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ABSTRACT

RESOLVING THE PUZZLE OF "REVERSED FAVORITISM" IN AFRICAN AGRICULTURE

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The political economy literature highlights the redistribution of resources to political support groups - often along *regional* or *ethnic* lines - as an axiom of political systems. In contrast to this dominant pattern, Kasara (2007) documents a puzzling result of discriminatory rent extraction by political leaders from farmers in their ethnic home region. Linking a new database on the *ethnic* and *regional* affiliation of political leaders to fine-grained survey data, I disentangle ethnic and regional affiliations and show that their intersection explains the phenomenon which I will label in the following "reversed favoritism." More specifically, I provide evidence that agricultural price hikes indeed do *not* reduce poverty among co-ethnic farmers in the leader's birth region. My results indicate that leaders seem to act politically rational as they only apply this treatment in regions where they enjoy high trust. I show in an exploratory analysis that the counter-intuitive support of discriminatory policies can be explained by transfers in other areas, namely development aid.

Keywords: Political Economy, Favoritism, Ethnicity, African Agriculture, Development Aid

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Resolving the puzzle of "reversed favoritism" in African agriculture

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Abstract

The political economy literature highlights the redistribution of resources to political support groups – often along *regional* or *ethnic* lines – as an axiom of political systems. In contrast to this dominant pattern, Kasara (2007) documents a puzzling result of discriminatory rent extraction by political leaders from farmers in their ethnic home region. Linking a new database on the ethnic and regional affiliation of political leaders to fine-grained survey data, I disentangle *ethnic* and *regional* affiliations and show that their intersection explains the phenomenon which I will label in the following "reversed favoritism." More specifically, I provide evidence that agricultural price hikes indeed do *not* reduce poverty among co-ethnic farmers in the leader's birth region. My results indicate that leaders seem to act politically rational as they only apply this treatment in regions where they enjoy high trust. I show in an exploratory analysis that the counter-intuitive support of discriminatory policies can be explained by transfers in other areas, namely development aid.

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1 Introduction

For a long time, the political economy literature has considered redistributive politics as a powerful means to ensure political support (Dixit and Londregan, 1996; Bueno De Mesquita, 2005). Several studies provide empirical evidence that politicians garner political support by allocating resources to regional (Hodler and Raschky, 2014; Burgess et al., 2015; Widmer and Zurlinden, 2022; Bommer et al., 2022) and ethnic support groups (Franck and Rainer, 2012). The redistribution along political fault lines – often labeled as favoritism – would, thus, be a global "axiom of politics" (De Luca et al., 2018). Recent research shows that redistribution is both organized along *ethnic* and *regional* lines. Hodler and Raschky (2014) provide evidence that the birth *region* of the standing chief executive of a country has a higher night light luminosity, indicating that in these areas there is stronger economic activity. Using data from the Demographic and Health Surveys (DHS), Franck and Rainer (2012) show that favoritism translates in to better health and education outcomes for co-*ethnics* of chief executives. Those patronage networks can involve several ethnicities that are part of a larger coalition, where still the chief executive has a primary role (Arriola, 2009; Francois et al., 2015; Dickens, 2018). However, the African farming sector offers a puzzling anomaly in this literature, which is supported both by qualitative and quantitative evidence.

For example, Kanyinga (1994) indicates that Kenya's first president Kenyatta, extracted resources from his home region Gatundu, which was relatively underdeveloped compared to other regions in the country. Kasara (2007) supports this evidence for a broader cross-country sample and demonstrates that crops that are grown in the ethnographic home region of the leader are taxed discriminatorily. Or, in other words, farmers from the home region of the head of state receive lower farm gate prices than non-affiliated farmers. However, this finding is contrasted by cross-country evidence by Bates and Block (2009, 2010), who document a positive bias towards farmers from the leader's regional support group. This constitutes a contradiction in the literature.

My paper aims to resolve this contradiction by considering the previously overlooked interaction between ethnic and regional affiliation. I link high-resolution geolocated survey data on poverty for 30 African countries (Afrobarometer, 2018) and remote sensing data on expected agricultural price hikes (Monfreda et al., 2008; IMF, 2018; World Bank, 2018) recently developed, comprehensive data detailing the regional and ethnic affiliations of political leaders (Bomprezzi et al., 2024).

