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Who Benefits from Free Trade?

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ABSTRACT

How is wealth distributed when the economy grows? I study this question in the context of African countries and ethnic groups. If wealth is distributed proportional to population, larger ethnic groups should benefit more when economic activity increases. Using nighttime light and individual level data to geographically locate wealth, I find the exact opposite: Smaller ethnic groups, particularly those in political power, benefit more from increased economic activity than larger ones. The results indicate that political elites in power redistribute wealth from larger ethnic groups. As a result, people's satisfaction with democracy and trust in institutions reduces, casting a shadow on the implementation of trade liberalization policies in developing countries. Instrumental variables estimating exploiting exogenous variation in trading activity confirm initial results.

1. Introduction

People engage in economic activity to exchange goods and increase their wealth. It is then a foundation of economics that more exchanged goods in the aggregate also leads to more wealth. But who reaps this wealth? Those who produce and exchange goods, or their ruling elites? In this paper I ask who benefits from the 'gains from trade' and how it affects social cohesion and democratic development.

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

In this paper, I analyze how wealth is distributed by assigning increased economic activity to ethnic groups by their population shares: an equal distribution would imply that larger ethnic groups benefit more than smaller groups when the economy grows. I use data on bilateral trade between African countries and the distribution of ethnic groups prior to colonialization (Murdock, 1959) to assess wealth gains measured by nighttime light data and seven georeferenced surveys from the Afrobarometer project. Controlling for an extensive range of fixed effects, I isolate the impact of increased trade exposure by interacting trade activity with the population shares of each group.

The analysis reveals three insights. First, gains in wealth are not equally shared: Nighttime light data and individual survey data reveal a negative relationship between trade exposure and wealth across the entire African continent. Second, wealth gains accumulate in ethnic groups in political power, providing evidence for elite capture. Third, this undermines the democratic process: Elite capture of wealth has negative consequences for individuals' satisfaction with democracy and trust in institutions. This paper thus yields new insights on the distribution of wealth gains and casts a shadow on trade policies' impact on development.

The analysis unfolds in two parts. First, how are wealth gains distributed, and second, how does this affect social stability. There are two issues related to reversed causality and omitted variable bias that have to be addressed throughout the analysis. First, trade increases wealth, but richer countries also trade more. Second, government policies or infrastructure might influence trade and are often correlated with the ethnic group in power (Burgess et al., 2015). I thus utilize insights from the trade literature's study on the effects of china's accession to the WTO to obtain quasi-exogenous variation. Similar to Autor et al. (2013) I capture each groups' exposure to trade flows by aggregating realized bilateral exports to the country-of-origin level (*shift*) and interact this trade activity with each group's pre-colonial population (*share*). Country-by-year and country-by-ethnicity fixed effects then address these concerns by capturing the average effect of increased

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trade activity and ethnic status in each country, respectively, isolating how increased wealth is distributed among ethnic groups: If wealth gains are distributed proportional to size, this interaction term will equal to zero.

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

The second part of the analysis concerns the impact on social stability. When wealth gains are not equally shared, it might lead to lower trust, social stability, and a deterioration of democratic institutions. Using the Afrobarometer's questions on satisfaction with democracy and trust in institutions, I highlight a significant negative impact on social stability. Similar to Berman et al. (2023), individuals linked to groups in power are aware that their economic and political situation is better and thus identify more with their ethnic group. Elite capture of the gains from trade thus shape the distribution of wealth in Africa today. Relocating factories and economic activity into their own ethnic homelands likely explains the negative impacts on trust institutions and satisfaction with democracy: Being left behind by the elites that govern the country, people lose trust in the democratic process. This paper is thus among the first to causally show that including free trade policies in multilateral agreements might thus add to the growing dissatisfaction with democracy in many developing countries.

I argue that the interaction between trade activity and population share, conditional on country-by-year and country-by-ethnicity fixed effects, identifies how wealth is distributed among ethnic groups in Africa. However, endogeneity concerns regarding the political status of ethnic groups as well as its interaction with trade activity may remain. If the political status of ethnic groups is determined by an endogenous component capturing each group's propensity to rule and a random component determining whether the group actually rules, country-by-ethnicity fixed effects perfectly capture the endogenous component, isolating the variation of the random shock to its political status.

However, if ethnic groups in political power actively pursue policies to increase trade activity because they believe to benefit from it, the interaction of trade activity and ethnic group may still be biased. Then, in order to obtain a causal estimate, either shifts, i.e. trade activity, or shares, i.e. ethnic groups, need to be exogenous (Borusyak et al., 2022). Thus, I propose two entirely different instruments to obtain exogenous variation that shifts trade activity.

The first strategy exploits cross-sectional variation in cross-border networks. I utilize the pre-colonial distribution of ethnic groups in all continental African countries and exploit that colonial powers set country borders irrespective of the underlying ethnic homelands. This creates ethnic networks across country borders that are essentially random, as country borders were drawn in 1884 without taking into consideration that countries could become independent more than 60 years later (Michalopoulos & Papaioannou, 2016). Leveraging the strength of this initial ethnic network across neighboring countries, I obtain a valid instrument that exogenously shifts bilateral exports.

The second strategy is akin to a leave-one-out estimator and is identified from panel variation in economic activity. Each country c's realized trade flows are replaced by the average trade flows from all non-bordering countries to all other non-bordering African countries. This ensures that no characteristic of country c is directly used to predict its trade activity and that all variation comes from the average increase in economic activity of Africa.

Similar to Frankel and Romer (1999), I then aggregate predicted exports between neighboring countries ($\widehat{shift}$) and interact this predicted trade activity with population shares ($share$) to instrument realized trade exposure in the *shift-share* estimation on the distribution of wealth gains. With F-statistics on the first stage of 79 for the cross-border instrument and 13 for the leave-one-out instrument, the resulting point estimates confirm initial results.

