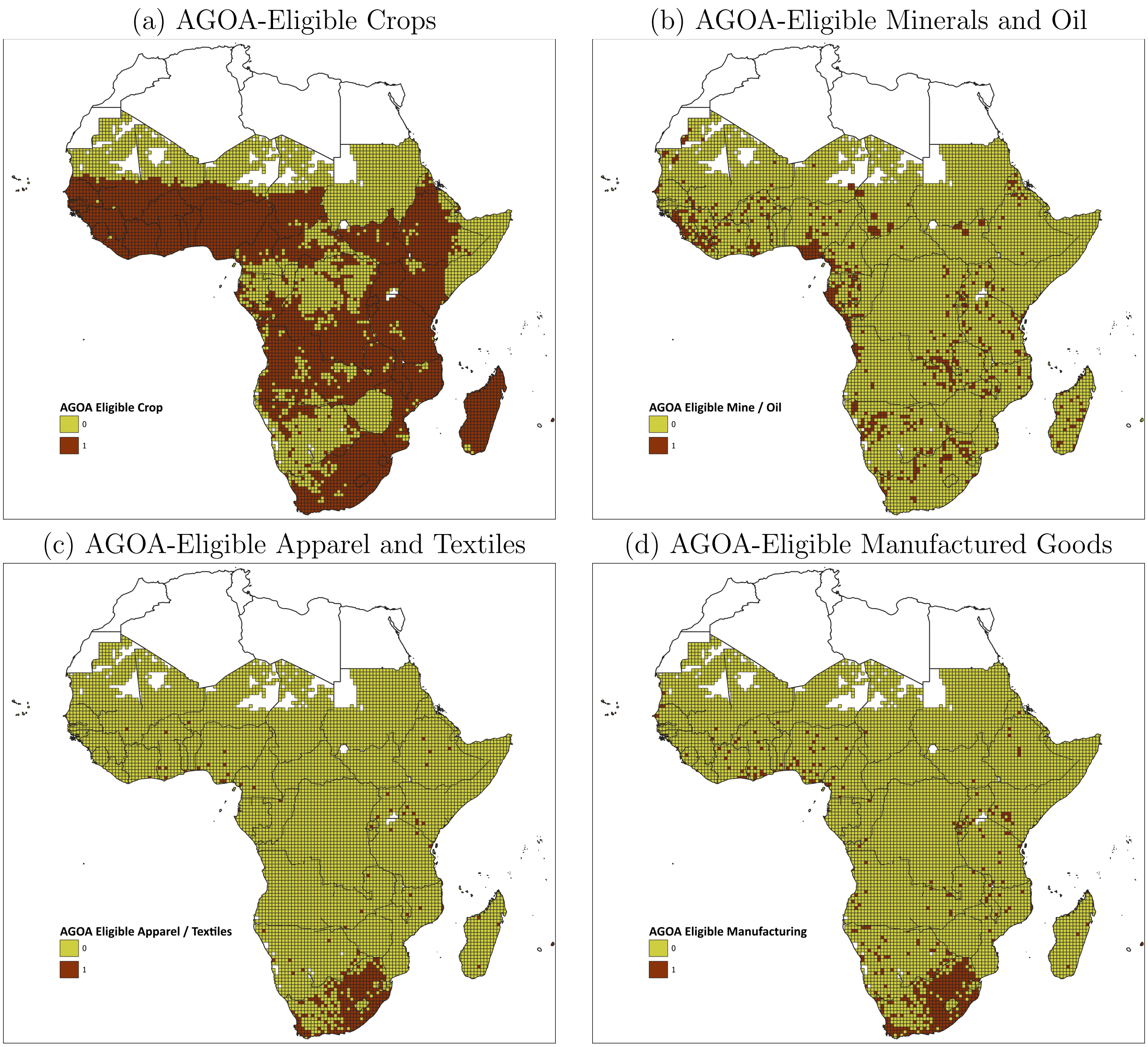
$$AGOAGeo_{ict} = AGOA_{ct} \times Proximity_{ic} \tag{2}$$

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 idea that areas closer to the port experience a general improvement in trade access, regardless of their production structure.

[13]AGOA eligibility for textiles and apparel are different from general AGOA eligibility. For example, during the time frame of our study the AGOA membership of Guinea did not include apparel.

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

Figure 2: Location of AGOA-Eligible Products



(a) AGOA-Eligible Crops

(b) AGOA-Eligible Minerals and Oil

(c) AGOA-Eligible Apparel and Textiles

(d) AGOA-Eligible Manufactured Goods

Notes: Panel (a) plots all cells that produces AGOA-eligible crops. Panel (b) plots all cells that produce AGOA-eligible minerals or oil. Panel (c) plots all cells that produce AGOA-eligible apparel and textiles. Panel (d) plots all cells that produce other AGOA-eligible manufactured goods. See Appendix A.1 for data sources and variable definitions.

A second alternative measure defines exposure to AGOA more narrowly:

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

where $Export_{cj}$ is a binary variable that indicates whether country c exported good j in the pre-AGOA period. To measure export capacity, we use data from CEPII. We set two different bars for a country's export capacity in a certain good by requiring positive exports to either anywhere in the world (see Figure 3c) or the U.S. (see Figure 3d). 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 crop exposure to AGOA:

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

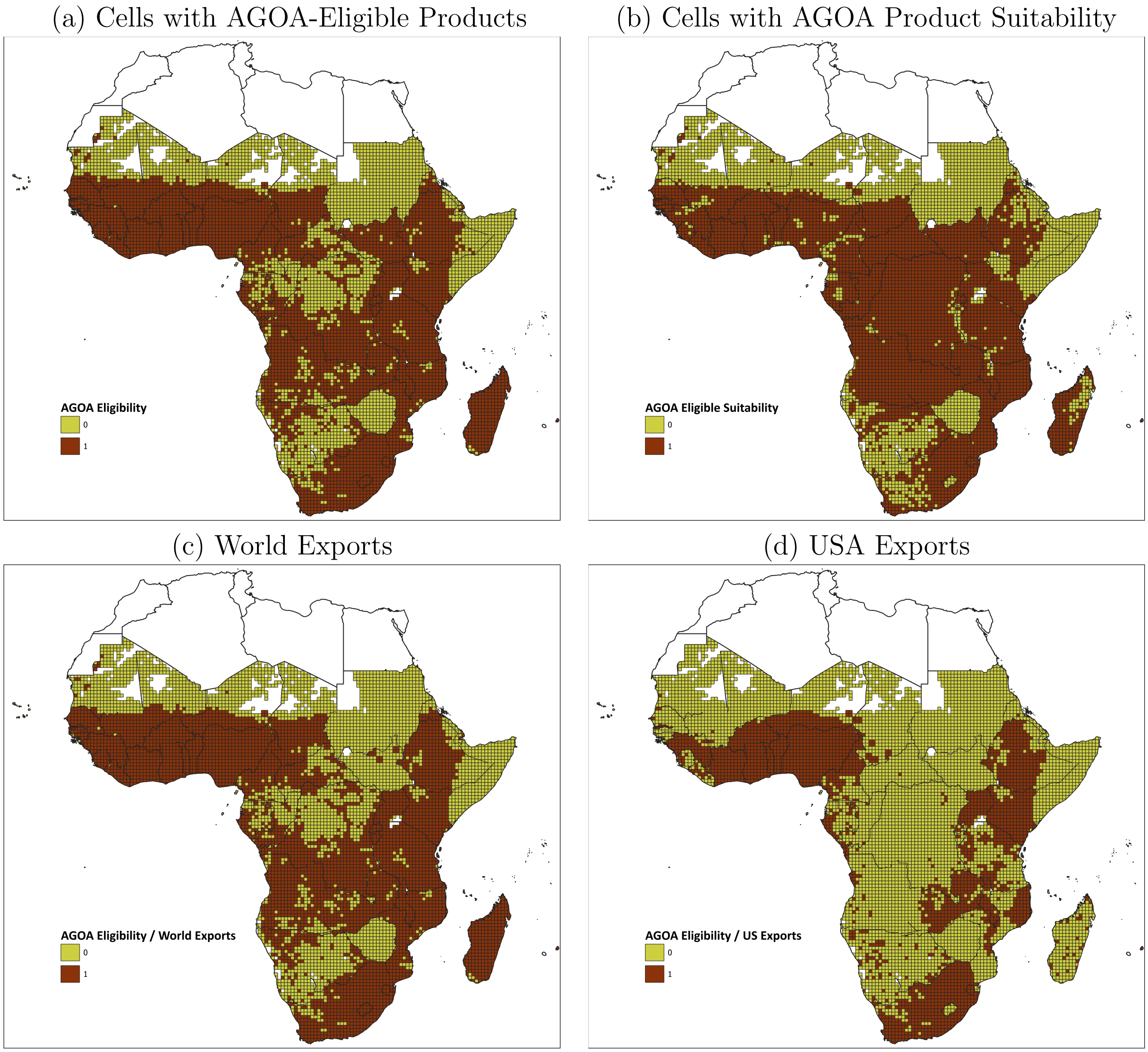
where $Suitability_{icj}$ measures whether a location's land is suitable for AGOA-eligible crop j using data from the FAO's Global Agro-Ecological Zones (GAEZ) database. For all other AGOA-eligible products (such as minerals, oil, textiles and apparel), we continue to use actual production. Exposure measure 4 takes the view that as long as the land is suitable for the production of AGOA-eligible goods, the location experiences an improvement in market access when joining AGOA (see Figure 3b) .

2.3 Ethnic Remoteness

In sub-Saharan Africa ethnicity and language largely overlap. Data on the population's ethnic composition at the $0.05° \times 0.05°$ grid-cell level come from the language database recently constructed by Desmet et al. (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 $0.05° \times 0.05°$ grid-cell level dataset on the ethnolinguistic composition of the population for the entire globe. We aggregate this information up to the $0.5° \times 0.5°$ 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

Figure 3: Trade Access through AGOA: Alternative Definitions



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

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

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

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

Panel (a) of Figure 4 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:

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

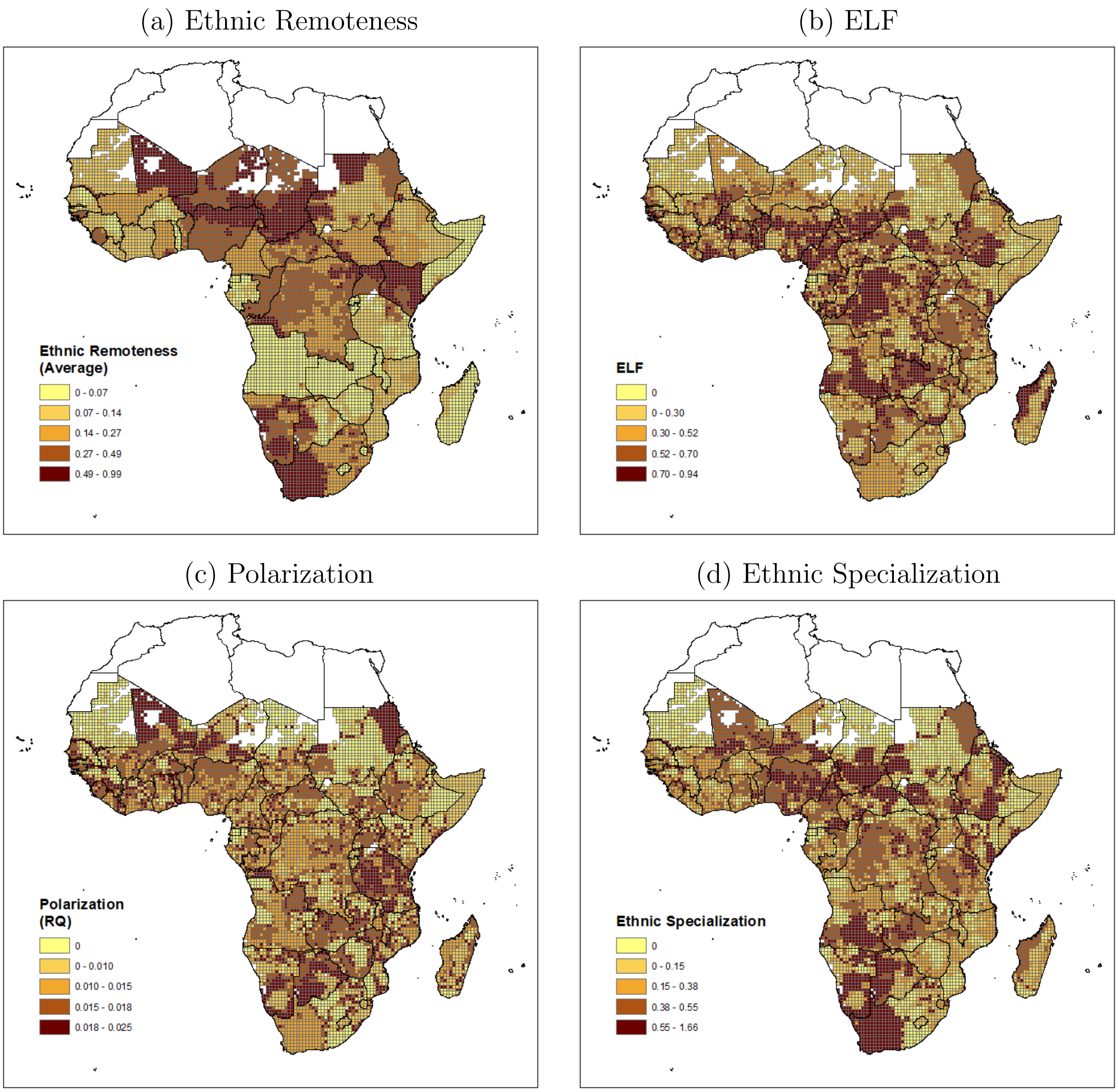
where $d_{n,dom}$ is the distance between ethnic group n and the country's largest ethnic group dom.