I find that neither ethnic nor regional affiliation affects farmers' poverty when considered separately. However, their intersection reveals a "reversed favoritism": farmers who share both the leader's ethnicity and reside in their birth region experience discriminatory treatment. This distinction between ethnic and regional favoritism thus helps resolve the puzzle of reversed favoritism in African agriculture. Still, why would leaders disadvantage their core supporters? One explanation is that farmers may prefer a co-ethnic leader, even if non-benevolent, to an outsider (Padró i Miquel, 2007). Second, leaders may compensate for the unfavorable treatment in agricultural prices with transfers in other fields, where, however, so far, a lack of information on "missing transfers" constrained analyses (Kasara, 2007).

This paper advances the ambiguity in the literature by testing for those underlying channels based on Afrobarometer survey data on farmers' perceptions. More specifically, I show that "reversed favoritism" manifests only among farmers with double ethnic and regional affiliation who support the leader. In contrast, affiliated farmers who do not express support for the leader are not affected by this discriminatory price treatment. On the first look, discriminating supporters seems at odds with reciprocity concerns and social contract theory (Besley, 2020). However, other transfers may compensate for the discriminatory treatment with respect to agricultural prices. For instance, anecdotal evidence suggests that Malawi's former president Bingu wa Mutharika targeted a large-scale maize subsidy program towards his ethnicity (Abman and Carney, 2020) and later also received support from international donors for those policies. Based on geolocated information on World Bank (AidData, 2017) and Chinese (Strange et al., 2017; Dreher et al., 2019) development aid projects, I address the issue of "missing transfers" and show that development aid compensates co-ethnic farmers in the leader's birth region. Thus, my results lend support to the hypothesis that "reversed favoritism" is following political rationales.

Based on these findings, this paper contributes to the broader literature on favoritism in three ways. First, results suggest that a careful consideration of the intersection of different types of favoritism can help to create valuable insights into the underlying mechanisms. Second, the article highlights that favoritism needs to be examined across policy areas to gain a more comprehensive picture (Kramon and Posner, 2013). Third, it lends further support to the literature on the politicization of development aid allocation, supporting worries about aid effectiveness (Dreher et al., 2018). The following section introduces the underlying data as well as the empirical approach, while Section 3 presents results. Section 4 discusses the findings and concludes.

2 Data and Empirical Strategy

2.1 Dependent Variable – Multidimensional Poverty Index

Following the capabilities approach of Sen (1993) and its empirical application (e.g., Klasen, 2000), I consider different dimensions of well-being to construct a poverty index along the lines of McGuirk and Burke (2020). More specifically, I construct an index based on the five items in the Afrobarometer which refer to poverty.[1] The survey questions read "Over the past year, how often, if ever, have you or your family gone without: food to eat/clean water for home use/medicines or medical treatment/fuel to cook/cash income." These items are listed on a 1 ("never") to 5 ("always") scale and are aggre-

[1]Afrobarometer is particularly suitable as it offers above the ethnic identifiers also information on agricultural employment and material deprivation.

gated into an unweighted poverty index.[2] Focusing on Afrobarometer rounds 3, 6, and 7, which contain both information on agricultural employment and ethnic affiliation, I am left with around 17,500 observations from 67 surveys conducted in 30 countries and 419 subnational regions. Afrobarometer samples data randomly but does not provide a panel structure of respondents. Thus, the study relies on repeated cross-sections with gaps.[3]

2.2 Agricultural Price Treatment

I rely on a proxy variable for agricultural producer prices for the main treatment on farmers' potential gains. The reason for using a proxy is twofold: First, regional price measures are usually not available for a larger panel of countries. Second, regional price measures could be potentially affected by political affiliation and local poverty and, thus, would be endogenous. The proxy variable follows the basic idea that global commodity prices affect regions more strongly that are particularly suitable to grow those crops (Berman and Couttenier, 2015; McGuirk and Burke, 2020). More specifically, I employ data on commodity prices of five main cash crops cocoa, coffee, cotton, tea, and tobacco (World Bank, 2018; IMF, 2018).[4] The information is then matched with an agricultural market exposure measure, where I rely on crops' regional share of the harvested area from Monfreda et al. (2008), who combine information from national censuses as well as UN agencies. This localized producer price index (PPI) can be summarized as:

$$PPI_{crt} = \sum_{j=1}^{n} P_{jt} \times S_{cjr}, \tag{1}$$

[2]Nightlight luminosity, Demographic and Health Surveys, or Living Standard Measurement Surveys would be alternative data sources to assess poverty on the subnational level. While I prefer Afrobarometer data due to its more comprehensive information on ethnicity and employment, I show that indicators are meaningfully correlated in the appendix.