These findings contribute to our understanding of Africa's long-run development and the important role its colonial history plays. In related work, Michalopoulos and Papaioannou (2016) show that ethnic groups split across country borders are poorer and lag behind non-split ethnic groups. Split ethnic groups were also less politically centralized in the pre-colonial period, which further emphasizes the fact that they exhibit lower levels of economic development today (Michalopoulos & Papaioannou, 2013). My findings suggest that split ethnic groups with large ethnic networks across borders benefit from increased trade activity, yet these gains disproportionately accumulate with the ethnic groups that hold political power. This is suggestive of a mechanism that aligns with the insights of Dickens (2018), who documents evidence of ethnic favoritism within split groups throughout sub-Saharan Africa. More broadly, evidence of ethnic favoritism in African politics is well documented in the literature (Burgess et al., 2015; Frank & Rainer, 2012; Kramon & Posner, 2016). Overall, my results highlight a novel channel through which patterns of development have persisted throughout the African continent.

I also contribute to the emerging discussion on the distributional effects of trade activity in the presence of ethnic favoritism. While it is clear that liberalizing trade generates winners and losers, identifying them empirically was near impossible. In this paper, I show how to identify winners and losers from aggregate data in developing countries, where firm-level data is non-existent or unreliable, yet identifying them is of paramount importance for social stability. Engel et al. (2021) provides an overview of the distributional effects of trade across regions and demographic groups over time. At the firm level, Baccini et al. (2017) highlight how preferential trade agreements increase trade disproportionately for large firms. This evidence is corroborated in the developing countries setting, where Dhingra and Tenreyro (2020) evaluate agribusinesses providing access to farmers and show that while businesses gained, farmers in villages that produced policy-affected crops saw reductions in consumption. Using the staggered implementation of the Africa Growth and Opportunity Act, Desmet and Gomes (2023) show that trade access increases income in general, but decreases it for remote ethnic groups. In contrast to existing studies focusing on tariff reductions, I provide evidence how trade flows differential affect groups based on their power status within government. Thus, my findings are similar to the political gains of ethnic groups from holding power (Burgess et al., 2015) and add to academic and policy debates on the distributional impacts of trade policies.

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

This paper is structured as follows. Section 2 presents the data and variable definitions used throughout the paper. Section 3 presents the empirical strategy. Section 4 estimates the effect of trade exposure and elite capture on economic and societal development in Africa. Section 5 presents robustness using two instrumental variables strategies. Section 7 concludes.

2. Data

Economic activity. Data on bilateral trade are obtained from UN Comtrade World Bank Integrated Trade Systems from 1990–2020. I use import and export data to maximize coverage of reported trade, acknowledging that the point estimates are likely lower bounds on the true effect of exports between countries.[2] Exports for every country c to every destination d on the African continent are aggregated to the country-by-year level $Export_{c,t} = \sum_{d \in D} Export_{c,d,t}$ and used as *shifters* to the economic activity.

Ethnic population. The ethnic group of each individual or region is derived from the spatial intersection of the map in Murdock (1959) with modern country borders.[3] In total Africa contains 833 ethnic groups in 48 African countries. The population share of ethnicity e in country c is then calculated by aggregating detailed grid-cell population data from the United Nations Environment Program in 1960 to the ethnicity-by-country level. These population shares then act as *shares* to assign economic activities to individuals and groups.

Nighttime lights. Data on economic development is derived from the most recent satellite data on nighttime lights (Visible Infrared Imaging Radiometer Suite, VIIRS) at a resolution of 500 m at the equator (Elvidge et al., 2021). This data is an improvement over the older DMSP-OLS Nighttime Light Series (Elvidge et al., 1997) and the new standard in the literature.[4] Two variables are constructed to measure economic development: $Lit_{e,c,t}$ calculates the fraction of pixels with a luminosity greater than zero for each country-ethnic group observation. $\log(NTL+1)_{e,c,t}$ calculates the logarithm of average luminosity for each country-ethnic group observation.

Household wealth. Information on household wealth is derived from the georeferenced version of the Afrobarometer survey rounds 1–7 (BenYishay et al., 2017). The ethnic group of each individual is determined by the spatial intersection of Murdock (1959) with the individual's location. I follow the procedure in Bühler and Madestam (2023) and create three standardized indexes from a list of questions capturing household wealth, satisfaction democracy, and trust in institutions. Appendix C explains the methodology, shows p-values adjusted for multiple hypothesis testing, and lists all used questions from the latest round.

Ethnic power relations. The political status of every country-ethnic group observation is derived from Wimmer et al. (2009). The georeferenced data is intersected with the country-ethnic group from Murdock (1959) and the spatial location of the individual. In case an exact match cannot be found, I follow a two step procedure: First, I use the closest ethnic group within 250 km in the same country before linking the remaining ethnic groups based on their names and country.[5] $InPower_{e,c,t}$ denotes whether the individual or group belongs to an ethnicity e enjoying a monopoly or dominant status in country c and year t.

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

3. Empirical strategy

I study how wealth is distributed geographically, using nighttime light and individual level data in Africa. The unit of observation is a country-ethnic group that is derived from the intersection of 833 precolonial homelands of ethnic groups (Murdock, 1959) with 53 modern-day country borders. In total, there are 1,383 country-ethnic group observations in each year. Nearly half of all ethnic groups in Africa are split between two or more countries.

The estimation equation is derived from a simple principle: Increased economic activity, proxied by trade activity, should increase wealth of ethnic groups.

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

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

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

Variation in trade exposure. Thus, to estimate ethnic-group level exposure to aggregate trade flows and how wealth is distributed, I estimate the following equation interacting aggregate bilateral exports with population shares for each group:

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

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

Contrary to Eq. (1), where more trade implies larger economic development, the sign of γ is unclear as it captures how trade activity differentially affects ethnic groups. Consider a stylized example of country c having two ethnic groups $e_1 = 30\%$ and $e_2 = 70\%$. If the gains from trading were proportionally shared among all ethnic groups, we would expect that γ is zero as the average (level-) effect is captured by β_1 inside the country-by-year fixed effects. A ten unit increase in

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

[3] The results are robust to using modern day ethnic distributions and ethnolinguistic distribution of ethnic groups in Weidmann et al. (2010).