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

[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.

Figure 4: 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 different 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 definitions.

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 to 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 4 show ELF and POL at the grid-cell level. Visually, it is clear that the spatial variation in ELF and POL are quite different from the spatial variation in ethnic remoteness. In fact, the cell-level correlation between ethnic remoteness and ELF is only 0.09, and the corresponding correlation with POL is 0.13.

2.5 Ethnic Complementarity

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

Ethnic specialization. Ethnic specialization measures the extent to which occupational specialization 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 $\sum_q \mid x_n^q - x^q \mid$, where x^q is the share of the country's population traditionally employed in occupation q. The extent of ethnic specialization of cell ℓ is then

$$ES_\ell = \sum_n s_{\ell n} \sum_q \mid x_n^q - x^q \mid \tag{10}$$

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 4 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 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.

[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).

2.6 Other Control Variables

As weather shocks are important predictors 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,

$$\log(y_{ict} + 1) = \alpha AGOAccess_{ict} + AGOAccess_{ict}\mathbf{E}'_{ic}\beta + \mathbf{X}'_{ict}\gamma + \delta_{ic} + \eta_{ct} + u_{ict} \tag{11}$$

where y_{ict} is the number of fatalities in cell i of country c in year t, $AGOAccess_{ict}$ is the degree of trade openness of cell i in country c in year 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 in year t, $\mathbf{X}_{ict}$ is a vector of cell-level time-varying characteristics (weather shocks), δ_{ic} are cell fixed effects, η_{ct} are country-time fixed effects, and u_{ict} is an idiosyncratic error term. By using cell and country-time fixed effects, we address several concerns. Cell fixed effects absorb all time-invaryng 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]

Both of our treatment variables, $AGOAccess_{ict}$ and $AGOAccess_{ict}\mathbf{E}'_{ic}$, are continuous in nature. Specifically focusing on the second treatment variable, it consists of $AGOA_{ct} \times Proximity_{ic} \times \max_{j \in J}\{Production_{icj}\} \times \mathbf{E}'_{ic}$, where $Proximity_{ic}$ and $\mathbf{E}'_{ic}$ are continuous. The absence of binary treatment variables precludes using a standard dynamic differences-in-differences event study approach. This explains our choice of empirical specification (11).

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 interactions 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

[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.

deviation increase in ethnic remoteness in a cell that is fully open to trade increases the fatalities from conflict by 5.3%. The corresponding number when going from the ethnically least remote cell to the ethnically most remote cell is a predicted increase in fatalities by 20.0%.

Table 1: AGOA and Conflict: Ethnic Remoteness

	Intensity of Conflict from UCDP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGOAccess	-0.046***	-0.108***	-0.102***	-0.097***	-0.106***	-0.115***	-0.108***
	(0.009)	(0.017)	(0.017)	(0.017)	(0.016)	(0.030)	(0.020)
AGOAccess × ER		0.202***	0.206***	0.210***	0.206***	0.201***	0.202***
		(0.046)	(0.048)	(0.049)	(0.053)	(0.045)	(0.047)
AGOAccess × ELF			-0.017				
			(0.022)				
AGOAccess × POL				-0.108			
				(0.080)			
AGOAccess × Specialization					-0.013		
					(0.042)		
AGOAccess × Kinship						0.017	
						(0.054)	
AGOAccess × Segmented							-0.000
							(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 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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) and (8) follow equation (4) by defining exposure based on whether a cell has the adequate suitability

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***	-0.115***				
			(0.009)	(0.018)				
AGOAExp (World) × ER				0.214***				
				(0.048)				
AGOAExp (US)					-0.054***	-0.114***		
					(0.011)	(0.020)		
AGOAExp (US) × ER						0.233***		
						(0.066)		
AGOASuit							-0.031***	-0.073***
							(0.009)	(0.017)
AGOASuit × ER								0.131***
								(0.045)
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 AGOA-eligible goods to either the rest of the world or the U.S. as defined in equation (3). Columns (7) and (8) measure 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

conditions to produce an AGOA-eligible product.[18] As can be seen, when using any of these alternative measures of exposure to AGOA, our results remain unchanged.

Different types of goods. In Appendix Section B.2.2, we investigate whether there are differences in the effect of AGOA exposure between cells that produce different types of AGOA-eligible goods. We distinguish between four types of goods: crops, textiles and apparel, other manufactured goods, and oil and minerals. For all four types, there is a peace dividend from improved trade access. However, only for crops do we find that ethnically remote cells experience a smaller drop in conflict. The absence of statistically significant results for non-agricultural products might be due to the small number of cells in that category. As can be seen in Appendix Tables B5 and B6, almost all treated cells produce crops, and almost all cells that produce non-agricultural AGOA-eligible goods also produce AGOA-eligible crops.

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,

[18]Recall that for crops, suitability is defined as land suitability according to FAO data, whereas for other goods, suitability is defined as actually producing the goods.

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 B15 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.[19] 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.

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 B7 considers a number of alternative measures of diversity.[20]

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

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

[20] Appendix Figure A2 shows maps of these alternative indices.

Table 3: AGOA and Conflict: Robustness to Environmental Variables

	Intensity of Conflict from UCDP			
	(1)	(2)	(3)	(4)
AGOAccess	-0.108***	-0.183***	-0.114***	-0.099***
	(0.017)	(0.027)	(0.018)	(0.017)
AGOAccess × ER	0.202***	0.185***	0.193***	0.195***
	(0.046)	(0.047)	(0.047)	(0.046)
AGOAccess × Crop Unsuitability		0.016***		
		(0.004)		
AGOAccess × Malaria Suitability			0.022***	
			(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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(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, following 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 B16). More importantly, in both Tables B7 and B16 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.

Generalized System of Preferences. Before accession to AGOA in 2001, the least developed countries (LDCs) in our sample already benefited from improved access to the U.S. market through the expansion of the Generalized System of Preferences (GSP) in 1997. Of the 48 countries in sub-Saharan Africa, 28 are in this group. It is important to explore whether differentiating between the impact of both shocks affects our results.

By analogy with exposure to AGOA, we define a cell's exposure to GSP as the product of three factors: a binary variable that indicates whether the cell's country is part of GSP, a continuous variable that measures proximity to the nearest major port, and a binary variable that indicates whether the cell produces GSP-eligible goods. Introducing a separate role for GSP also requires redefining exposure to AGOA in the LDCs. We say that a cell in an LDC receives an additional shock from AGOA only if it produces goods that are on the AGOA-eligible list but not on the GSP-eligible list.

To see the effect of introducing a separate channel for GSP, we run our baseline specification, but control for GSP exposure both as a separate term and interacted with ethnic remoteness. Table B13 shows that GSP did not have a statistically significant impact on conflict, though the signs on the coefficients are consistent with a peace dividend that is smaller in ethnically remote locations. The absence of a statistically significant effect may reflect the limited export capacity of LDCs to the U.S. (Figure 3, panel (c)). More importantly, controlling for GSP as a separate shock does not change our main findings. AGOA continues to have a benign effect of conflict, but less so in ethnically remote locations.

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

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

	Intensity of Conflict from UCDP						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGOAccess	-0.046***	-0.080***	-0.075***	-0.069***	-0.080***	-0.083***	-0.078***
	(0.009)	(0.012)	(0.013)	(0.013)	(0.012)	(0.025)	(0.014)
AGOAccess × ER^{dom}		0.123***	0.125***	0.127***	0.123***	0.123***	0.123***
		(0.029)	(0.030)	(0.031)	(0.032)	(0.029)	(0.029)
AGOAccess × ELF			-0.014				
			(0.022)				
AGOAccess × POL				-0.100			
				(0.080)			
AGOAccess × Specialization					0.002		
					(0.039)		
AGOAccess × Kinship						0.007	
						(0.055)	
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 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 B8 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 test the consistency of the income channel 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.[21]

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

[21] 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	0.366***	0.464***	0.475***	0.485***	0.476***	0.387***	0.452***
	(0.028)	(0.041)	(0.047)	(0.047)	(0.043)	(0.066)	(0.048)
AGOAccess × ER		-0.321***	-0.315***	-0.307***	-0.299***	-0.337***	-0.317***
		(0.085)	(0.085)	(0.085)	(0.087)	(0.086)	(0.085)
AGOAccess × ELF			-0.031				
			(0.055)				
AGOAccess × POL				-0.209			
				(0.213)			
AGOAccess × Specialization					-0.090		
					(0.097)		
AGOAccess × Kinship						0.189	
						(0.130)	
AGOAccess × Segmented							0.021
							(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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 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 B9 includes alternative measures of fractionalization and polarization, Appendix Table B10 considers alternative transformations of our dependent variable, and Appendix Table B14 differentiates between the GSP and the AGOA shocks. These additional exercises have no qualitative impact on our main coefficients of interest.

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)			0.361***	0.466***				
			(0.029)	(0.042)				
AGOAExp (World) × ER				-0.341***				
				(0.086)				
AGOAExp (US)					0.249***	0.332***		
					(0.041)	(0.052)		
AGOAExp (US) × ER						-0.321***		
						(0.108)		
AGOASuit							0.214***	0.339***
							(0.034)	(0.044)
AGOASuit × ER								-0.387***
								(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 AGOA-eligible goods to either the rest of the world or the U.S. as defined in equation (3). Columns (7) and (8) measure 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	0.464***	0.622***	0.471***	0.472***
	(0.041)	(0.076)	(0.042)	(0.044)
AGOAccess × ER	-0.321***	-0.285***	-0.311***	-0.327***
	(0.085)	(0.085)	(0.085)	(0.085)
AGOAccess × Crop Unsuitability		-0.033**		
		(0.013)		
AGOAccess × Malaria Suitability			-0.024	
			(0.023)	
AGOAccess × Tsetse Suitability				-0.007
				(0.017)
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

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

$$I_{jeict} = \alpha AGOAccess_{ict} + AGOAccess_{ict}\mathbf{E'}_{jec}\beta_1 + AGOAccess_{ict}\mathbf{E'}_{ic}\beta_2 + \mathbf{X'}_{ict}\gamma + \delta_{ic} + \eta_{ct} + \theta_e + u_{jeict} \tag{14}$$

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, δ_{ic} are cell fixed effects, η_{ct} are country-time fixed effects, θ_e are ethnicity fixed effects, and u_{jeict} is an idiosyncratic error term.

Individual data. We use individual-level data from the 12 countries that were included in all six rounds of the Afrobarometer surveys conducted between 1999–2015. This includes the first round that was conducted between 1999 and 2001, before the entry into AGOA for most countries.[22] 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,

[22] Table A3 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.

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).[23]

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 4.2 percent. Overall, this provides support to the hypothesis that an individual's ethnic remoteness makes it more difficult to take advantage of trade liberalization.

Profession and other individual controls. One concern is that ethnically remote individuals might work in professions that benefit less from trade liberalization. Another concern is that ethnically remote individuals might have other specific characteristics that affect their capacity to take advantage of a positive trade shock. In columns (4)–(6) of Table 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.[24]

Robustness. 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 poverty in the wake of trade liberalization. Controlling for individual characteristics, such as

[23] 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.

[24] 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.

Table 8: AGOA and Food Poverty

	Individual Food Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess	-0.110**	-0.101**	-0.113**	-0.152**	-0.150**	-0.167**
	(0.052)	(0.051)	(0.055)	(0.069)	(0.069)	(0.072)
AGOAccess × Indiv ER	0.172***		0.167***	0.200***		0.179***
	(0.046)		(0.050)	(0.044)		(0.050)
AGOAccess × Cell ER		0.120*	0.016		0.183***	0.076
		(0.061)	(0.077)		(0.060)	(0.081)
Individual Controls				✓	✓	✓
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 ethnolinguistic group FE. Columns (4)-(6) include additional individual controls for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 4.6 percent.