[3]I provide descriptive statistics for the full set of survey respondents in Appendix Table B.3. As Afrobarometer surveys are not necessarily representative at the regional level, I truncate the sample at the 10% level of regions with the lowest number of observations.

[4]I chose these particular crops as they are among the most important African export commodities and play a smaller role for domestic consumption (Akiyama and Larson, 1994).

where P_{jt} is the price of good j in period t, which is indexed for each product at 100 for the first Afrobarometer period (July to December 1999).[5] S_{cjr} are local production capacities to grow commodity j in the respective country-region cr. In order to reduce concerns that contemporary production capacities are endogeneous to poverty, I use initial production capacity from the year 2000. The global price of each commodity is then interacted with those local capacities. As the temporal variation comes from global commodity prices, the changes are arguably exogenous concerning local conditions in subnational localities, especially, when conditioning the econometric analysis on a rich set of fixed effects. The intuition of expected price shocks is similar to the reduced form of a shift-share instrument (Bartik, 1991) as increasingly used in the literature (Colantone and Stanig, 2018a,b).

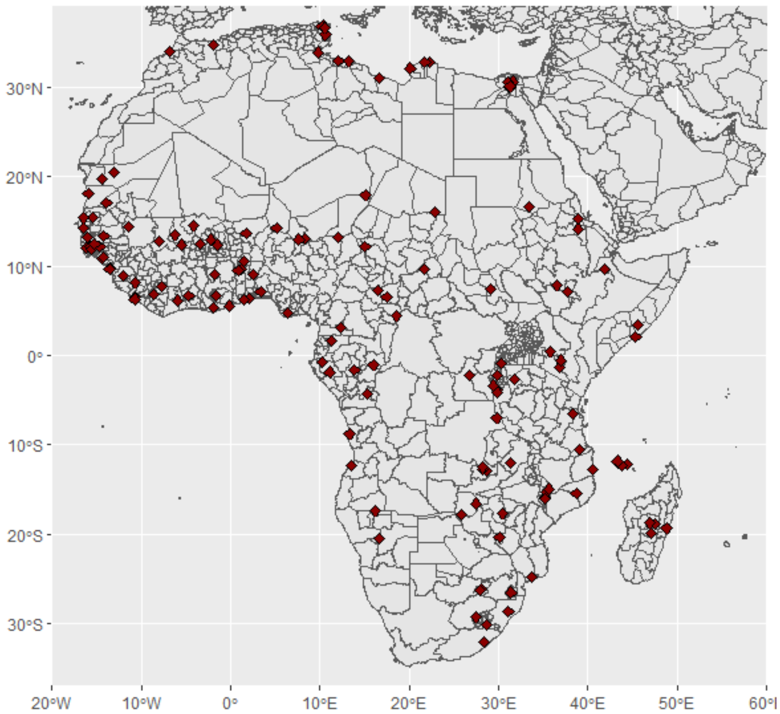
2.3 Leader Data

An important recent advancement in the political economy literature has been the broad use of geospatial data. Systematic research distinguishing regional and ethnic affiliation has, however, so far been constrained by the scarcity of publicly available data. In the Political Leaders' Affiliation Database (PLAD), the authors compile leader birthplaces with exact point locations via the GeoNames database (Bomprezzi et al., 2024). Those data are used to link leaders' birth regions to regions at the first administrative level (e.g., provinces) from the GADM database version 2.8 of Hijmans et al. (2018). Figure 1 depicts leaders' birth regions and shows that those are distributed broadly within countries.

Ghana's 4^{th} republic serves as a good illustration. After having three consecutive presidents hailing from three different regions of the South, Jerry Rawlings, John Kufuor, and John Atta Mills, a president from the North was elected, John Mahama. Above regional affiliation, the ethnic origin of a leader is likely to play a distinct role in resource

[5] Certainly, producer prices are correlated with the consumption side, which can influence individual poverty drastically (Hendrix and Haggard, 2015). Considering cash crops for the PPI reduces this issue.