[4] Results using the older series confirm the main result: Political Elites capture 20%–100% more of the wealth than non-connected groups.

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

Table 1
Trade exposure and wealth gains.
Using nighttime light satellite imagery.

	Fraction lit		Average luminosity	
	(1)	(2)	(3)	(4)
Trade Exposure	−0.008***	−0.009***	−0.029**	−0.024**
	(0.003)	(0.003)	(0.012)	(0.011)
Trade Exposure × In Power		0.010**		0.028*
		(0.004)		(0.016)
Country × year fixed effects	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes
Observations	10,314	8541	10,314	8541
Mean dependent variable	0.033	0.034	0.106	0.116

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

wealth (ΔY_e) is then proportionately shared among all ethnic groups $\Delta Y_1 = 3;\ \Delta Y_2 = 7$.

A positive coefficient would suggest that large ethnic groups capture a disproportionate share of the benefits, redistributing from small ethnic groups to larger ones. Instead of their proportional share from the ten unit increase in wealth, a share γ is redistributed from e_1 to e_2: $\Delta Y_1 = 3 - \gamma;\ \Delta Y_2 = 7 + \gamma$. A negative coefficient suggests the opposite and is indicative of elite capture: The smaller ethnic group e_1 captures a share γ from e_2 and receives a disproportionate amount of the wealth gains $\Delta Y_1 = 3 + \gamma;$.[6]

Appendix A.1 explains in great detail how Eq. (2) can be derived and discusses why the inclusion of $\alpha_{c,e}$ and $\alpha_{c,t}$ capture unobserved selection biases in the original Eq. (1). As *Trade Exposure*$_{e,c,t}$ is now an unbiased estimate of how ethnic groups benefit from economic output, I continue and test the effect of political capture.

Variation in political status. To verify the presence of elite capture, I utilize exogenous variation in each group's political status. Each group's political status depends on both endogenous and random factors: As the endogenous factors can be approximated by each group's historical judicial development, propensity to rule, or economic development today (Michalopoulos & Papaioannou, 2013, 2014), country-by-ethnicity fixed effects isolate random variation in power status. Then, additionally controlling for country-by-year fixed effects isolates the random variation that determines each group's access to power.

I thus interact Eq. (2) with data on political relations and estimate:

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

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

4. Results

How are the wealth gains from increased economic activity distributed in heterogeneous societies? Who captures the gains from trade and how does this affect societal development? I answer these questions using nighttime light satellite imagery (Table 1) and individual survey data in African countries (Table 2).

I begin by using nighttime light satellite imagery as a proxy for wealth in Table 1. Columns (1) and (2) present results on the fraction of pixels lit for each country-ethnic group. The results suggest that a 10% increase in trade results in a 37% decrease in the fraction of pixels lit.[7] If the group is in power, however, the interaction term in column (2) suggest a 15% increase in nighttime luminosity.[8] These results carry over when considering average luminosity in columns (3) and (4).

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

These group-level estimates from nighttime lights carry over to individual estimates using the Afrobarometer Surveys. In Table 2 columns (1) and (2), I construct a standardized measure of relative household wealth and use it to assess how wealth is distributed among ethnic groups. The same picture emerges: A 10% increase in exports decreases household wealth by 10% of a standard deviation for groups not in power, and increases wealth by 4.6% of a standard deviation for groups in power.

As the Afrobarometer is mainly a survey about political values, I construct two indices capturing 'satisfaction with democracy' and 'trust in institutions' from questions listed in Appendix C.[9] I show the average effect of trade exposure on these indices in Table 2, columns (3)-(6). Increasing trade activity reduces ethnic groups' satisfaction with democracy and their trust in institutions effectively undermining state building efforts.

Tables 1 and 2 thus provide evidence that wealth gains are not shared proportional to each ethnic groups' population share. This result cannot be explained by time-varying country factors or time-invariant characteristics of ethnic groups such as population density, pre-colonial distributions, or the ethnic group being split; country × year and ethnic × country fixed effects absorb these confounders completely. These results are also not driven by outliers as dropping countries individually does not alter the estimate significantly (Figure A.1).[10]

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

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

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

[9] These questions set the Afrobarometer apart from the DHS that mainly captures health-related questions. Results on wealth using the DHS are replicated in Section D.

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

Table 2
Trade exposure, wealth, and society: Household wealth from the Afrobarometer.

	Household wealth		Satisfaction with democracy		Trust in institutions	
	(1)	(2)	(3)	(4)	(5)	(6)
Trade Exposure	−0.069***	−0.077**	−0.206***	−0.264***	−0.126**	−0.152***
	(0.025)	(0.034)	(0.057)	(0.060)	(0.049)	(0.052)
Trade Exposure × In Power		0.036***		−0.026		−0.012
		(0.013)		(0.020)		(0.011)
Country × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	218,950	194,775	218,950	194,775	218,950	194,775

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

Table 3
Trade exposure, wealth, and society: Ethnic status and identification.

	Ethnic group's economic condition better	Ethnic group's political condition better	Identify more with ethnicity than nationality	Ethnic group treated more unfairly
	(1)	(2)	(3)	(4)
Trade Exposure	−0.004	0.079	0.047	0.286**
	(0.045)	(0.075)	(0.110)	(0.120)
Trade Exposure × In Power	0.011*	0.640**	0.082*	0.010
	(0.006)	(0.288)	(0.047)	(0.044)
Country × year fixed effects	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Observations	54,852	38,221	111,011	150,826

In this table, I show how trade exposure impacts the perceived status of ethnic groups as measured by the Afrobarometer *Trade Exposure* is defined by realized trade flows to all African countries aggregated to the country-by-year level interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$. *Country × year fixed effects* account for unobserved characteristics varying at the country and year level, including total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Individual controls* are a full set of age, gender, education, and urban dummies. Questions are detailed in the Appendix. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4
Trade exposure, wealth, and society: Heterogeneity analysis.