Table 10 explores robustness to using alternative definitions of exposure to AGOA. As before, these include making exposure conditional on exports to the U.S. or using an exposure measure based on land suitability, rather than on actual production of AGOA-eligible goods. Our findings are unchanged: belonging to a group that is ethnically remote from the country average increases the chance of experiencing food poverty when trade with the U.S. is liberalized.

Appendix Table B21 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 B22 introduces additional cell-level interactions of ethnic diversity and ethnic complementarity with trade openness. Appendix Tables B23 and B24 add cell-level interactions with alternative measures of diver-

Table 9: AGOA and Income Poverty

	Individual Income Poverty					
	(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess	-0.078	-0.111*	-0.126*	-0.096	-0.120	-0.141*
	(0.073)	(0.066)	(0.068)	(0.078)	(0.074)	(0.074)
AGOAccess × Indiv ER	0.194***		0.166***	0.209***		0.182***
	(0.057)		(0.060)	(0.053)		(0.056)
AGOAccess × Cell ER		0.319***	0.193*		0.303**	0.170
		(0.093)	(0.102)		(0.129)	(0.137)
Individual Controls				✓	✓	✓
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). Indiv ER refers to the individual ethnic remoteness from her fellow citizens in the country. Cell ER refers to cell-level ethnic remoteness of the cell in which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguistic group FE. Columns (4)-(6) include additional individual controls for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

sity and environmental variables. Our main result is robust to introducing these different variables. Appendix Tables B25–B26 show that these results are robust to measuring remoteness as distance to the dominant group. From these different exercises, we conclude that it is more difficult for ethnically remote individuals to reap the gains from trade. This is consistent with an interpretation that ethnic distance acts as a barrier that limits the benefits from trade openness.

5 Conclusion

This paper explored how ethnicity affects the relation between trade liberalization and conflict. 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

Table 10: AGOA and Food Poverty: Alternative Definitions of AGOA Exposure

	Geo		X World		X US		Suitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: No individual controls								
AGOA	-0.302	-0.142	-0.072*	-0.113**	-0.011	-0.033	-0.013	-0.048*
	(0.400)	(0.419)	(0.043)	(0.055)	(0.029)	(0.033)	(0.032)	(0.029)
AGOA × Indiv ER		0.217***		0.161***		0.099**		0.133***
		(0.052)		(0.050)		(0.046)		(0.044)
AGOA × Cell ER		-0.010		0.020		0.046		0.043
		(0.083)		(0.077)		(0.070)		(0.068)
Observations	114176	114176	114176	114176	114176	114176	114176	114176
Panel B: Individual Controls								
AGOA	-0.291	-0.093	-0.100	-0.167**	0.004	-0.027	-0.018	-0.066**
	(0.491)	(0.473)	(0.064)	(0.072)	(0.038)	(0.037)	(0.043)	(0.033)
AGOA × Indiv ER		0.231***		0.176***		0.145***		0.165***
		(0.051)		(0.050)		(0.049)		(0.048)
AGOA × Cell ER		0.050		0.077		0.089		0.087
		(0.085)		(0.080)		(0.075)		(0.074)
Observations	72112	72112	72112	72112	72112	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). Indiv ER refers to the individual ethnic remoteness from her fellow citizens in the country. Cell ER refers to cell-level ethnic remoteness of the cell in which the individual resides. All regressions in both panels control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguistic group FE. Regressions in Panel B control for additional individual controls, which include FEs for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 come from the Seamless Digital Chart of the World (Version 10.0), which accompanies the World Geodatasets data from Global Mapping International. The maps were created by the authors using ArcGIS® software by Esri®.
Conflict intensity (ACLED, UCDP)	We measure conflict using fatalities in each cell for a specific year. Data are obtained from two event-based databases: The Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013) for 1989–2017 and the Armed Conflict Location & Event Data Project (ACLED) (Raleigh et al., 2010) for 1997–2017.
Travel time to nearest port (IFPRI)	Travel time to nearest major port in hours in the year 2000. Source: HarvestChoice (2015)
Linguistic composition of cells (Desmet et al., 2020)	Distribution of language groups at the resolution of 5 km × 5 km from Desmet et al. (2020). They construct the data combining three sources of information: data on the spatial distribution of population from Landscan (Source: `http://web.ornl.gov/sci/landscan/`), data on the linguistic composition of countries from Ethnologue Version 17 (Lewis et al., 2014), and maps on the geographic distribution of 6,905 distinct languages from the World Language Mapping System (Version 17) produced by Global Mapping International (Source: `https://worldgeodatasets.com/language/`). Using this information, they then use an iterative proportional fitting algorithm to construct a comprehensive $0.05° \times 0.05°$ grid-cell level dataset on the ethnolinguistic composition of the population for the entire globe.
Poverty (Afrobarometer)	The sample is based on individual level data from six rounds of the Afrobarometer surveys conducted between 1999 and 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: enough food to eat?". It is coded as 0 (if answer is never) or 1 (if answer is just once or twice / several times / many times / always). 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 just once or twice / several times / many times / always).
Nightlight (DMSP-OLS)	Nighttime light emission per square kilometer 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 extend series of VIRSS data generated by Nechaev et al. (2021), which make VIRSS and OLS data comparable. When there are two satellites for the same year, we take the average between both.
Precipitation (CHIRPS)	Average amount of daily precipitation (in mm) in the cell, based on daily precipitation data provided by the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) database (Funk et al., 2014). CHIRPS provides $0.05° \times 0.05°$ resolution satellite imagery supplemented with in-situ monitoring station data. To ensure comparability of the measure across cells, we use double-standardized rainfall deviations (Hidalgo et al., 2010). We first account for seasonal patterns by standardizing monthly rain totals by cell and month for the period 1989–2020. For each cell, these indicators are then summed up by year and standardized over the same period.

(continued on next page)

Variable (Source)	Description
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 and IIASA (2012)
Tse Tse fly suitability (FAO)	These data come 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 level for the year 2000 (average during the period 1997–2003). *US tariff line data* – Data on AGOA-eligible US tariffs 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 identifiable crops from Ramankutty et al. (2008), with the USITC tariff 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 AGOA-eligible tariff line. The 72 eligible crops are: alfalfa, almond, apple, apricot, artichoke, asparagus, avocado, bambara, barley, bean, blueberry, broadbean, cabbage, carrots, cauliflower, cerealnes, cherry, chicory, citrusnes, clover, cotton, cowpea, cucumberetc, currant, date, fig, 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, safflower, soybean, spinach, strawberry, stringbean, sugarbeet, sunflower, tangetc, tobacco, tomato, vegetablenes, walnut, watermelon, wheat. Appendix C.1 provides further details on how we match the crops from FAO to US tariff lines.
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 provides the geo-location of 33 minerals. From these we select the minerals which constitute the main product of at least one AGOA-eligible tariff lines. The AGOA-eligible minerals include: bauxite (aluminum), iron, silver, zinc, cobalt, manganese (ferromanganese), niobium, tungsten, and vanadium. We use the geolocation of the mines to identify cells containing at least one mine of any AGOA-eligible mineral. Appendix C.2 provides further details on how we match the minerals from S & P Global to US tariff lines.
AGOA Eligibile Oil (PETRODATA)	Data on oil are based on the PETRODATA dataset (Lujala et al., 2007) which contains information on oil and gas fields throughout the world. It covers 884 records for onshore and 378 for offshore reserves of natural gas and crude oil during the period 1946–2003. It includes a shapefile of polygons representing petroleum fields, which lets us identify cells overlapping oil fields.

(continued on next page)

Variable (Source)	Description
AGOA-Eligible Manufacturing (D & B)	To match AGOA-eligible manufactured goods to cells, we proceed in four steps. *Step 1: Match tariff lines to NAICS codes.* Our AGOA tariff lines correspond to the year 2000. However, the industry-level data are available at the 2022 North America Industry Classification System (NAICS) code level. We link the tariff lines from the year 2000 with NAICS at the 4-digit level from 2022 to determine which industries contain AGOA-eligible tariff lines for textile, apparel or other manufacturing or agro industries. To do so, we first match the entire set of tariff lines from the year 2000 with the Standard Industrial Classification (SIC) codes using the concordance provided by Pierce and Schott (2012). We then use the SIC code of each tariff line in 2000 to link them with all possible NAICS2022 codes at the 4-digit level, using data from the U.S. Bureau of Labor Statistics: `https://www.bls.gov/ces/naics/#3.2.3`. This provides us with a dataset at the NAICS2022 level, indicating how many tariff lines are present in each industry and the share that are AGOA-eligible (with separate categories for apparel and textiles). *Step 2: Identify locations of AGOA-eligible industries.* We identify the locations of all industries that have at least one tariff line categorized under AGOA. We take the full set of industries from the publicly available listings in the Business Directory of Dun & Bradstreet (DB), which utilizes the four-digit NAICS classification. We then select the matched industries and collect all the locations of these industries for sub-Saharan African countries from Dun & Bradstreet (DB). This process yields a comprehensive list of locations pertaining to 93 industries at the industry-country level, producing 39,089 observations. *Step 3: Assign latitude and longitude to each location.* The previous step gives us 7,651 unique locations to geolocalize. We start by assigning each location to a city. Since not all locations in Dun & Bradstreet correspond to a city, we proceed as follows. First, we do a fuzzy match of our locations with the names of cities in the comprehensive version of the World City Database (WCD) constructed by Simple Maps (2023). This yields 3,191 matches (of which 1,759 exact matches). For the remaining unmatched locations, we conduct an individual Google search to manually assign them to a city. If a location corresponds to a neighborhood or a district of a city, we retain that information to enhance precision in geocoding. If we are unable to match a location with a city after the Google search, we return to D&B to retrieve the exact address of one of the companies in these locations. Finally, we are left with only 115 unmatched locations. For all the matched locations, we obtain longitude and latitude from either the WCD or the "Awesome Table" add-on in Excel. To ensure accuracy when using the add-on, we exclude locations whose latitude and longitude coincide with the centroid of the country. With this quality control measure, we remove 354 locations. *Step 4: Match with grid cells.* We perform a spatial join between our geocoded locations and grid cells to assign each AGOA-eligible industry location to a cell. For locations that fall between two cells, both cells are assigned to the location, which occurred in 14 cases. Additionally, 56 observations were not assigned a cell through the spatial join. We manually reviewed these observations, discarding 23 locations identified as clear errors. Furthermore, 31 locations located in erroneous countries were also removed. Our final dataset comprises 7,142 unique locations. *Final Industry database.* In the final industry dataset, each 4-digit NAICS industry tends to match to many different tariff lines. We consider a sector to be treated by AGOA if at least 25% of the tariff lines are AGOA-eligible. See the exact list of sectors in Appendix C.3.
GSP variables	To create the GSP variables we follow the same procedure as for the AGOA variables. However, instead of focusing on AGOA-eligible tariff lines, we focus on GSP-eligible tariff lines in year 1997.

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Variable (Source)	Description
AGOA Suitability (FAO)	We obtain crop suitability data from the FAO's Global Agro-Ecological Zones (FAO and IIASA, 2012). This dataset provides estimates of suitability for individual crops at a 5 arc-minutes resolution for historical, current, and future conditions. Specifically, we use the suitability index, which takes values from 0–10,000 depending on how suitable each cell is (variable name is "Suitability index range (0 – 10,000); 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. 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 4,000 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 the corresponding 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).

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
Eritrea	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 stop in the year 2017, though AGOA might have continued to subsequent years.

Table A2: Years of access to Apparel and Textiles

Country	Apparel years	Textile Years	No. of years	No. of years
Benin	2005 – 2017	2005 – 2017	13	13
Botswana	2001 – 2017	2002 – 2017	17	16
Burkina Faso	2006 – 2017	2006 – 2017	13	13
Cameroon	2002 – 2017	2002 – 2017	16	16
Cape Verde	2002 – 2017	2002 – 2017	16	16
Central African Republic	2001 – 2003; 2017	2001 – 2003; 2017	4	4
Chad	2006 – 2017	2006 – 2017	12	12
Cote d'Ivoire	2003 – 2004; 2013 – 2017	2003 – 2004; 2013 – 2017	7	7
Ethiopia	2001 – 2017	2001 – 2017	17	17
Gambia	2008 – 2014	2008 – 2014	7	7
Ghana	2002 – 2017	2002 – 2017	16	16
Kenya	2001 – 2017	2001 – 2017	17	17
Lesotho	2001 – 2017	2001 – 2017	17	17
Liberia	2011 – 2017	2011 – 2017	7	7
Madagascar	2001 – 2009	2001 – 2009	9	9
Malawi	2001 – 2017	2001 – 2017	17	17
Mali	2003 – 2012	2003 – 2012	10	10
Mauritius	2001 – 2017	2007 – 2017	17	13
Mozambique	2002 – 2017	2002 – 2017	16	16
Namibia	2002 – 2017	2002 – 2017	16	16
Niger	2004 – 2009; 2014 – 2017	2004 – 2009; 2014 – 2017	13	13
Nigeria	2004 – 2017	2004 – 2017	14	14
Rwanda	2004 – 2017	2004 – 2017	14	14
Senegal	2002 – 2017	2002 – 2017	16	16
Sierra Leone	2004 – 2017	2004 – 2017	14	14
South Africa	2001 – 2017	-	17	0
Swaziland	2001 – 2014	2001 – 2014	14	14
Tanzania	2002 – 2017	2002 – 2017	16	16
Uganda	2001 – 2017	2001 – 2017	17	17
Zambia	2001 – 2017	2001 – 2017	17	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 Apparel and Textiles categories. Data are based on Appendix A of Fernandes et al. (2023). Some countries, such as Burundi, Guinea and Mauritania, had access to AGOA but not to the categories of Apparel and Textiles. Our data go till the year 2017.