Figure 1: Leaders' Birth Regions



Note: Red dots indicate African leaders' birthplaces (most precise point locations from Bomprezzi et al. (2024)). Borders refer to first-order administrative regions (ADM1).

redistribution (De Luca et al., 2018). Returning to Ghana, all Southern presidents were affiliated to the Asante group, whereas John Mahama belongs to the Gonja ethnic group. However, the case of Zambia illustrates that regional and ethnic affiliation are two distinct concepts: While the Copperbelt region is the birth region of three recent presidents, Frederick Chiluba, Levy Mwanawasa and Edgar Lungu, all of them hailed from different ethnicities. Chiluba identified as a Bembe, Mwanawasa was from the Lenje and Lungu has roots in the Ngoni ethnic group. In the PLAD database, we offer rich data both on leaders' birthplace and ethnic origin.[6] Based on these variables, I link

[6]The data advances the Archigos database on Political Leaders (Goemans et al., 2009) so that it extends the available information on leaders of 177 countries around the world over the 1989-2023 period, including information on tenure, birth dates, birth place, ethnicity and education.

Afrobarometer survey respondents' affiliation to leaders, both ethnically and regionally.

Figure 2: Regional and Ethnic Affiliation of Respondents

Birth Region	Ethnicity 0	Ethnicity 1
0	62.64%	25.17%
1	4.16%	8.02%

Note: Co-ethnicity considers only respondents from the same country.

Source: Author's calculation based on Bomprezzi et al. (2024) and Afrobarometer (2018).

There is obviously a strong positive correlation between living in a leaders' birth region and sharing the leader's ethnicity as historic settlement patterns are oftentimes persistent (Miguel and Gugerty, 2005). Yet, there are distinct heterogeneities in ethnic segregation across countries (Ejdemyr et al., 2018; Hodler et al., 2021). Figure 2 indicates that in the underlying dataset, a considerable fraction of the leaders' co-ethnics lives in other provinces. Similarly, a substantial number of citizens from other ethnicities reside in the home region of the leader.

2.4 Empirical Strategy

In order to formally test if changes in producer prices differentially affect the poverty status of farmers contingent on ethnic or regional political affiliation, I estimate the following specification:

$$\begin{aligned} W_{cirt} = \alpha &+ \beta_1 \Delta PPI_{crt} + \beta_2 \Delta PPI_{crt} \times Birth_{crt} \times Ethnicity_{cirt} + \beta_3 \Delta PPI_{crt} \\ &\times Birth_{crt} + \beta_4 \Delta PPI_{crt} \times Ethnicity_{cirt} + \beta_5 Birth_{crt} \times Ethnicity_{cirt} \\ &+ \beta_6 Birth_{crt} + \beta_7 Ethnicity_{cirt} + X_i \beta_8 + \theta_{ct} + \gamma_s + \kappa_{cr} \times t + \epsilon_{cirt}, \end{aligned} \tag{2}$$

where W_{cirt} is the poverty indicator of an individual i in country-region cr in period t, ΔPPI_{crt} is the first difference of the corresponding producer price index for cash crops in country-region cr and period t. ΔPPI_{crt} is interacted with $Birth_{crt}$, a binary indicator for a country-region cr being the leader's birth region in period t, and with $Ethnicity_{cirt}$, being a dichotomous variable, which is one if the respondent i shares the ethnicity of country c's leader in period t. In order to increase efficiency, all regressions account for individual covariates X_i related to poverty, e.g., age, education, gender, and rural/urban residence.