	Fraction lit					
	Log distance to ethnic group in power		Log distance to capital cities		Historical trade exposure	
	(1)	(2)	(3)	(4)	(5)	(6)
Trade Exposure	−0.001	−0.001	0.007	−0.019	−0.007**	−0.007***
	(0.003)	(0.002)	(0.054)	(0.059)	(0.003)	(0.003)
Trade × Heterogeneity	−0.002**	−0.002**	−0.002	0.001	0.011	0.014*
	(0.001)	(0.001)	(0.007)	(0.007)	(0.007)	(0.008)
Trade Exposure × In Power		0.009*		0.010*		0.011***
		(0.005)		(0.005)		(0.004)
Country × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,314	8541	10,314	8541	9135	7740

In this table, I analyze the heterogeneities that determine how trade exposure impacts nighttime luminosity. *Trade Exposure* is defined by realized trade flows to all African countries aggregated to the country-by-year level interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$. *Trade × Heterogeneity* interacts aggregate trade $\sum_{d \in D} Export_{c,d,t}$ with the heterogeneity as denoted in the columns: Log distance to the ethnic group in power (political center), log distance to capital cities (economic center), and historical trade exposure as in Dickens (2022). *Country × year fixed effects* account for unobserved characteristics varying at the country and year level, including total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

If my argument is correct, that is, that trade benefits members of the ethnic group in power, we can also study whether their members are aware of this fact. In the first two columns of Table 3, I test whether ethnic groups that are in power realize that their economic and political condition is better than the condition of other groups. Indeed, a significant impact suggests that increasing trade exposure solidifies the view that political elites are benefiting economically and politically. Similar to Berman et al. (2023), this also implies that individuals identify more strongly with their ethnic group rather than their nationality (column 3). Interestingly, members of the ethnic groups not in power are aware of this and state that their ethnic group is treated more unfairly (column 4).

4.1. Mechanism

Next, I want to discuss both the why some groups benefit from free trade as well as how. In doing so, I show how regional spillovers determine where the gains from trade land and that the effects are most likely driven by a relocation of movable production, i.e. manufacturing, into the ethnic homelands of elites.

Why do some ethnic groups benefit from trade, while others loose? I hypothesize that the distribution of wealth is located in the home regions of ethnic groups and only spills over to adjacent regions, as well as that groups with historical exposure to trade benefit more. I begin by studying whether the ethnic groups that are geographically closer to either the ethnic group in power or the capital city are benefiting differentially from trade. Table 4 studies these regional spillover of wealth in columns (1)-(4). Column (2) shows ethnic groups that are not in power and are geographically further away from the political center are benefiting ever less from trade. Column (4) shows that this is not the case for capital cities. These results thus suggest that the political *de-facto* center of power matters for wealth distribution, not the *de-jure* capital. Ethnic groups in power redistribute to their own benefit, and the further away a competing group is, less it benefits from trade.

The second heterogeneity pertains to historical trade exposure. Dickens (2022) shows that a change in land productivity variation is a suitable proxy for changes in inter-ethnic trade in the pre-colonial era. Dickens goes on to show that, at the onset of the Columbian Exchange, an increase in land productivity variation increased an ethnic group's reliance on trade during the colonial period. Thus, using Galor and Özak (2016) Caloric Suitability raster I calculate the change in land productivity as a proxy measure of historical trade exposure. Indeed, Column (6) of Table 4 shows that ethnic groups with historical exposure to trade, actually benefit from contemporaneous trade exposure.

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

Both mechanisms predict that exposure to manufacturing exports has worse impacts on economic development than agriculture or resource exports. Whereas resources and agricultural fields are immutably fixed in space, factories can be relocated. Table A.1 provides suggestive evidence in favor of such relocation as exposure to manufacturing exports significantly reduces nighttime luminosity, and thus wealth.

These findings do not stand in contrast to Kasara (2007), who finds that governments discriminate against their own ethnic group as ethnically connected farmers face raising agricultural taxes. First, I estimate the impact of additional trade exposure, rather than additional taxes on domestic producers. Whereas Kasara identifies the impact of connectedness on individual farmers, I aim to estimate the impact of connectedness on the entire ethnic group. Thus, the results suggest that even if domestic producers are discriminated against by their own co-ethnic government, their ethnic group still benefits *on average*. Second, the value of agricultural exports only represents 21% of the total export value between countries. Estimating the impact of manufacturing exports (42%) on connected ethnic groups in power yields remarkable similar point estimates (Table A.2); suggesting that the effects are not driven by any particular type of export.

Third, and most strikingly, Table 3 reports that people report their own group is economically and politically better off than competing groups if they are in power. In line with Berman et al. (2023), people are also identifying more with their own ethnic group. It is thus quite likely that the picture is more nuanced. Even if certain producers do not benefit from being connected to the ruling elites (Kasara, 2007), society as a whole – if connected – benefits (Burgess et al., 2015).

5. Robustness

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

In order to assess the severity of this bias and validate my findings I propose two instrumental variables strategies: The first instruments shifts the size of cross-border ethnic networks to predict increased trade volumes between neighbors. This *Cross-Border* instrument exploits cross-sectional variation in the precolonial distribution of ethnic groups between neighboring countries. The second instrument uses non-neighboring countries' exports to other African countries to predict a country's exports. This *Leave-One-Out* instrument exploits panel variation in the average trade activity of non-neighboring countries. Thus, both instruments exploit different sources of variations to predict shifts in trade activity.

5.1. Cross-border instrument

I begin by developing a gravity-type equation that incorporates heterogeneous ethnic groups across multiple country pairs. Then, I exploit the quasi-exogenous placement of borders to obtain exogenous variation in pre-colonial population shares in each exporting country. I then use each ethnic groups' connections to the importing country to exogenously shift trade activity.