A.3 Afrobarometer Data

We use the 12 countries that were included in all 6 Afrobarometer rounds, spanning the period 1999 to 2015. 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 A3 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 A3: Afrobarometer Round 1 and year of entry to AGOA

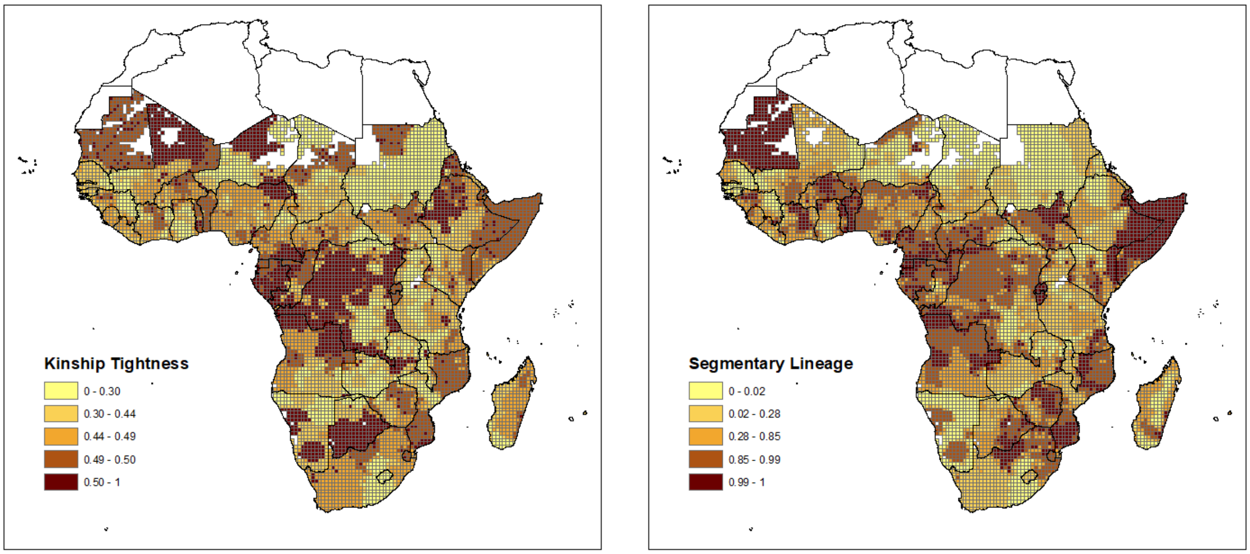
Country	AGOA entry	Survey Year
Botswana	2001	1999
Ghana	2001	1999
Lesotho	2001	2000
Malawi	2001	1999
Mali	2001	2001
Namibia	2001	1999
Nigeria	2001	2000
South Africa	2001	2000
Tanzania	2001	2001
Uganda	2001	2000
Zambia	2001	1999
Zimbabwe	NA	1999

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

A.4 Data Maps

Figure A1: Kinship Tightness and Segmentary Lineage

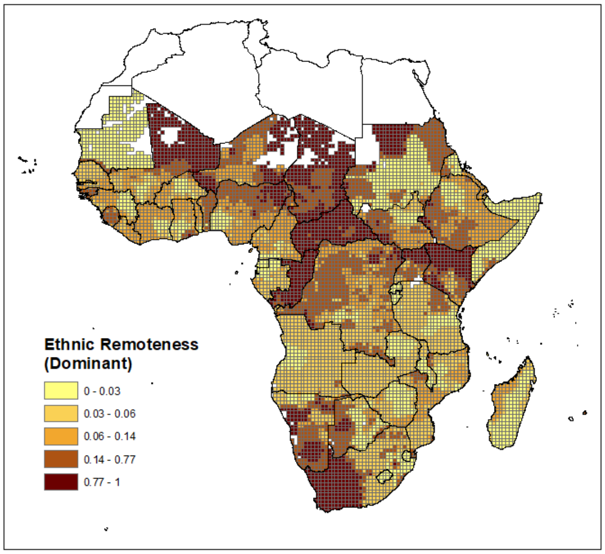
(a) Kinship Tightness (b) Segmentary Lineage



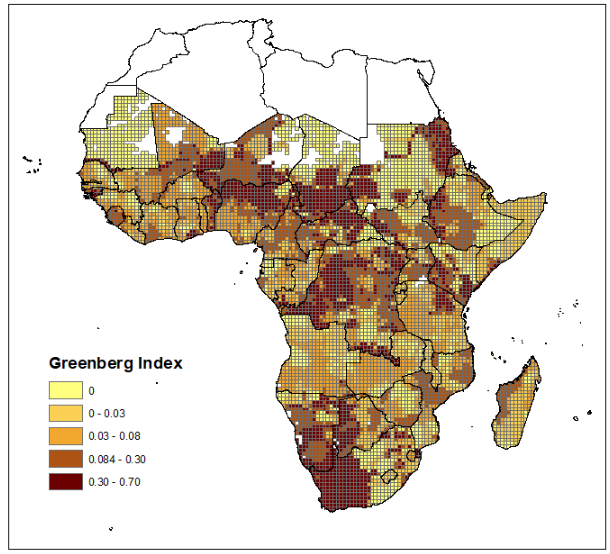
Notes: Panel a) plots the average kinship tightness in a cell (Enke, 2019). Panel b) plots the average segmentary lineage in a cell (Moscona et al., 2020). The distribution of ethnic groups is based on data from Desmet et al. (2020). See Appendix A.1 for further details on data sources and variable definitions.

Figure A2: Alternative Ethnic Remoteness and Ethnic Diversity

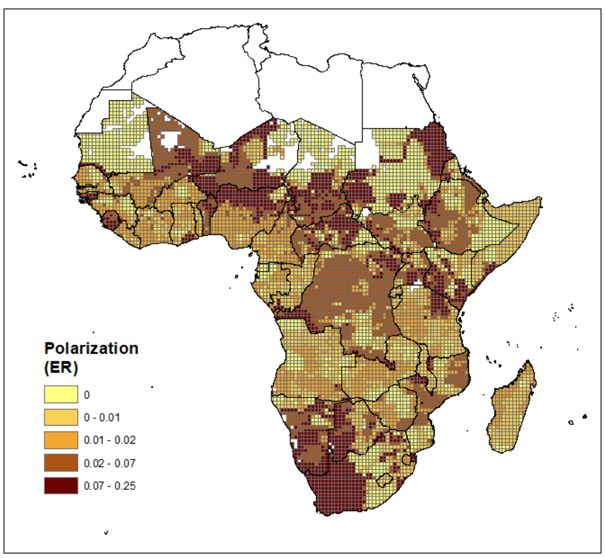
(a) Ethnic Remoteness from the Dominant Group



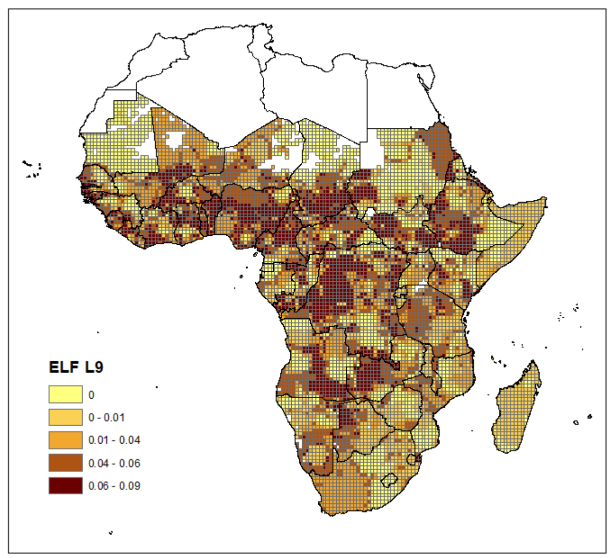
(b) Greenberg Index



(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 residents of the cell (equation (12)). Panel c) plots the Polarization index (equation (13)), *à la* Esteban and Ray (1994) . Panel d) plots the fractionalization index at aggregation level 9 *à la* Desmet et al. (2012). The distribution of ethnic groups is based on data from Desmet et al. (2020). See Appendix A.1 for further details on data sources and variable definitions.

B Additional Tables

B.1 Summary Statistics

Table B1: Summary Statistics (Cell-level)

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)	1.77	2.798	0	12.028	241072
Openness	0.863	0.102	0.095	1	269497
AGOAccess	0.278	0.418	0	1	269497
AGOAGeo	0.382	0.438	0	1	269497
AGOAExp (World)	0.271	0.415	0	1	269497
AGOAExp (US)	0.165	0.352	0	1	269497
AGOAccess (Crops)	0.268	0.414	0	1	269497
AGOAccess (Crops)/WExports	0.263	0.411	0	1	269497
AGOAccess (Crops)/USExports	0.147	0.336	0	0.998	269497
AGOAccess (Minerals/Oil)	0.037	0.181	0	0.998	269497
AGOAccess (Minerals/Oil)/WExports	0.028	0.158	0	0.998	269497
AGOAccess (Minerals/Oil)/USExports	0.02	0.134	0	0.995	269497
AGOAccess (Manufacturing)	0.031	0.168	0	1	269497
AGOAccess (Manufacturing)/WExports	0.031	0.168	0	1	269497
AGOAccess (Manufacturing)/USExports	0.027	0.159	0	1	269497
AGOAccess (Apparel)	0.02	0.137	0	0.998	269497
AGOAccess (Apparel)/WExports	0.02	0.137	0	0.998	269497
AGOAccess (Apparel)/USExports	0.02	0.136	0	0.998	269497
AGOASuit	0.275	0.415	0	1	269497
AGOASuit (Crops)	0.255	0.405	0	1	269497
ER	0.295	0.26	0	0.989	269497
ER^{dom}	0.274	0.358	0	1	269497
Ethnic 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
POL	0.11	0.08	0	0.25	269497
POL^{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
AGOAGeo	0.02	-0.00
AGOAccess	0.15	0.05
AGOAExp (World)	-0.11	-0.12
AGOAExp (US)	0.03	-0.04
AGOASuit	-0.18	-0.14
Ethnic 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
POL^{rq}	0.13	0.09
POL^{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
AGOAOpen	0.74	0.37	0	1	114176
AGOAccess	0.54	0.5	0	1	114176
AGOAExp (World)	0.89	0.32	0	1	114176
AGOAExp (US)	0.70	0.46	0	1	114176
AGOASuit	0.81	0.39	0	1	114176
Cell ER	0.25	0.22	0.01	0.97	114176
Indiv ER	0.24	0.25	0	1	114176
Cell ER^{dom}	0.17	0.28	0	1	114176
Indiv ER^{dom}	0.16	0.34	0	1	114176
Female	0.5	0.5	0	1	114070
Rural	0.6	0.49	0	1	113846
Age	36.78	14.83	15	115	112896
		Panel B			
Income Poverty	0.76	0.42	0	1	108463
Openness	0.92	0.04	0.44	1	108463
AGOAOpen	0.78	0.34	0	1	108463
AGOAccess	0.51	0.5	0	1	108463
AGOAExp (World)	0.88	0.32	0	1	108463
AGOAExp (US)	0.68	0.47	0	1	108463
AGOASuit	0.81	0.39	0	1	108463
Cell ER	0.24	0.22	0.01	0.97	108463
Indiv ER	0.23	0.25	0	1	108463
Cell ER^{dom}	0.16	0.27	0	1	108463
Indiv ER^{dom}	0.16	0.34	0	1	108463
Rainfall Deviation	0.81	0.59	0	4.67	108463
Temperature Deviation	0.07	0.74	-2.13	2.54	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^{dom}
Indiv ER^{dom}	0.89	-
Cell ER	0.80	0.60
Cell ER^{dom}	0.66	0.67