Furthermore, all specifications include country-period fixed effects, θ_{ct}, survey round fixed effects, γ_s, and country-region fixed effects, κ_{cr}. The country-period fixed effects capture all country-specific events in a particular six-month period, including, for instance, famines, food riots, or political turmoil. Country-region fixed effects account at the first level of sub-national administrative areas for all time-invariant factors, including average poverty or cultural fundamentals. The rich set of control variables and fixed effects reduces omitted variable bias concerns already substantially. However and most importantly, I exploit arguably exogenous variation in producer prices at the local level as my main treatment. It is defined as an interaction of global commodity prices with local productive capacities.[7] For the analysis of development aid, I add to Equation 2 further interactions of aid with the dichotomous indicators for $Birth_{crt}$ and $Ethnicity_{cirt}$. Due to the limited overlap with the Afrobarometer data, I can only employ a reduced set of fixed effects for this cross-section, namely period and state fixed effects, but no fixed effects for administrative regions. To tackle potential endogeneity, I rely on a Bartik-style instrument, inspired by Nunn and Qian (2014), refined in Lang (2021), Dreher et al. (2021), and Bluhm et al. (2025). For a discussion of the aid data and the instrumental variable, please see the online appendix.

[7] Taking pre-determined values from the year 2000 reduces endogeneity concerns even further. The country-region fixed effects capture those initial crop shares in harvested area.

3 Results

3.1 Main Results

In order to assess how favoritism differentially affects agricultural rents depending on individual affiliation, I separately add *regional* and *ethnic* affiliation as well as their interaction to Table 1. Column 1 depicts the baseline results and suggests that farmers' poverty is negatively correlated with the prices of cash crops in line with economic expectations. A one standard deviation increase in producer prices is associated with a 0.22 standard deviation decrease in the poverty index. Results in column 2 provide no evidence for additional significant effects of regional (*Birth*) or ethnic (*Ethnicity*) affiliation. Thus, when I consider the two concepts separately, I find no empirical support for (reversed) favoritism.

Table 1: Main Results

Dep. Variable: Poverty Index of individual i in region r in country c					
	(1)	(2)	(3)	(4)	(5)
ΔPPI	-1.2855***	-1.4401***	-1.4177***	-2.3134*	-7.4269**
	(0.4575)	(0.4913)	(0.4882)	(1.3235)	(3.3475)
$\Delta PPI \times \mathit{Birth}\,(1)$		0.0995	0.0215	0.1566	-26.1339
		(0.4916)	(0.4694)	(6.0824)	(26.6332)
$\Delta PPI \times \mathit{Ethnicity}\,(1)$		0.0824	0.0516	-0.2660**	-0.1014
		(0.1422)	(0.1488)	(0.1299)	(0.3363)
$\Delta PPI \times \mathit{Birth}\,(1) \times \mathit{Ethnicity}\,(1)$			0.8888***	0.5149	16.9003
			(0.2968)	(0.4609)	(10.0118)
N	15997	15997	15997	7989	7434

Note: Only the main interactions are displayed for brevity. All regressions include country-period, survey round, and regional (province) level fixed effects. All models include individual control variables. Standard errors two-way clustered by region and by country-period in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

However, as regional and ethnic affiliation may overlap, considering only the individual coefficients is likely to mask interactive effects. To address this point, I also examine the interaction of the two concepts (column 3). While there is still evidence for poverty-reducing effects of farming outside the leader's birth region, this effect is more than compensated for individuals that are living in the birth region (evidenced by the positive coefficient of $\Delta PPI \times Ethnicity \times Birth$). I consider the net effect for co-ethnic farmers in the leader birth region by testing the significance of the linear combination of coefficients in column 3 and find that co-ethnic farmers in the leader's birth region do not benefit from increasing prices ($p = 0.555$).[8]

Taken at face value, my results are both in line with an interpretation that co-ethnic farmers in the birth region are discriminated against in times of price hikes, but also shielded from increased poverty if agricultural prices drop. Thus from a welfare perspective, it is important to disentangle these contrasting effects for this particular group.

For this purpose, I consider only positive price changes in column 4 and only negative price changes in column 5. Again based on a test of a linear combination of coefficients, I find that the double-affiliated farmers do not benefit from higher agricultural prices (column 4) ($p = 0.750$). This finding corresponds with Kasara's claim that denser ethnic networks in the home region improve monitoring and, thus, rent extraction capacities.[9]

In column 5, the triple interaction $\Delta PPI \times Ethnicity \times Birth$ turns insignificant. However, when I test for a net effect for farmers with both an ethnic and a regional affiliation, I find again no significant net effect of changes in the agricultural producer price ($p = 0.604$). Thus, double-affiliated farmers are in return shielded from price drops and suffer less than farmers without any affiliation in times of agricultural price slumps. The following section delves deeper into the underlying channels, building on Afrobarometer's individual perception measures.