A stylized model of trade. In the trade literature, the value of bilateral exports is modeled in gravity-type equations (Anderson, 1979). Here, the value of trade is correlated with the size of the exporter and importer economy and the geographic distance between them, as larger and more geographically close economies trade more. In this framework, the addition of a population share of people from country of origin c in destination country d ($PS(c)_{d,t}$) identifies the strength of cross-country networks:

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

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

Implicitly, Eq. (3) assumes that migrants to destination d identify with the nationality of their country of origin c.[11] African countries

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

however, combine a multitude of ethnic groups, each with their own identity. Allowing for multiple ethnic groups (e) from the set of ethnic groups in each country ($e \in E_c \cap E_d$), the general form of Eq. (3) is given by:

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

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

The formulation of Eq. (4) is supported by three observations. First, it is the empirical equivalent of an otherwise standard model of international trade (Chaney, 2008; Melitz, 2003) that adds an ethnicity-specific fixed cost capturing lower entry costs into an export market for ethnically connected firms.[12]

Second, the interpretation is equivalent to the search and matching literature where a match is defined when two individuals of the same characteristics are drawn. Since these characteristics are stochastic, the likelihood of a match is given in probabilities. Here, characteristics are distributed along ethnic lines and thus the fraction of the population representing an ethnicity in the importing country is equivalent to the likelihood that an exporting firm from the exporting country finds a match in the importing country. Then, the estimated β can be interpreted as an elasticity that captures the change in match probability of each ethnicity when its population changes on either side of the border.[13] This interpretation is similar to the standard in Eq. (3); both can be interpreted as a probability of drawing two connected people in each country. Eq. (4), however, incorporates the heterogeneous population structures in African countries and allows for a large amount of subgroups within two countries that are connected.

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

Identification assumption. I obtain exogenous variation in the population shares determining the ethnic connections $\sum_{e \in E_c \cap E_d} PS_{c,t,e} \times PS_{d,t,e}$ across two countries from the exogenous placement of country borders at the 1884 Berlin conference regulating European colonization in Africa. By the stroke of a pen in Berlin, members of the same ethnic group were placed in different countries. As every different stroke would have resulted in a different composition of ethnic groups in countries c and d, their population shares are essentially random; and so is the cross-country network that I use to shift trade activity.

The construction of the instrument for Zambia is shown as an example in Fig. 1. To validate this instrument, I argue that (i) the local dispersion of ethnic groups and (ii) the borders between African countries are placed without the intention to increase trade, migration, or economic activity in modern times.

First, to address endogenous sorting, I obtain exogenous variation in ethnic connections from the precolonial distribution of 833 ethnic groups (Murdock, 1959). I combine the geographic location of each group with grid-cell population data in 1960 to obtain population estimates of ethnic enclaves and their home population at the time of independence. In contrast to modern population figures, my measure of ethnic connectedness is unaffected by migration, catastrophes, hunger, or civil conflict dispersing people across Africa since independence.[14] Similar to the existing literature (McKenzie & Rapoport, 2007; Munshi, 2003), this strategy solves the reverse causality problem if populations were randomly placed in countries.

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

I argue that these borders were arbitrarily drawn and do not reflect the interests of ethnic groups; to the contrary, they divide them into more than one country. The only determinant of an ethnic group being divided across two counties is its geographical size (Michalopoulos & Papaioannou, 2013, 2016).[15] To address remaining endogeneity concerns, I only use borders where ethnic groups have been split when estimating the impact of ethnic networks on trade flows. I thus abstract from comparing influential with negligible ethnic groups and use a balanced sample across similar ethnic groups.

5.2. Leave-One-Out instrument

The second instrument exploits time variation in Africa's trading activity instead of cross-border networks to predict trade flows. Yet, these cross-border networks also motivate a modification to the standard *Leave-One-Out* methodology to completely isolate time variation from cross-sectional variation.

The standard *Leave-One-Out* estimator uses neighboring observations to predict the value of the endogenous variable in a cross-sectional setting. The idea being that geographically neighboring observations are subject to the same cross-sectional shocks, without an endoge-

[12] These costs can be lower information costs, more reliable information about market structures or bribes, and fewer cases of fraud between business partners. In Appendix E, I follow Bühler (2018) and show that Eq. (4) follows if firms face a fixed cost of exporting $PS_{c,e}^{-\eta} f_{cd}$ with $\eta \in [0,1)$ providing concavity for the impact of fixed costs f_{cd} on the exporting firms' profits. These fixed costs represent costs of setting up a distribution network, informing about markets, administration and paying for permits. A similar model has been suggested by Krautheim (2012) and it nests the established (Chaney, 2008) model with $\eta = 0$.