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

Table B5: Share of Cells Producing Different Types of Goods, by Country

Country	Crops	Textiles	Apparel	Manufacturing	Minerals/Oil	Apparel & Textiles
Angola	0.75	0.00	0.00	0.01	0.06	0.00
Benin	1.00	0.00	0.02	0.04	0.04	0.02
Botswana	0.22	0.02	0.04	0.10	0.11	0.04
Burkina Faso	0.97	0.01	0.00	0.03	0.14	0.01
Burundi	0.89	0.00	0.00	0.11	0.17	0.00
Cameroon	0.69	0.01	0.01	0.03	0.13	0.01
Cape Verde	0.27	0.00	0.00	0.20	0.00	0.00
Central African Republic	0.52	0.00	0.00	0.00	0.00	0.00
Chad	0.51	0.00	0.00	0.00	0.06	0.00
Comoros	0.80	0.00	0.00	0.20	0.00	0.00
Congo (DRC)	0.57	0.00	0.00	0.01	0.05	0.00
Cote D'Ivoire	0.96	0.01	0.01	0.06	0.10	0.01
Djibouti	0.18	0.00	0.00	0.06	0.00	0.00
Eritrea	0.41	0.00	0.00	0.01	0.10	0.00
Ethiopia	0.70	0.01	0.01	0.01	0.02	0.01
Gabon	0.39	0.01	0.00	0.02	0.39	0.01
Ghana	0.94	0.03	0.01	0.10	0.13	0.03
Guinea	0.97	0.00	0.01	0.01	0.28	0.01
Guinea-Bissau	0.88	0.00	0.00	0.04	0.04	0.00
Kenya	0.87	0.02	0.02	0.05	0.03	0.03
Lesotho	0.95	0.14	0.05	0.14	0.00	0.14
Liberia	0.82	0.00	0.00	0.02	0.31	0.00
Madagascar	0.93	0.01	0.00	0.03	0.11	0.01
Malawi	0.92	0.02	0.00	0.10	0.19	0.02
Mali	0.46	0.00	0.00	0.00	0.03	0.00
Mauritania	0.19	0.00	0.00	0.00	0.05	0.00
Mauritius	0.33	0.33	0.33	0.33	0.00	0.33
Mozambique	0.88	0.01	0.00	0.03	0.06	0.01
Namibia	0.34	0.02	0.01	0.10	0.16	0.03
Niger	0.40	0.00	0.00	0.00	0.02	0.00
Nigeria	0.98	0.01	0.02	0.07	0.17	0.02
Republic of Congo	0.35	0.00	0.01	0.02	0.14	0.01
Rwanda	0.88	0.00	0.06	0.25	0.13	0.06
Senegal	0.92	0.01	0.01	0.05	0.10	0.01
Seychelles	0.00	0.00	0.00	0.11	0.00	0.00
Sierra Leone	0.87	0.00	0.00	0.05	0.34	0.00
South Africa	0.84	0.37	0.51	0.58	0.12	0.55
South Sudan	0.87	0.00	0.00	0.00	0.07	0.00
Swaziland	0.86	0.14	0.14	0.14	0.07	0.21
Tanzania	0.93	0.01	0.01	0.04	0.11	0.01
The Gambia	0.93	0.00	0.00	0.07	0.00	0.00
Togo	1.00	0.03	0.00	0.03	0.09	0.03
Uganda	0.95	0.03	0.02	0.04	0.13	0.03
Zambia	0.78	0.01	0.01	0.03	0.11	0.01
Average	0.67	0.03	0.04	0.06	0.09	0.04

Notes: This table presents the share of cells producing the different types of AGOA-eligible goods.

Table B6: Share of Cells Producing Both AGOA-Eligible Non-Crop Goods and AGOA-Eligible Crops, by Country

Country	Apparel & Textiles	Apparel	Textiles	Manufacturing	Minerals/Oil	All Non-Crop
Angola	.	.	.	0.86	0.81	0.82
Benin	1.00	1.00	.	1.00	1.00	1.00
Botswana	0.89	0.88	1.00	0.70	0.44	0.51
Burkina Faso	1.00	.	1.00	1.00	1.00	1.00
Burundi	.	.	.	1.00	1.00	1.00
Cameroon	1.00	1.00	1.00	1.00	0.54	0.57
Cape Verde	.	.	.	0.67	.	0.67
Central African Republic	.	.	.	1.00	1.00	1.00
Chad	.	.	.	1.00	0.81	0.81
Comoros	.	.	.	1.00	.	1.00
Congo (DRC)	1.00	1.00	1.00	1.00	0.76	0.78
Cote D'Ivoire	1.00	1.00	1.00	1.00	1.00	1.00
Djibouti	.	.	.	1.00	.	1.00
Eritrea	.	.	.	1.00	0.71	0.71
Ethiopia	1.00	1.00	1.00	1.00	1.00	1.00
Gabon	1.00	.	1.00	1.00	0.45	0.47
Ghana	1.00	1.00	1.00	1.00	1.00	1.00
Guinea	1.00	1.00	.	1.00	1.00	1.00
Guinea-Bissau	.	.	.	1.00	1.00	1.00
Kenya	1.00	1.00	1.00	1.00	1.00	1.00
Lesotho	1.00	1.00	1.00	1.00	.	1.00
Liberia	.	.	.	1.00	0.94	0.94
Madagascar	1.00	1.00	1.00	0.86	0.96	0.94
Malawi	1.00	.	1.00	1.00	1.00	1.00
Mali	1.00	1.00	1.00	1.00	0.86	0.87
Mauritania	.	.	.	0.00	0.07	0.07
Mauritius	1.00	1.00	1.00	1.00	.	1.00
Mozambique	1.00	1.00	1.00	1.00	1.00	1.00
Namibia	0.75	1.00	0.71	0.71	0.61	0.60
Niger	1.00	.	1.00	1.00	0.14	0.14
Nigeria	1.00	1.00	1.00	1.00	0.98	0.99
Republic of Congo	0.00	0.00	.	0.33	0.29	0.30
Rwanda	1.00	1.00	.	1.00	1.00	1.00
Senegal	1.00	1.00	1.00	1.00	0.70	0.77
Seychelles	.	.	.	0.00	.	0.00
Sierra Leone	.	.	.	1.00	0.92	0.93
South Africa	0.98	0.98	0.98	0.97	0.83	0.94
South Sudan	.	.	.	1.00	0.75	0.76
Swaziland	1.00	1.00	1.00	1.00	1.00	1.00
Tanzania	1.00	1.00	1.00	0.92	1.00	0.98
The Gambia	.	.	.	1.00	.	1.00
Togo	1.00	.	1.00	1.00	1.00	1.00
Uganda	1.00	1.00	1.00	1.00	1.00	1.00
Zambia	1.00	1.00	1.00	0.89	0.82	0.83
Average	0.97	0.98	0.98	0.94	0.79	0.84

Notes: This table shows the proportion of cells that produce AGOA-eligible non-crop goods and also produce AGOA-eligible crops. For instance, the value 0.89 in the 'Apparel & Textiles' column for Botswana indicates that 89% of cells producing textiles and apparel also produce crops. Missing values signify that no cells in the country produce goods in this category.

B.2 Robustness: Cell-Level Regressions

B.2.1 Baseline Definition of AGOA

Table B7: AGOA and Conflict: Different Diversity Measures

	(1)	(2)	(3)	(4)
AGOAccess	-0.108***	-0.105***	-0.101***	-0.116***
	(0.017)	(0.017)	(0.016)	(0.018)
AGOAccess × ER	0.280***	0.244***	0.213***	0.331***
	(0.066)	(0.058)	(0.051)	(0.072)
AGOAccess × Greenberg	-0.152**			
	(0.061)			
AGOAccess × ELF2		-0.082*		
		(0.043)		
AGOAccess × ELF9			-0.030	
			(0.027)	
AGOAccess × POL^{er}				-0.722***
				(0.205)
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 B8: AGOA and Conflict: Alternative Transformations of Dependent Variable

	Intensity of Conflict from UCDP			
	Log (y+1)	IH	Log (y+0.5)	0-1
AGOAccess	-0.108***	-0.112***	-0.127***	-0.030***
	(0.017)	(0.018)	(0.020)	(0.005)
AGOAccess × ER	0.202***	0.211***	0.240***	0.059***
	(0.046)	(0.048)	(0.054)	(0.012)
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 B9: AGOA and Luminosity: Different Diversity Measures

	(1)	(2)	(3)	(4)
AGOAccess	0.465***	0.459***	0.466***	0.471***
	(0.041)	(0.041)	(0.044)	(0.041)
AGOAccess × ER	-0.398***	-0.396***	-0.319***	-0.428***
	(0.096)	(0.092)	(0.086)	(0.103)
AGOAccess × Greenberg	0.149			
	(0.115)			
AGOAccess × ELF2		0.145		
		(0.093)		
AGOAccess × ELF9			-0.006	
			(0.063)	
AGOAccess × POL^{er}				0.597
				(0.383)
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 B10: AGOA and Luminosity: Alternative Transformations of Dependent Variable

	Income Proxied by Nighlight			
	Log (y+1)	IH	Log (y+0.5)	0-1
AGOAccess	0.464***	0.466***	0.507***	0.131***
	(0.041)	(0.041)	(0.046)	(0.010)
AGOAccess × ER	-0.321***	-0.321***	-0.342***	-0.073***
	(0.085)	(0.086)	(0.096)	(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 Manufacturing, Crops, Minerals or Oil, and Textiles

Table B11: AGOA and Conflict (UCDP): Split by Products

	AGOAccess		X World		X US		Suitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOA (Crops)	-0.037***	-0.101***	-0.040***	-0.110***	-0.014	-0.091***	-0.015	-0.051***
	(0.009)	(0.018)	(0.009)	(0.019)	(0.011)	(0.024)	(0.010)	(0.018)
AGOA (Manufacturing)	-0.061**	-0.040	-0.061**	-0.038	-0.045	0.035	-0.067**	-0.067
	(0.028)	(0.041)	(0.028)	(0.041)	(0.031)	(0.045)	(0.029)	(0.041)
AGOA (Minerals/Oil)	-0.052***	-0.040**	-0.063***	-0.042*	-0.072***	-0.065**	-0.054***	-0.050***
	(0.016)	(0.019)	(0.020)	(0.023)	(0.024)	(0.032)	(0.016)	(0.019)
AGOA (Apparel)	-0.065*	0.008	-0.064*	0.009	-0.091***	-0.048	-0.066**	-0.015
	(0.034)	(0.048)	(0.034)	(0.049)	(0.034)	(0.049)	(0.033)	(0.048)
AGOA (Crops) × ER		0.208***		0.224***		0.288***		0.113**
		(0.051)		(0.052)		(0.080)		(0.052)
AGOA (Manufacturing) × ER		-0.068		-0.076		-0.239**		0.001
		(0.088)		(0.088)		(0.094)		(0.087)
AGOA (Minerals/Oil) × ER		-0.030		-0.063		0.006		-0.010
		(0.061)		(0.078)		(0.092)		(0.061)
AGOA (Apparel) × ER		-0.187		-0.182		-0.097		-0.145
		(0.119)		(0.119)		(0.119)		(0.119)
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. The different columns split *Production* between crops, manufacturing, minerals and oil, and apparel (including textiles). Columns 1 and 2 use our main definition of AGOAccess used in equation (1). 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. Columns 7 and 8 measure AGOAccess considering if a location's land is suitable for AGOA-eligible crop 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 B12: AGOA and Luminosity: Split by Products

	AGOAccess		X World		X US		Suitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOA (Crops)	0.212***	0.303***	0.322***	0.392***	0.211***	0.249***	0.212***	0.303***
	(0.032)	(0.046)	(0.030)	(0.046)	(0.044)	(0.060)	(0.032)	(0.046)
AGOA (Manufacturing)	-0.045	0.117	-0.093	0.066	-0.135**	0.016	-0.045	0.117
	(0.057)	(0.091)	(0.058)	(0.092)	(0.062)	(0.101)	(0.057)	(0.091)
AGOA (Minerals/Oil)	0.260***	0.358***	0.199***	0.322***	0.184**	0.321**	0.260***	0.358***
	(0.055)	(0.083)	(0.064)	(0.100)	(0.077)	(0.127)	(0.055)	(0.083)
AGOA (Apparel)	-0.065	-0.242**	-0.047	-0.189*	0.020	-0.094	-0.065	-0.242**
	(0.069)	(0.116)	(0.068)	(0.111)	(0.067)	(0.112)	(0.069)	(0.116)
AGOA (Crops) × ER		-0.307***		-0.223**		-0.153		-0.307***
		(0.092)		(0.095)		(0.126)		(0.092)
AGOA (Manufacturing) × ER		-0.539***		-0.541***		-0.478**		-0.539***
		(0.200)		(0.203)		(0.220)		(0.200)
AGOA (Minerals/Oil) × ER		-0.406*		-0.481*		-0.493		-0.406*
		(0.236)		(0.276)		(0.368)		(0.236)
AGOA (Apparel) × ER		0.530**		0.416*		0.341		0.530**
		(0.229)		(0.226)		(0.235)		(0.229)
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 our main definition of AGOAccess used in equation (1) splitting *Production* between crops, manufacturing, minerals and oil, and apparel (including textiles). Columns 3, 4, 5, and 6 use a definition of AGOAccess taking into account if the country has export capacity in AGOA-eligible goods as defined in equation (3) to the US and to the rest of the world, splitting *Production* between crops, manufacturing, minerals and oil, and apparel (including textiles). Columns 7 and 8 measure AGOAccess considering if a location's land is suitable for AGOA-eligible crop as defined in equation (4), splitting *Production* between the same aforementioned sectors. 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 B13: AGOA vs. GSP and Conflict (UCDP)