[8] In particular, I use Stata's *lincom* command to test for a cumulative net effect of $\beta_1 \Delta PPI_{crt} + \beta_2 \Delta PPI_{crt} \times Birth_{crt} \times Ethnicity_{cirt} + \beta_3 \Delta PPI_{crt} \times Birth_{crt} + \beta_4 \Delta PPI_{crt} \times Ethnicity_{cirt}$.

[9] Indeed, contemporary ethnic heterogeneity in Kenyatta's home region Kiambu (0.0328) is much lower than in Daniel arap Moi's birth region Baringo (0.4506) (Gershman and Rivera, 2018).

3.2 Support for Political Leaders

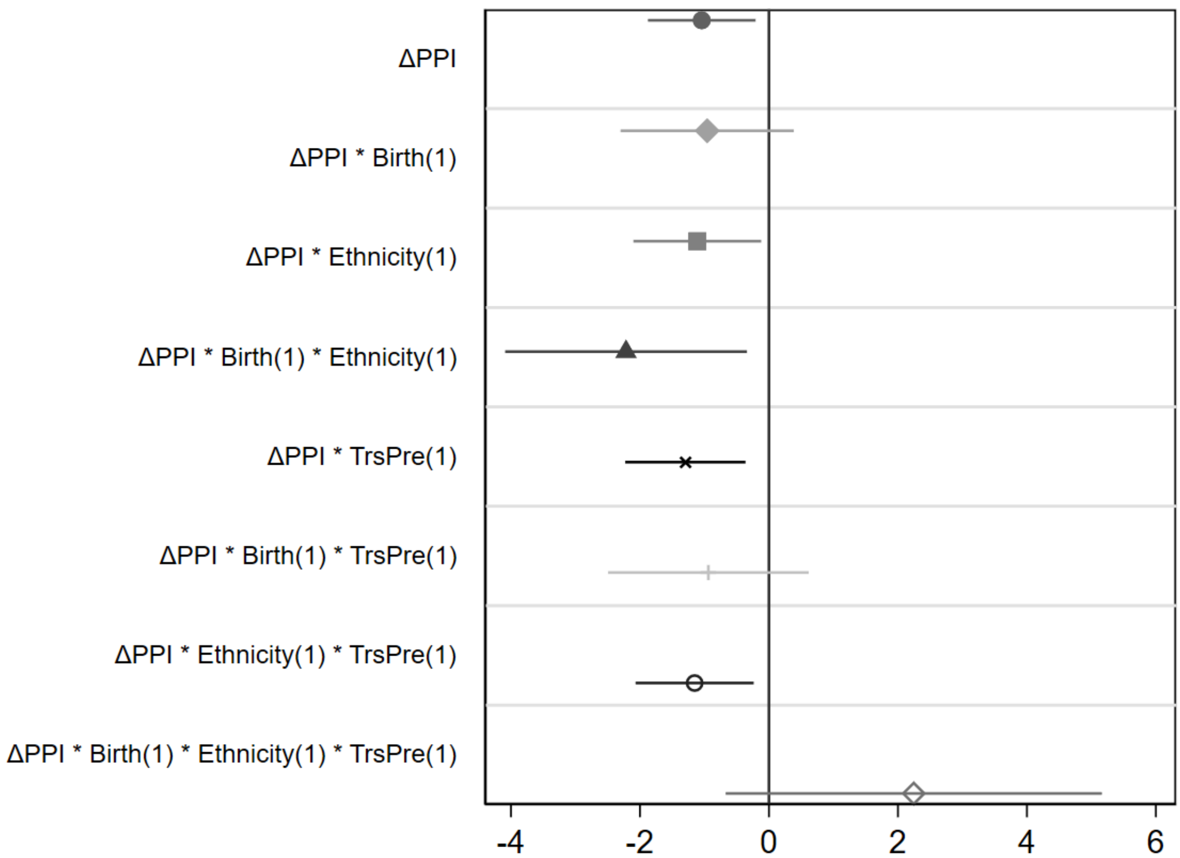
The previous section indicated that farmers with a double affiliation to the leader in terms of ethnicity and region do not benefit from agricultural price increases. But why do these farmers accept such a treatment? As stated previously, Kasara suggests so called "psychic benefits" of sharing the ethnicity with the head of state as a mechanism. However, due to lack of data availability, she was not able to test this claim.