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

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

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

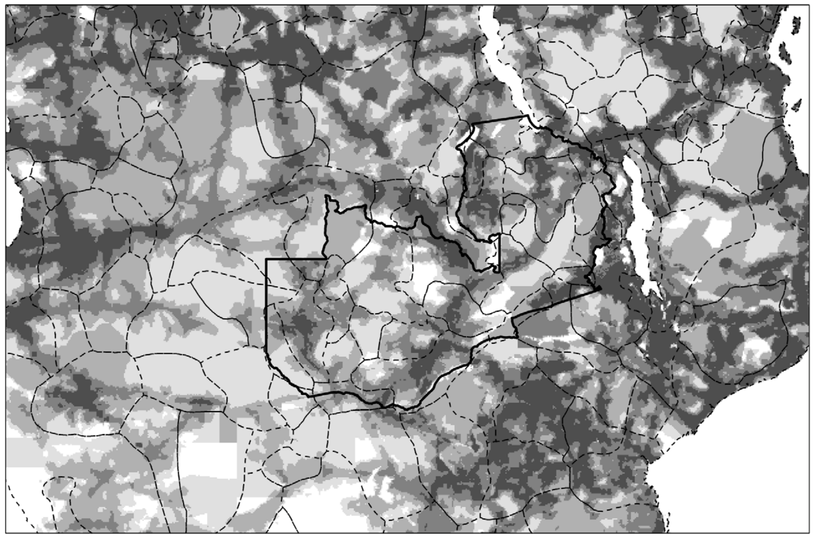

Fig. 1. Construction of the *Cross-Border* instrument.
Notes: Using Zambia (solid line), this map exemplifies the construction of the *Cross-Border* instrument. Ethnic groups, as defined by Murdock (1959) span multiple countries (dashed line). Population figures are shown as the shaded background with darker colors representing denser population. The ethnic network is defined as the population share of ethnic group *e* in Zambia multiplied with its population share outside Angola (to the West of Zambia). The *Cross-Border* instrument is then the sum of all ethnic networks between Zambia and Angola. This instrument is valid as no single country border follows an ethnic border and some borders are straight lines. Then, as country borders determine population shares, which in turn define the strength of the instrument, the instrument is exogenous from the individual's perspective.

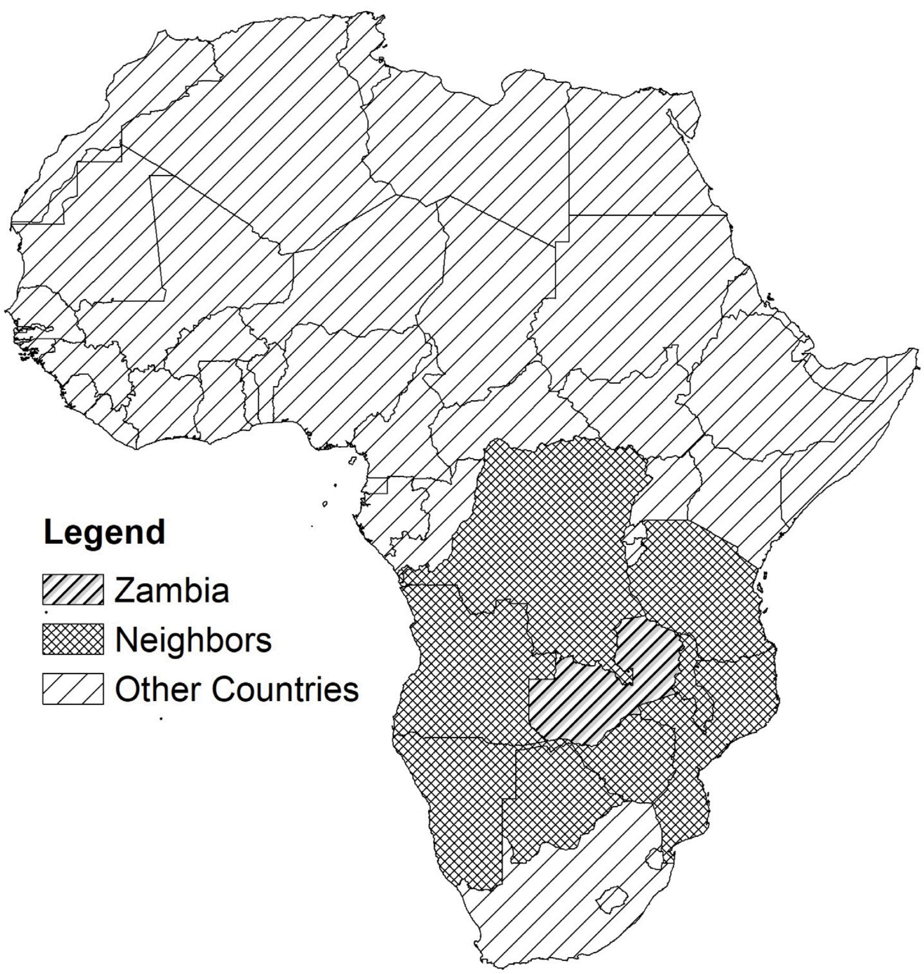

Fig. 2. Construction of the *Leave-One-Out* instrument.
Notes: Using Zambia, this map exemplifies the construction of the *Leave-One-Out* instrument. Zambia's exports to all countries are replaced by the average bilateral exports of all "Other countries" to all "Other countries". In the data, this means that instead of the possible 2,256 trade observations (48 × 47), only 1854 are used on average. Due to cross-border networks, "Neighbors" are excluded from this to isolate variation that is entirely driven by increasing trade activity in Africa.

nous component that determines the strength of this shock. As the *Cross-Border* instrument already exploits this cross-sectional variation, I adjust the *Leave-One-Out* instrument to completely abstract from cross-sectional variation and isolate time-varying trends.

Instead of using the exports of neighboring country d' to predict exports of country c, I treat all neighboring countries of c as a unit ($D'(c) \subset D | d' \in D'(c)$: is neighbor of c). I then use the exports of all non-neighboring countries' $d \notin D'(c)$ to other countries $d \notin D'(c)$ to predict each country's trade activity. Fig. 2 highlights the construction of this instrument using the example of Zambia, its neighboring countries, and all other African countries.

This procedure has several advantages. First, it prevents a SUTVA-type violation of the exclusion restriction: If trade activity is redirected towards more connected countries, it is likely that neighboring countries' exports are at least partially redirected from non-neighboring country d to country c. Thus, while using neighboring countries' exports generate a stronger instrument, it is likely that part of the strength arises from a correlation to unobserved networks between the two countries. For a violation of the exclusion restriction, a possible trade-diversion effect would imply that the exports of country d'' are affected by the exports of country d' which is a neighbor of c. Such a second-order violation is unlikely.

Second, this modified *Leave-One-Out* instrument exploits time variation in trading activity, rather than cross-sectional shifts. This is confirmed by the low correlation between the instruments (F-test: 2.55). Thus, finding similar point estimates when using either instrument supports the overall finding of the paper, as it is unlikely that violations of the exclusion restriction or the exogeneity assumption affect both instruments to the same extent.