	(1)	(2)	(3)	(4)	(5)
AGOAccess (No GSP)	-0.041***		-0.122***		-0.122***
	(0.011)		(0.028)		(0.028)
GSPAccess		0.001		-0.012	-0.011
		(0.012)		(0.018)	(0.018)
AGOAccess × ER			0.241***		0.240***
			(0.081)		(0.081)
GSPAccess × ER				0.046	0.042
				(0.042)	(0.042)
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. GSPAcess represents the shock experienced in cells belonging to countries that benefited from GSP provisions in 1997 for being least developed countries (LDCs). AGOAccess represents the pure AGOA shock experienced by cells from the year 2001 onwards. 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 B14: AGOA vs. GSP and Luminosity

	(1)	(2)	(3)	(4)	(5)
AGOAccess (No GSP)	0.272***		0.403***		0.400***
	(0.049)		(0.064)		(0.064)
GSPAccess		0.347***		0.351***	0.349***
		(0.031)		(0.049)	(0.049)
AGOAccess × ER			-0.399***		-0.402***
			(0.121)		(0.121)
GSPAccess × ER				-0.015	-0.012
				(0.110)	(0.110)
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 (fatalities + 1), where fatalities is based on data from UCDP. GSPAcess represents the shock experienced in cells belonging to countries that benefited from GSP provisions in 1997 for being least developed countries (LDCs). AGOAccess represents the pure AGOA shock experienced by cells from the year 2001 onwards. 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 B15: AGOA and Conflict: Ethnic Remoteness (ACLED)

	Intensity of Conflict from ACLED						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGOAccess	-0.032***	-0.093***	-0.103***	-0.101***	-0.092***	-0.089***	-0.083***
	(0.012)	(0.021)	(0.022)	(0.022)	(0.020)	(0.033)	(0.022)
AGOAccess × ER		0.202***	0.195***	0.196***	0.203***	0.202***	0.198***
		(0.053)	(0.054)	(0.055)	(0.058)	(0.052)	(0.053)
AGOAccess × ELF			0.028				
			(0.026)				
AGOAccess × POL				0.083			
				(0.099)			
AGOAccess × Specialization					-0.008		
					(0.052)		
AGOAccess × Kinship						-0.009	
						(0.060)	
AGOAccess × Segmented							-0.016
							(0.016)
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 B16: 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	0.203***	0.202***	0.200***	0.229***
	(0.072)	(0.063)	(0.056)	(0.078)
AGOAccess × Greenberg	-0.003			
	(0.064)			
AGOAccess × ELF2		0.000		
		(0.046)		
AGOAccess × ELF9			0.005	
			(0.031)	
AGOAccess × POL^{er}				-0.152
				(0.208)
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 B17: AGOA and Conflict: Environmental Variables (ACLED)

	(1)	(2)	(3)	(4)
AGOAccess	-0.093***	-0.158***	-0.103***	-0.065***
	(0.021)	(0.034)	(0.022)	(0.022)
AGOAccess × ER	0.202***	0.189***	0.187***	0.183***
	(0.053)	(0.053)	(0.053)	(0.051)
AGOAccess × Crop Unsuitability		0.014**		
		(0.005)		
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 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 B18: AGOA and Conflict: Alternative Transformations of Dependent Variable (ACLED)

	(1)	(2)	(3)	(4)
AGOAccess	-0.093***	-0.094***	-0.105***	0.013***
	(0.021)	(0.022)	(0.024)	(0.005)
AGOAccess × ER	0.202***	0.205***	0.230***	0.010
	(0.053)	(0.054)	(0.061)	(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 B19: 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)			-0.039***	-0.110***				
			(0.012)	(0.022)				
AGOExp (World) × ER				0.233***				
				(0.054)				
AGOAExp (US)					-0.040***	-0.100***		
					(0.015)	(0.025)		
AGOAExp (US) × ER						0.234***		
						(0.076)		
AGOASuit							-0.002	-0.038*
							(0.013)	(0.023)
AGOASuit × ER								0.116**
								(0.054)
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 B20: AGOA and Conflict (ACLED): Split by Products

	AGOAccess		X World		X US		Suitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGOA (Crops)	-0.026**	-0.088***	-0.035***	-0.110***	0.002	-0.057**	0.014	-0.016
	(0.012)	(0.022)	(0.012)	(0.022)	(0.013)	(0.026)	(0.015)	(0.024)
AGOA (Manufacturing)	-0.043	-0.039	-0.043	-0.036	-0.017	0.068	-0.049	-0.066
	(0.039)	(0.061)	(0.039)	(0.061)	(0.041)	(0.066)	(0.039)	(0.061)
AGOA (Minerals/Oil)	-0.039*	-0.043	-0.055**	-0.057	-0.083***	-0.131**	-0.041**	-0.053*
	(0.021)	(0.030)	(0.025)	(0.040)	(0.032)	(0.054)	(0.021)	(0.031)
AGOA (Apparel)	0.011	0.061	0.014	0.070	-0.018	-0.028	0.005	0.026
	(0.043)	(0.070)	(0.043)	(0.070)	(0.044)	(0.076)	(0.043)	(0.069)
AGOA (Crops) × ER		0.207***		0.243***		0.228**		0.099
		(0.058)		(0.058)		(0.094)		(0.062)
AGOA (Manufacturing) × ER		-0.013		-0.023		-0.271**		0.061
		(0.133)		(0.132)		(0.135)		(0.130)
AGOA (Minerals/Oil) × ER		0.032		0.022		0.193		0.054
		(0.079)		(0.102)		(0.125)		(0.079)
AGOA (Apparel) × ER		-0.124		-0.134		0.060		-0.064
		(0.143)		(0.143)		(0.156)		(0.141)
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 our main definition of AGOAccess used in equation (1), splitting *Production* between crops, manufacturing, minerals and oil, and apparel (including textiles). Columns 3, 4, 5, and 6 use a definition of AGOAccess taking into account if the country has export capacity in AGOA-eligible goods as defined in equation (3) to the US and to the rest of the world, splitting *Production* between crops, manufacturing, minerals and oil, and apparel (including textiles). Columns 7 and 8 measure AGOAccess considering if a location's land is suitable for AGOA-eligible crops as defined in equation (4), splitting *Production* between crops, manufacturing, minerals and oil, and apparel (including textiles). 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.3 Robustness: Individual Level Data

B.3.1 Food Poverty: Baseline Definition of AGOA

Table B21: AGOA and Food Poverty – Remoteness from the Dominant Group

	(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess	-0.077*	-0.078*	-0.078*	-0.113*	-0.115*	-0.117*
	(0.047)	(0.045)	(0.047)	(0.064)	(0.064)	(0.064)
AGOAccess × Indiv ER^{dom}	0.089***		0.088***	0.116***		0.105***
	(0.028)		(0.031)	(0.027)		(0.032)
AGOAccess × Cell ER^{dom}		0.063*	0.004		0.100***	0.033
		(0.037)	(0.046)		(0.036)	(0.049)
Individual Controls				✓	✓	✓
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). Indiv ER refers to the individual ethnic remoteness from the dominant group in the country. Cell ER refers to cell-level ethnic remoteness of the cell in which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguistic group FE. Columns (4)-(6) include additional individual controls for professions, age bracket, gender, and rural location. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B22: AGOA and Food Poverty: Additional Cell Controls

	(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess	-0.113**	-0.111**	-0.115**	-0.105*	-0.109*	-0.128**
	(0.055)	(0.056)	(0.056)	(0.054)	(0.066)	(0.055)
AGOAccess × Indiv ER	0.167***	0.168***	0.168***	0.168***	0.168***	0.169***
	(0.050)	(0.050)	(0.049)	(0.049)	(0.050)	(0.049)
AGOAccess × Cell ER	0.016	0.019	0.014	0.029	0.015	0.028
	(0.077)	(0.077)	(0.076)	(0.080)	(0.075)	(0.077)
AGOAccess × Cell ELF		-0.007				
		(0.038)				
AGOAccess × Cell POL			0.017			
			(0.129)			
AGOAccess × Cell Specialization				-0.044		
				(0.067)		
AGOAccess × Cell Kinship					-0.012	
					(0.100)	
AGOAccess × Cell Segmented						0.036
						(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). Indiv ER refers to the individual ethnic remoteness from her fellow citizens in the country. Cell ER refers to cell-level ethnic remoteness of the cell in which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguistic group FE. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B23: AGOA and Food Poverty: Alternative Diversity controls

	(1)	(2)	(3)	(4)	(5)
AGOAccess	-0.113**	-0.116**	-0.118**	-0.109**	-0.124**
	(0.055)	(0.053)	(0.053)	(0.054)	(0.054)
AGOAccess × Indiv ER	0.167***	0.168***	0.169***	0.168***	0.165***
	(0.050)	(0.049)	(0.049)	(0.050)	(0.049)
AGOAccess × Cell ER	0.016	0.113	0.118	0.029	0.143**
	(0.077)	(0.075)	(0.075)	(0.076)	(0.070)
AGOAccess × Cell Greenberg		-0.129*			
		(0.068)			
AGOAccess × Cell ELF2			-0.133*		
			(0.069)		
AGOAccess × Cell ELF9				-0.029	
				(0.045)	
AGOAccess × Cell POL^{er}					-0.421**
					(0.198)
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). Indiv ER refers to the individual ethnic remoteness from her fellow citizens in the country. Cell ER refers to cell-level ethnic remoteness of the cell in which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguistic group FE. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B24: AGOA and Food Poverty: Environmental Controls

	(1)	(2)	(3)	(4)
AGOAccess	-0.113**	-0.034	-0.107*	-0.102*
	(0.055)	(0.069)	(0.054)	(0.052)
AGOAccess × Indiv ER	0.167***	0.168***	0.184***	0.163***
	(0.050)	(0.049)	(0.049)	(0.049)
AGOAccess × Cell ER	0.016	0.024	0.030	-0.003
	(0.077)	(0.077)	(0.067)	(0.083)
AGOAccess × Crop Unsuitability		-0.015*		
		(0.009)		
AGOAccess × Malaria Suitability			0.043	
			(0.031)	
AGOAccess × Tsetse Suitability				-0.009
				(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). Indiv ER refers to the individual ethnic remoteness from her fellow citizens in the country. Cell ER refers to cell-level ethnic remoteness of the cell in which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguistic group FE. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B25: AGOA and Income Poverty: Additional Cell Controls (Dominant)

	(1)	(2)	(3)	(4)	(5)	(6)
AGOAccess	-0.061	-0.048	-0.041	-0.057	-0.050	-0.059
	(0.072)	(0.074)	(0.075)	(0.074)	(0.084)	(0.073)
AGOAccess × Indiv ER^{dom}	0.088**	0.087**	0.086**	0.088**	0.088**	0.088**
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
AGOAccess × Cell ER^{dom}	0.109*	0.134**	0.143**	0.123	0.113*	0.106*
	(0.059)	(0.065)	(0.063)	(0.080)	(0.062)	(0.061)
AGOAccess × Cell ELF		-0.043				
		(0.052)				
AGOAccess × Cell POL			-0.197			
			(0.149)			
AGOAccess × Cell Specialization				-0.027		
				(0.103)		
AGOAccess × Cell Kinship					-0.030	
					(0.134)	
AGOAccess × Cell Segmented						-0.007
						(0.041)
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). Indiv ER refers to the individual ethnic remoteness from the dominant group in the country. Cell ER refers to cell-level ethnic remoteness of the cell in which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguistic group FE. sym* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B26: AGOA and Income Poverty: Alternative Diversity Indices (Dominant)