The Afrobarometer data offer opportunities to consider this channel. More specifically, I examine whether reversed favoritism relates to the level of trust the farmers express towards the leader and consider in Figure 3 whether farmers with a double affiliation accept this reversed favoritism.[10] To ease comparability, I do not split the sample, but interact the main variables of interest with an indicator if farmers trust their leader. For this purpose, I estimate a model analogous to Equation 2 and add further interactions with a dummy variable, which equals one for respondents with high trust in the president. Figure 3 displays linear combinations of the coefficients for sub-groups and provides confidence intervals for those cumulative effects.[11] The combined effects in Figure 3 show that price changes are significantly negatively related to poverty among farmers who are neither ethnically nor regionally affiliated to the leader.

[10] Specifically, I consider the survey item "How much do you trust the president, or haven't you heard enough about her/him to say?"

[11] For instance, Birth(1)*Ethnicity(1)*PPI is based on $\beta_1 \Delta PPI_{crt} + \beta_2 \Delta PPI_{crt} \times Ethnicity_{cirt} + \beta_3 \Delta PPI_{crt} \times Birth_{crt} + \beta_4 \Delta PPI_{crt} \times Birth_{crt} \times Ethnicity_{cirt}$.

Figure 3: Trust in the president



Note: The figure shows linear combinations of the respective effect sizes. TrsPre equals one if the respondents indicated that they trust the president "somewhat" or "a lot." All regressions include country-period, survey round, regional (province) level fixed effects, and individual control variables. Standard errors two-way clustered by region and by country-period in parentheses, where confidence intervals refer to * ($p < 0.10$).

Moreover, I find negative coefficients across the board, with the single exception of farmers that share a double affiliation and express high trust in the political leader. These results suggest that my main results in Table 1 are driven by individuals who put high trust in the leader. Hence, leaders seem to take farmers' perceptions into account when engaging in reversed favoritism. Assuming that farmers are rational actors, these short-term "psychic benefits" are likely to persist only if political leaders succeed to bolster them with material benefits in the long-term. A question which I consider in the following subsection concerning compensating transfers.

3.3 Development Aid as a Compensating Transfer

In this section, I explicitly consider how development aid benefits (un-)affiliated farmers to test the mechanism of (so far) "missing transfers." In this context, Kramon and Posner (2013) suggest that distributional implications might highly depend on the policy area considered – or as they state: "the outcome one studies affects the answer one gets." While these studies states that it is problematic to derive implications on net effects without considering other important transfers, previous data availability inhibited the analysis of transfers on a sub-national level and only became recently possible for development aid. Due to its high fungibility (Van de Walle and Mu, 2007; Cruzatti et al., 2023), aid is one transfer, which is particularly susceptible to favoritism. For an exploratory analysis of "missing transfers" as an alternative treatment, I combine data from AidData (2017) on World Bank development aid and from Strange et al. (2017) (geo-coded by (Dreher et al., 2019)) for Chinese aid. In particular, I add to the model from Table 1 column 3 interactions of *Birth* and *Ethnicity* with $log(AID_{t-1}+0.01)$. The datasets intersect for the years 2000-2012 but only overlap with the required information on agricultural employment and leader ethnicity for the third Afrobarometer round.

In contrast to the more robust analysis of price changes, my results on development aid should be considered as suggestive evidence as the overlap of aid and Afrobarometer data allows only for a cross-sectional analysis of farmers and the use of a reduced set of fixed effects. Against this background, I use a combination of aid from China and the World Bank to increase statistical power in my constrained cross-sectional sample. In particular for China, the previous literature suggests that it is susceptible to discretional targeting due to the Chinese principle of non-interference in domestic politics (Isaksson and Kotsadam, 2018; Dreher et al., 2019; Bomprezzi et al., 2024).