Third, the variation exploited for the *Leave-One-Out* instrument lends itself to an easier interpretation. As I exploit time variation in trading activity of the African continent, the interpretation is the same as in the OLS: how does increased trade activity affect wealth and who benefits?

5.3. First-stage results

I now use both the *Cross-Border* and *Leave-One-Out* instrument to predict aggregate trade activity of country c in period t.

$$\log Export_{c,t} = \delta \log \sum_{d' \in D'} \widehat{Export}_{c,d',t} + \alpha_c + \alpha_t + \varepsilon_c \qquad \text{(Cross-Border)}$$

$$\log Export_{c,t} = \delta \log \sum_{d \in D} \overline{Export}_{c,d,t} + \alpha_c + \alpha_t + \varepsilon_c \qquad \text{(Leave-One-Out)}$$

To obtain a valid first-stage F-statistic that is not inflated by multiple observations in each country and year, I begin by estimating the first stage at the country by year level predicting realized trade activity $Export_{c,t} = \sum_{d \in D} Export_{c,d,t}$. For the *Cross-Border* instrument, I obtain predicted values of bilateral trade flows $\widehat{Export}_{c,d',t}$ from the dyadic regression in Eq. (4) using ethnic connections with neighboring countries d' to shift trade activity.[16] For *Leave-One-Out* instrument I obtain average values of bilateral trade flows $\overline{Export}_{c,d,t}$ from the average export flows of all non-neighboring countries to all other non-neighboring countries excluding c. Both instruments are then aggregated to the country-by-year level and regressed against the realized trade activity $Export_{c,t}$, controlling for country and year fixed effects.

Fig. 3 plots the strength of the *Cross-Border* instrument (left) and *Leave-One-Out* instrument (right). A one percent increase in predicted trade activity increases actual trade activity by 0.388 percent in the left panel and 0.856 in the right panel. The difference suggests that time variation, and thus economic growth in Africa, is an important explanatory factor of trading activity for each country. Yet, the F-statistics also show that cross-border connections strongly predict export activity. The 1-percentile bins are closely centered around the predicted values with an F-statistic of 79.85 in the left figure, but more widely dispersed in the right (F-statistic 13.86).

Thus, Fig. 3 reveal two instruments with strong F-statistics above 10 that are uncorrelated with each other (F-statistic 2.55) and exploit different variations. While cross-border networks, and thus cross-sectional shifts, are a strong predictor of the level of trading activity (left Figure), the leave-one-out estimation reveals that trends in economic activity unrelated to ethnic connections predict trends in trading activity.

5.4. Second-stage results

In the second stage, I predict realized trade activity with predicted trade activity, controlling for country-by-year and country-by-ethnicity fixed effects:

$$Y_{e,c,t} = \beta \widehat{Export}_{c,t} \times Population\ Share_{e,c} + \alpha_{c,t} + \alpha_{c,e} + \varepsilon_{c,e,t}$$

I remain agnostic and cluster standard errors at the same level at the country-by-ethnic group level as bootstrapped standard errors are almost identical (Appendix Table B.8).[17]

In Table 5, I present the results on nighttime luminosity. Columns (1) and (2) replicate earlier findings from Table 1 and serve as a benchmark for IV estimates in the remaining columns. Using the cross-border instrument, the estimated size is within one standard error of the original OLS estimate and thus not statistically different (column 3). Using the leave on out instrument, I obtain slightly larger point estimates in absolute terms. Both estimates, however, confirm the initial result: People do not benefit equally from increased trade activity.

The reduced form estimates in columns (4) and (6) then interact predicted trade exposure with the political power status of the ethnic group. The results are indistinguishable from the OLS suggesting that wealth gains are redistributed from larger ethnic groups to smaller ethnic groups that are in political power.

In Table 6, I present the results on household wealth (Panel A), satisfaction with democracy (Panel B), and trust in institutions (Panel C). Again, the results on reported household wealth mirror the results on nighttime light luminosity: wealth gains are redistributed towards politically powerful groups. People exposed to more trading activity also report less satisfaction with democracy and less trust in institution, regardless of specification or instrument.

6. Conclusion

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

[16] The regressions and procedures are outlined in Appendix B.

[17] As I use predicted values in the interaction term, the standard errors should be corrected for loosing a degree of freedom. However, to ensure comparability with the OLS results, I report standard errors clustered by country and ethnicity.