	(1)	(2)	(3)	(4)	(5)
AGOAccess	-0.061	-0.059	-0.060	-0.060	-0.057
	(0.072)	(0.073)	(0.073)	(0.073)	(0.073)
AGOAccess × Indiv ER^{dom}	0.088**	0.088**	0.088**	0.088**	0.087**
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
AGOAccess × Cell ER^{dom}	0.109*	0.126*	0.118*	0.115	0.153**
	(0.059)	(0.068)	(0.067)	(0.073)	(0.070)
AGOAccess × Cell Greenberg		-0.032			
		(0.102)			
AGOAccess × Cell ELF2			-0.016		
			(0.101)		
AGOAccess × Cell ELF9				-0.010	
				(0.078)	
AGOAccess × Cell POL^{er}					-0.229
					(0.325)
Observations	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: 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). Indiv ER refers to the individual ethnic remoteness from the dominant group in the country. Cell ER refers to cell-level ethnic remoteness of the cell in which the individual resides. All regressions control for rainfall and temperature shocks, country-specific cell FE, country-specific year FE and individual ethnolinguistic group FE. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Sector-Wise Matching to AGOA Tariff Lines

C.1 Crops Matching

Crop FAO	Description FAO	HSTS-8 US Tariff Line	Decision
alfalfa	Alfalfa.	Alfalfa (lucerne) meal and pellets.	1
almond	Almonds, with shell.	Almonds, fresh or dried, in shell.	1
apple	Apples.	Apples, otherwise prepared or preserved, nesi.	1
apricot	Apricots.	Apricots, fresh.	1
artichoke	Artichokes.	Artichokes, prepared or preserved otherwise than by vinegar or acetic acid, not frozen.	1
asparagus	Asparagus.	Asparagus, nesi, fresh or chilled.	1
avocado	Avocados.	Avocados, fresh or dried.	1
bambara	Bambara beans, bambara groundnut, earth pea.	Beans nesi, fresh or chilled, shelled or unshelled.	1
barley	Barley, two-row barley, six-row barley, four-row barley.	Barley, other than for malting purposes.	1
bean	Beans, dry; kidney/haricot bean, lima/butter bean, adzuki bean, mungo bean, black gram, scarlet runner bean, rice bean, moth bean, and tepary bean.	Beans nesi, fresh or chilled, shelled or unshelled.	1
berrynes	Berries nes; blackbeery, loganberry, white/red mulberry, myrtle berry huckleberry, dangleberry, and other berries not separately identified.	Boysenberries, frozen, in water or containing added sweetening.	0
blueberry	Blueberries, wild bilberry, whortleberry, american blueberry.	Blueberries, otherwise prepared or preserved, nesi.	1
broadbean	Broad beans, horse beans, broad bean, and field bean.	Beans nesi, uncooked or cooked by steaming or boiling in water, frozen, reduced in size.	1
cabbage	Cabbages and other brassicas chinese, mustard cabbage, pak-choi, with/red/savoy cabbage, brussels sprouts, collards, kale, and kohlarabi.	Kohlrabi, kale and similar edible brassicas nesi, including sprouting broccoli, fresh or chilled.	1
carrots	Carrots and turnips.	Carrots, fresh or chilled, reduced in size.	1
cauliflower	Cauliflowers and broccoli brassica.	Cauliflower seeds of a kind used for sowing.	1
cerealnes	Cereals, nes, including canagua or coaihua, quihuicha or inca wheat, adlay or job's tears, wild rice and other cereal crops that are not identified separately.	Cereals nesi (including wild rice).	1
cherry	Cherries, sweet cherry, hard-fleshed cherry and hear cherry.	Cherries, dried.	1
chestnut	Chestnut.	Acorns and horse-chestnuts, of a kind used in animal feeding.	0
chicory	Chicory roots, unroasted chicory roots.	Roasted chicory and other roasted coffee substitutes and extracts, essences and concentrates thereof.	1
citrusnes	Fruit, citrus nes; bergamot, citron, chinotto, kumquat and some minor varieties of citrus.	Citrus fruit or peel of citrus or other fruit, except mixtures, preserved by sugar (drained, glace or crystallized).	1
clover	Clover.	White and ladino clover seed of a kind used for sowing.	1

(continued on next page)

Crop FAO	Description FAO	HSTS-8 US Tariff Line	Decision
cocoa	Cocoa, beans, including whole or broken, raw or roasted.	Chocolate/oth preps with cocoa, ov 2kg but n/o 4.5 kg, n/o 65% by wt of sugar, not in blocks 4.5 kg or more, subj to GN 15.	0
coffee	Coffee, green (arabica, robusta, liberica). Raw coffee in all forms.	Coffee substitutes containing coffee.	0
cotton	Seed cotton; unginned cotton, cottonseed, cotton lint and linters.	Cotton seeds, whether or not broken.	1
cowpea	Cow peas; dry cowpea, blackeye pea/bean.	Black-eye cowpeas, shelled, prepared or preserved otherwise than by vinegar or acetic acid, not frozen.	1
cucumberetc	Cucumbers and gherkins.	Cucumbers, including gherkins, fresh or chilled, if entered May 1 to June 30, inclusive, or Sept. 1 to Nov. 30, inclusive, in any year.	1
currant	Currant black, red and white. Trade data may include gooseberries.	Currant and berry fruit jellies.	1
date	Dates, including fresh and dried fruit.	Dates, fresh or dried, other than whole.	1
fig	Figs.	Figs, fresh or dried, other than whole (including fig paste).	1
flax	Flax fibre and tow broken, scutched, hackled, etc, but not spun. Production in its raw state.	Flaxseed (linseed), whether or not broken.	0
fruitnes	Fruit, fresh nes; azarole, babaco, elderberry, jujube, litchi, loquat, medlar, pawpaw, pomegranate, prickly pear, rose hips, rowanberry, service-apple, tamarind, tree-strawberry, and other fresh fruit not identified separately.	Fruit nesi, dried, other than that of headings 0801 to 0806, and excluding mixtures.	0
grape	Grapes; table and wine grapes.	Grapes, dried, other than raisins.	1
grapefruit	Grapefruit (inc pomelos).	Grapefruit (other than peel or pulp), otherwise prepared or preserved, nesi.	1
greenbean	Beans, green.	Beans nesi, uncooked or cooked by steaming or boiling in water, frozen, reduced in size.	1
greenbroadbean	Vegetables, leguminous.	Leguminous vegetables nesi, uncooked or cooked by steaming or boiling in water, frozen.	1
greencorn	Maize, green, particularly var saccharata. Saccharata is known as sweet corn.	Sweet corn, uncooked or cooked by steaming or boiling in water, frozen.	1
greenonion	Onion, shallots, green; welsh onions, and young onions pulled before the bulb has enlarged.	Dried onion powder or flour.	0
groundnut	Groundnuts, with shell.	Peanuts (ground-nuts), not roasted or cooked, in shell, subject to add. US note 2 to Ch.12.	1
hazelnut	Hazelnuts, with shell.	Hazelnuts or filberts, fresh or dried, in shell.	1
hop	Hops; hop cones, fresh or dried, whether or not ground, powdered or in the form of pellets.	Saps and extracts of hops.	1
lemonlime	Lemons and limes.	Lemons, fresh or dried.	1
linseed	Linseed. An annual herbaceous that is cultivated for its fibre as well as its oil.	Linseed oil, crude, and its fractions, not chemically modified.	1
maize	Maize corn. A grain with a high germ content. Used largely for animal feed and commercial starch production.	Corn (maize) oil, crude, and its fractions, not chemically modified.	0
maizefor	Maizefor, forage.	Corn (maize) oil, crude, and its fractions, not chemically modified.	0

(continued on next page)

Crop FAO	Description FAO	HSTS-8 US Tariff Line	Decision
melonetc	Melons, other.	Other melons nesoi, fresh, if entered during the period from June 1 through November 30, inclusive.	1
melonseed	Melonseed.	Other melons nesoi, fresh, if entered during the period from June 1 through November 30, inclusive.	0
millet	Millet; japanese millet, african millet, proso millet, ditch millet, pearl or cattail millet and foxtail millet.	Millet.	1
mixedgrain	Grain, mixed. A mixture of cereal species that are sown and harvested together. The mixture wheat/rye is known as meslin, but in trade is usually classified with wheat.	Grains of barley, hulled, pearled, clipped, sliced, kibbled or otherwise worked, but not rolled or flaked.	0
mixedgrass	Mixedgrass, forage.	Rye grass seed of a kind used for sowing.	0
mushrooms	Mushrooms and truffles.	Mushrooms, fresh or chilled.	1
mustard	Mustard seed; white and black mustard.	Rapeseed, colza or mustard oil, crude, and their fractions, not chemically modified, nesi.	1
nutnes	Nuts, nes; pecan, butter or swarri nut, pili nut, java almond, chinese olives, paradise or sapucaia, queensland, macadamia nut, pignolia nut, and other nuts that are not identified separately.	Nuts nesi, fresh or dried, shelled.	1
oilseedfor	Oilseedfor, forage.	Flours and meals of oil seeds or oleaginous fruits other than those of mustard or soybeans.	0
oilseednes	Oilseed, nes; beech nut, and other oilseeds, oleaginous fruits, and nuts that are not identified separately.	Flours and meals of oil seeds or oleaginous fruits other than those of mustard or soybeans.	1
olive	Olives; table olives and olives for oil.	Olives, fresh or chilled.	1
onion	Onions, dry; onions at a mature stage, but not dehydrated onions.	Dried onions whole, cut, sliced or broken, but not further prepared.	1
orange	Oranges common, sweet orange, and bitter orange.	Orange juice, fortified with vitamins or minerals.	1
papaya	Papayas.	Papayas, frozen, in water or containing added sweetening.	1
peachetc	Peaches and nectarines.	Peaches, including nectarines, fresh, if entered during the period from June 1 through November 30, inclusive.	1
pear	Pears.	Pears and quinces, fresh, if entered during the period from July 1 through the following March 31, inclusive.	1
pineapple	Pineapples ananas.	Pineapples, fresh or dried, not reduced in size, in bulk.	1
plum	Plums and sloes.	Plums, prunes and sloes, fresh, if entered during the period from June 1 through December 31, inclusive.	1
potato	Potatoes.	Potatoes, uncooked or cooked by steaming or boiling in water, frozen.	1
pyrethrum	Pyrethrum; leaves, stems and flowers. For insecticides, fungicides and similar products.	Insecticides, nesoi, for retail sale or as preparations or articles.	0
quince	Quinces.	Pears and quinces, fresh, if entered during the period from July 1 through the following March 31, inclusive.	1

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Crop FAO	Description FAO	HSTS-8 US Tariff Line	Decision
rapeseed	Rapeseed Brassica. Valued mainly for its oil.	Rapeseed, colza or mustard oil, other than crude, and their fractions, whether or not refined, not chemically modified, nesi.	1
rasberry	Raspberries.	Raspberries and loganberries, fresh, if entered during the period from September 1 through the following June 30, inclusive.	1
rice	Rice, paddy. Also known as rice in the husk and rough rice.	Rice in the husk (paddy or rough).	1
rootnes	Roots and tuber, nes; arracha, arrowroot, chuga, sago palm, oca and ullucu, yam bean, jicama, mashua, Jerusalem artichoke, topinambur, and other tubers roots, or rhizomes, fresh that are not identified separately.	Fresh or chilled arrowroot, salep, Jerusalem artichokes and similar roots and tubers nesoi, whether or not sliced or in the form of pellets.	1
rubber	Rubber, latex. The liquid secreted by the rubber tree.	Sports footwear w/outer soles and uppers of rubber or plastics, nesi, valued over $3butnotover6.50/pair.	0
rye	Rye cereale; mainly used in making bread.	Rye flour.	1
ryefor	Ryefor, forage.	Rye grass seed of a kind used for sowing.	1
safflower	Safflower. Valued mainly for its oil.	Sunflower seed or safflower oil, other than crude, and their fractions, whether or not refined, but not chemically modified.	1
soybean	Soybeans; oil crop.	Soybean oil, other than crude, and its fractions, whether or not refined, but not chemically modified, nesi.	1
spinach	Spinach; New Zealand spinach, and orage spinach.	Spinach, New Zealand spinach and orache spinach (garden spinach), fresh or chilled.	1
stonefruits	Fruit, stone nes; other stone fruit not separately identified. For some countries, apricots, cherries, peachers, nectarines, and plums.	Apricots, fresh.	0
strawberry	Strawberries.	Strawberries, otherwise prepared or preserved, nesi.	1
stringbean	String beans.	Beans nesi, fresh or chilled, shelled or unshelled.	1
sugarbeet	Sugar beet.	Sugar beet, fresh, chilled, frozen or dried, whether or not ground.	1
sugarcane	Sugar cane.	Sugar confectionery nesoi, w/o cocoa, dairy products subject to add. US note 1 to chap. 4: subject to add US note 10 to chapter 4.	0
sugarnes	Sugar crops, nes; sugar maple, sweet sorghum, sugar palm and other minor sugar crops of local importance.	Sugar confectionery nesoi, w/o cocoa, dairy products subject to add. US note 1 to chap. 4: subject to add US note 10 to chapter 4.	0
sunflower	Sunflower. Valued mainly for its oil.	Sunflower-seed or safflower oil, crude, and their fractions, whether or not refined, not chemically modified.	1
sweetpotatos	Sweet potatos.	Potatoes, uncooked or cooked by steaming or boiling in water, frozen.	0
tangetc	Tangerines, mandarins, clementines, and satsumas mandarin.	Mandarins (including tangerines and satsumas); clementines, wilkings and similar citrus hybrids, fresh or dried.	1
tobacco	Tobacco, unmanufactured; unmanufactures dry tobacco, including refuse that is not stemmed or stripped, or is partly or wholly stemmed or strippied.	Tobacco, partly or wholly stemmed/stripped, n/threshed or similarly proc., not or n/over 35% wrapper, flue-cured burley etc, not for cigaret.	1