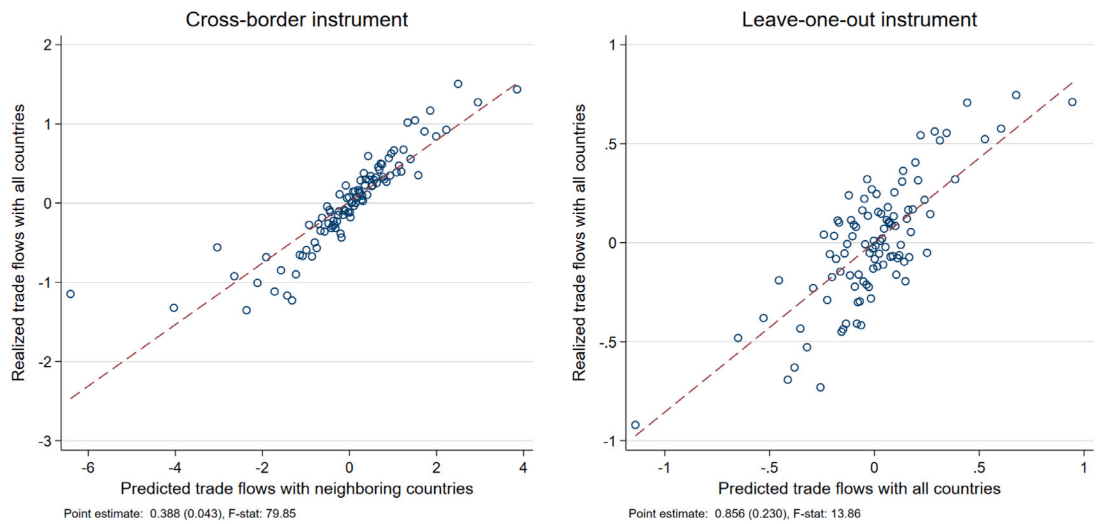

Fig. 3. First stage relationship of the instruments.
Notes: This figure plots the correlation between aggregated predicted and realized trade flows using the cross-border instrument (left) and the Leave-one-out instrument (right). Both plots show residualized values, controlling for country and year fixed effects. The linear fit is shown with the dashed line in each panel and its slope and F-statistic noted below. Both instruments are only weakly correlated (0.026, s.e.: 0.016) indicating that the exploited variation is different: The cross-border instrument (left) exploits cross-sectional variation between neighboring countries; the Leave-on-out instrument (right) exploits time variation in economic activity of non-neighboring countries.

Table 5
Trade exposure and wealth gains.
IV results.

	OLS		Cross-Border		Leave-One-Out	
	(1) OLS	(2) OLS	(3) IV	(4) RF	(5) IV	(6) RF
Panel A: Fraction of pixel lit						
Trade Exposure	−0.008***	−0.009***	−0.012***		−0.034***	
	(0.003)	(0.003)	(0.004)		(0.013)	
Trade Exposure × In Power		0.010**				
		(0.004)				
Predicted Trade Exposure				−0.008***		−0.042***
				(0.002)		(0.011)
Predicted Trade Exposure × In Power				0.007*		0.011***
				(0.004)		(0.003)
Panel B: Average nighttime luminosity						
Trade Exposure	−0.029**	−0.024**	−0.028**		−0.088*	
	(0.012)	(0.011)	(0.012)		(0.048)	
Trade Exposure × In Power		0.028*				
		(0.016)				
Predicted Trade Exposure				−0.019**		−0.078*
				(0.008)		(0.042)
Predicted Trade Exposure × In Power				0.025		0.035***
				(0.015)		(0.013)
Country × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Reduced form				Yes		Yes
Observations	10,314	8559	10,128	8398	10,314	8559
First Stage F-Test			29.452		17.831	

In this table, I show how trade exposure impacts the distribution of wealth as measured by nighttime luminosity. *Trade Exposure* is defined as realized trade flows to all African countries aggregated to the country-by-year level and interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$. In columns (3) and (5) it is instrumented by *Predicted Trade Exposure* using either the Border instrument or the Leave-One-Out instrument. *Fraction Lit* is calculated as the fraction of pixels not zero, *Average nighttime luminosity* as the log of average luminosity in each country-ethnic group observation plus one. *Country × year fixed effects* account for unobserved characteristics varying at the country and year level, including total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. The first stage F statistic is given in the last row. Corrected F-Statistics at the country-year level presented in Fig. 3. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6
Trade exposure and society.
Democracy, trust, and conflict.

	OLS		Cross-Border		Leave-One-Out	
	(1) OLS	(2) OLS	(3) IV	(4) RF	(5) IV	(6) RF
Panel A: Household Wealth						
Trade Exposure	−0.069***	−0.077**	−0.104**		−0.062	
	(0.025)	(0.034)	(0.042)		(0.043)	
Trade Exposure × In Power		0.036***				
		(0.013)				
Predicted Trade Exposure				−0.077**		−0.056
				(0.031)		(0.046)
Predicted Trade Exposure × In Power				0.039***		0.035**
				(0.013)		(0.014)
Panel B: Satisfaction with Democracy						
Trade Exposure	−0.206***	−0.264***	−0.330***		−0.278***	
	(0.057)	(0.060)	(0.072)		(0.068)	
Trade Exposure × In Power		−0.026				
		(0.020)				
Predicted Trade Exposure				−0.247***		−0.303***
				(0.055)		(0.079)
Predicted Trade Exposure × In Power				−0.020		−0.033
				(0.021)		(0.021)
Panel C: Trust in Institutions						
Trade Exposure	−0.126**	−0.152***	−0.187***		−0.137***	
	(0.049)	(0.052)	(0.061)		(0.049)	
Trade Exposure × In Power		−0.012				
		(0.011)				
Predicted Trade Exposure				−0.140***		−0.148***
				(0.046)		(0.055)
Predicted Trade Exposure × In Power				−0.008		−0.013
				(0.011)		(0.012)
Country × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × ethnicity fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Reduced form				Yes		Yes
Observations	218,950	194,775	193,671	193,671	194,775	194,775
First Stage F-Test			1395.224		271.850	

In this table, I show how trade exposure impacts household wealth as measured by the Afrobarometer. *Trade Exposure* is defined by realized trade flows to all African countries aggregated to the country-by-year level interacted with the population share of ethnicity e: $\sum_{d \in D} Export_{c,d,t} \times PopulationShare_{e,c}$. *Country × year fixed effects* account for unobserved characteristics varying at the country and year level, including total trade flows, GDP, and population. *Country × ethnicity fixed effects* for the size and impact of ethnicity e in country c. *Individual controls* are a full set of age, gender, education, and urban dummies. In columns (3) and (5) it is instrumented by *Predicted Trade Exposure* using either the Border instrument or the Leave-One-Out instrument. *Household wealth*, *Satisfaction with Democracy*, and *Trust in Institutions* represent standardized indexes constructed from variables asked in 7 rounds of the Afrobarometer. Details in the Appendix. The first stage F statistic is given in the last row. Corrected F-Statistics at the country-year level presented in Fig. 3. Significance denoted by standard errors clustered by country and ethnicity: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

CRediT authorship contribution statement

Mathias Bühler: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

I declare that I have no conflicts of interest to declare.

Data availability

Code to replicate all results included. Data to replicate all results except Afrobarometer included. Georeferenced Afrobarometer data is restricted but available at http://geo.aiddata.org.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.worlddev.2024.106622.

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