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Crop FAO	Description FAO	HSTS-8 US Tariff Line	Decision
tomato	Tomatoes.	Tomatoes, whole or in pieces, prepared or preserved otherwise than by vinegar or acetic acid.	1
vegetablenes	Vegetables, fresh nes; bamboo shoots, beets/chards, capers, cardoons, celery, chervil, cress, fennel, horseadish, marjoram, sweet, oyster plant, parsley, parsnips, radish, rhubarb, rutabagas/swedes, savory, scorzonera, sorrel, soybean sprouts tarragon, watercress, and other vegetables that are not separately identified because of their minor relevance.	Vegetables, nesoi, fresh or chilled.	1
walnut	Walnuts, with shell.	Walnuts, fresh or dried, shelled.	1
watermelon	Watermelons.	Watermelons, fresh, if entered during the period April 1 through November 30, inclusive.	1
wheat	Wheat.	Wheat or meslin flour.	1

Notes: This table contains the complete set of crops that appear in at least one AGOA-eligible tariff line for the year 2000. Only crops that are listed as the main component of the tariff line are included in our analysis. Column "Crop FAO" lists the crop names as given by FAO. Column "Description FAO" provides FAO's description of each crop. Column "HSTS-8 US Tariff Line" shows the exact name of one tariff line where the FAO crop appears. Column "Decision" takes a value of 1 if we classify the crop as AGOA-eligible. We classify a crop as AGOA-eligible if it is the primary product in at least one tariff line.

C.2 Mining Matching

Minerals	HSTS-8 US Tariff Line	Decision
Bauxite	Aluminum alloys, w/25% or more by weight of silicon, unwrought nesoi	1
Aluminum	Aluminum alloys, w/25% or more by weight of silicon, unwrought nesoi	1
Copper	Copper, containers a kind normally carried on the person, in the pocket or in the handbag	0
Gold	Watch cases of gold- or silver-plated base metal	0
Iron Ore	Iron/nonalloy steel, width 600mm+, flat-rolled products, clad	1
Lead	Iron/nonalloy steel, width 600mm+, flat-rolled products, plated or coated with lead, including terneplate	0
Silver	Silver ores and concentrates	1
Tin	Iron/nonalloy steel, width less th/600mm, flat-rolled products, plated or coated with tin	0
Zinc	Zinc (o/than alloy), unwrought, casting-grade zinc, containing at least 97.5% but less than 99.99% by weight of zinc	1
Cobalt	Cobalt alloy, unwrought	1
Ferromanganese	Ferromanganese containing by weight more than 4 percent of carbon	1
Manganese	Ferromanganese containing by weight more than 4 percent of carbon	1
Niobium	Niobium (columbium), unwrought; niobium, powders	1
Tungsten	Tungsten, unwrought (including bars and rods obtained simply by sintering)	1
Uranium	Alloys, dispersions (including cermets), ceramic products and mixtures containing natural uranium or natural uranium compounds	0
Vanadium	Vanadium (o/than waste & scrap) and articles thereof	1
Zircon	Zirconium, unwrought; zirconium, powders	1
Molybdenum	Molybdenum ores and concentrates, roasted	1

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Minerals	HSTS-8 US Tariff Line	Decision
Ferromolybdenum	Ferromolybdenum	1
Titanium	Titanium, unwrought; titanium, powders	1
Scandium	Rare-earth metals, scandium and yttrium, whether or not intermixed or interalloyed	1
Yttrium	Rare-earth metals, scandium and yttrium, whether or not intermixed or interalloyed	1
Chromium	Ferrochromium containing by weight more than 3 percent but not more than 4 percent of carbon	1
Ferrochrome	Ferrochromium containing by weight more than 3 percent but not more than 4 percent of carbon	1

Notes: This table contains the complete set of minerals from the S&P Metals and Mining dataset that appear in at least one AGOA-eligible tariff line for the year 2000. Only minerals that are listed as the main component of the tariff line are included in our analysis. Column "Minerals" lists the minerals as shown in the Metals & Mining dataset. Column "HSTS-8 US Tariff Line" shows the exact name of an AGOA-eligible tariff line where the mineral appears. Column "Decision" is marked as 1 if we classify the mineral as AGOA-eligible. A mineral is classified as AGOA-eligible if it is the primary product in at least one tariff line.

C.3 Industries Matching

NAICS Code	Industry	Total Tariffs	AGOA Tariffs	Apparel Tariffs	Textiles Tariffs	Decision
1111	Oilseed and Grain Farming	90	18	-	4	No
1112	Vegetable and Melon Farming	113	31	-	4	Agriculture
1113	Fruit and Tree Nut Farming	81	34	-	-	Agriculture
1114	Greenhouse, Nursery, and Floriculture Production	40	8	-	-	No
1119	Other Crop Farming	233	34	-	16	No
1121	Cattle Ranching and Farming	6	1	-	-	No
1123	Poultry and Egg Production	7	6	-	-	Agriculture
1124	Sheep and Goat Farming	12	1	-	5	Apparel/Textile
1125	Aquaculture	252	36	-	18	No
1129	Other Animal Production	26	5	-	3	No
1132	Forest Nurseries and Gathering of Forest Products	30	3	-	-	No
1141	Fishing	98	5	-	-	No
2111	Oil and Gas Extraction	234	16	-	-	No
2122	Metal Ore Mining	26	4	-	-	No
3111	Animal Food Manufacturing	14	8	-	-	Manufacturing
3112	Grain and Oilseed Milling	280	73	-	-	Manufacturing
3113	Sugar and Confectionery Product Manufacturing	235	23	-	-	No
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing	373	117	-	-	Manufacturing
3115	Dairy Product Manufacturing	302	189	-	-	Manufacturing
3116	Animal Slaughtering and Processing	180	79	-	5	Manufacturing
3117	Seafood Product Preparation and Packaging	102	23	-	-	No
3118	Bakeries and Tortilla Manufacturing	127	9	-	-	No
3119	Other Food Manufacturing	353	106	-	-	Manufacturing

(continued on next page)

NAICS Code	Industry	Total Tariffs	AGOA Tariffs	Apparel Tariffs	Textiles Tariffs	Decision
3121	Beverage Manufacturing	64	16	-	-	Manufacturing
3122	Tobacco Manufacturing	19	12	-	-	Manufacturing
3131	Fiber, Yarn, and Thread Mills	236	-	-	208	Apparel/Textile
3132	Fabric Mills	546	-	-	454	Apparel/Textile
3133	Textile and Fabric Finishing and Fabric Coating Mills	282	2	2	180	Apparel/Textile
3141	Textile Furnishings Mills	111	-	-	79	Apparel/Textile
3149	Other Textile Product Mills	957	13	405	182	Apparel/Textile
3151	Apparel Knitting Mills	16	-	2	-	No
3152	Cut and Sew Apparel Manufacturing	671	12	405	29	Apparel/Textile
3159	Apparel Accessories and Other Apparel Manufacturing	199	11	66	19	Apparel/Textile
3161	Leather and Hide Tanning and Finishing	144	12	-	3	No
3162	Footwear Manufacturing	93	80	-	-	Manufacturing
3169	Other Leather and Allied Product Manufacturing	83	32	-	-	Manufacturing
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing	59	1	-	-	No
3219	Other Wood Product Manufacturing	511	31	-	17	No
3221	Pulp, Paper, and Paperboard Mills	118	1	-	-	No
3222	Converted Paper Product Manufacturing	110	5	-	6	No
3231	Printing and Related Support Activities	49	-	4	3	No
3241	Petroleum and Coal Products Manufacturing	304	212	-	-	Manufacturing
3251	Basic Chemical Manufacturing	1292	356	-	-	Manufacturing
3252	Resin, Synthetic Rubber, and Artificial and Synthetic Fibers and Filaments Manufacturing	153	-	-	33	No
3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing	50	4	-	-	No
3254	Pharmaceutical and Medicine Manufacturing	159	33	-	-	No
3255	Paint, Coating, and Adhesive Manufacturing	103	30	-	-	Manufacturing
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing	73	8	-	-	No
3259	Other Chemical Product and Preparation Manufacturing	1257	262	-	3	No
3261	Plastics Product Manufacturing	272	13	-	14	No
3262	Rubber Product Manufacturing	125	12	-	10	No
3271	Clay Product and Refractory Manufacturing	83	12	-	-	No
3272	Glass and Glass Product Manufacturing	153	41	-	-	Manufacturing
3279	Other Nonmetallic Mineral Product Manufacturing	97	2	-	-	No
3311	Iron and Steel Mills and Ferroalloy Manufacturing	319	213	-	-	Manufacturing
3312	Steel Product Manufacturing from Purchased Steel	330	235	-	-	Manufacturing
3313	Alumina and Aluminum Production and Processing	307	23	-	-	No
3314	Nonferrous Metal (except Aluminum) Production and Processing	231	17	-	-	No
3315	Foundries	13	2	-	-	No
3321	Forging and Stamping	49	1	-	-	No
3322	Cutlery and Handtool Manufacturing	388	29	-	3	No
3323	Architectural and Structural Metals Manufacturing	97	2	-	-	No

(continued on next page)

NAICS Code	Industry	Total Tariffs	AGOA Tariffs	Apparel Tariffs	Textiles Tariffs	Decision
3324	Boiler, Tank, and Shipping Container Manufacturing	186	5	-	-	No
3325	Hardware Manufacturing	83	5	-	-	No
3326	Spring and Wire Product Manufacturing	118	42	-	-	Manufacturing
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	74	7	-	-	No
3328	Coating, Engraving, Heat Treating, and Allied Activities	128	4	-	3	No
3329	Other Fabricated Metal Product Manufacturing	404	38	-	3	No
3331	Agriculture, Construction, and Mining Machinery Manufacturing	202	2	-	-	No
3332	Industrial Machinery Manufacturing	546	20	-	14	No
3333	Commercial and Service Industry Machinery Manufacturing	439	2	-	3	No
3334	Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing	496	20	-	15	No
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing	114	3	-	-	No
3339	Other General Purpose Machinery Manufacturing	799	34	-	14	No
3342	Communications Equipment Manufacturing	129	4	-	-	No
3343	Audio and Video Equipment Manufacturing	180	36	-	-	No
3344	Semiconductor and Other Electronic Component Manufacturing	232	25	-	-	No
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	575	139	-	4	No
3351	Electric Lighting Equipment Manufacturing	165	1	-	3	No
3352	Household Appliance Manufacturing	203	1	-	4	No
3353	Electrical Equipment Manufacturing	104	1	-	-	No
3359	Other Electrical Equipment and Component Manufacturing	104	3	-	-	No
3361	Motor Vehicle Manufacturing	27	20	-	-	Manufacturing
3362	Motor Vehicle Body and Trailer Manufacturing	93	23	-	-	No
3363	Motor Vehicle Parts Manufacturing	266	7	5	9	No
3365	Railroad Rolling Stock Manufacturing	96	2	-	-	No
3366	Ship and Boat Building	360	23	-	14	No
3369	Other Transportation Equipment Manufacturing	86	35	-	-	Manufacturing
3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing	448	22	-	17	No
3372	Office Furniture (including Fixtures) Manufacturing	161	14	-	-	No
3379	Other Furniture Related Product Manufacturing	10	2	-	-	No
3391	Medical Equipment and Supplies Manufacturing	334	20	-	14	No
3399	Other Miscellaneous Manufacturing	771	59	11	64	No

Notes: This table provides a list of industries with at least one AGOA-eligible tariffline either in the general or the apparel or textile category. The "NAICS Code" column indicates each industry's classification code, while "Industry" provides the industry description. "Total Tariffs" shows the number of tariffs corresponding to the industry in 2000, and "AGOA Tariffs" indicates the count of AGOA-eligible tariffs within each industry. "Apparel Tariffs" and "Textiles Tariffs" specify the AGOA-eligible tariffs related to apparel and textiles, respectively. The "Decision" column denotes whether an industry qualifies as treated under AGOA, based on a threshold where at least 25% of tariff lines are AGOA-eligible, and categorizes the sector when applicable. Out of 93 total industries, 19 qualify under manufacturing, 8 under apparel or textiles, and 3 under agriculture; 63 industries do not meet the 25% threshold and are excluded from the analysis.