Table 2: Channel – Aid

Dep. Variable: Poverty Index of individual i in region r in country c		
	OLS	2SLS
	(1)	(2)
$ln(Aid\_t-1)$	0.0993**	0.0373
	(0.0442)	(0.0488)
$ln(Aid\_t-1) \times Leader\,(1)$	-0.0130	0.0012
	(0.0707)	(0.0568)
$ln(Aid\_t-1) \times Leadeth\,(1)$	0.0318	0.0520
	(0.0534)	(0.0525)
$ln(Aid\_t-1) \times Leader\,(1) \times Leadeth\,(1)$	-0.1718*	-0.1822*
	(0.0958)	(0.0960)
N	5695	5677

Note: Only the main interactions are displayed for brevity. For the 1^{st} stage results, please see Section Appendix A.2. All regressions include country and period fixed effects. All models include individual control variables. Standard errors clustered by country in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Donors do not allocate aid randomly but consider poverty as an allocation criterion (Kotsadam et al., 2018). Thus, the distribution of development aid may be endogenous to economic prosperity and effectiveness. For this reason, I make use of a shift-share instrumental variable approach, which builds on a Difference-in-Difference (DiD) logic. For both donors, I use a cumulative probability as the cross-sectional difference, which I construct by dividing the number of years a region has received aid in the past, by the number of years passed in my panel. I interact these donor-specific probabilities with global time series as shifters, namely the World Bank's surplus resources and the availability of Chinese development aid inputs. In this setting, the main identifying assumption is that, in absence of a change in the time series, there would be common trends in aid allocation, within high and low aid probability recipient regions. As in any DiD setup, I control for the main constituting terms of the interaction in both regression stages and consider only the interaction term as the conditionally exogenous instrument in the first stage. Thus in line with the framework of Borusyak et al. (2022), my identifying assumption hinges on the arguably exogenous global time series, while the shares do not need to be exogeneous.[12]

Table 2 column 1 depicts results for a combination of Chinese and World Bank aid on poverty from an OLS regression. The positive and statistically significant coefficient on $ln(Aid_{t-1}) \times Leader\,(1) \times Leadeth\,(1)$ suggest that development aid reduces poverty only for co-ethnic farmers in the leader's birth region.

Turning to the instrumental variable results in column 2, the coefficient on $ln(Aid_{t-1})$ turns insignificant. This is in line with the expected direction of the endogeneity bias if poverty serves as an allocation criterion for development aid (Svensson, 2000; Öhler et al., 2019). Most importantly, the significant negative coefficient on $ln(Aid_{t-1}) \times Leader\,(1) \times Leadeth\,(1)$ in column 2 supports the notion that political leaders provide other transfers, namely development aid, to reduce poverty among farmers with a double affiliation. My findings speak to Bates (2014), who suggests that agricultural subsidies and taxation co-exist. Targeted project-based policies (e.g., aid-financed subsidies) compensate for pricing-based disincentives (e.g., agricultural taxation). This supports previous evidence that private goods are effective means of favoritism (Abman and Carney, 2020).

4 Discussion and Conclusion

My paper addresses an open puzzle of the political economy literature on "reversed favoritism" in African agriculture by assessing whether political leaders favor (Bates and Block, 2009) or discriminate against (Kasara, 2007) their core support group. More specifically, this research paper was able to assess these hypotheses and underlying mechanisms more carefully linking high-resolution geospatial survey data from 30 African countries (Afrobarometer, 2018) to the new PLAD database (Bomprezzi et al., 2024) which provides information on leader's regional and ethnic affiliation.

[12] For more detail on the instrumental variable, please refer to Section Appendix A.2.

My results support Kasara's hypothesis by showing that price hikes for commodities that can be produced in the leader's birth region benefit co-ethnic farmers significantly *less*. While a lack of micro data inhibited previous analyses of mechanisms, I leverage the fine-grained geolocalized data to consider the channels of "psychic benefits" of having a co-ethnic leader and compensating transfers.

My results show that the discriminated group of co-ethnic farmers in the leader's birth region surprisingly maintains positive perceptions about the country's chief executive. As it is counter-intuitive that this particular farmers express *less* discontent than other groups despite this unfavorable treatment, I consider compensating transfers based on geolocalized data on development aid. My results demonstrate that the co-ethnic farmers in the leader's birth region are disproportionally compensated via development aid for the reversed favoritism in agricultural prices.

While the exploratory analysis on aid only served as an example, other public transfers may matter. For instance, analyses on other sectors of the economy may want to reveal if leaders help affiliated farmers to move to other sectors or regions (Stöcker et al., 2023). In this regard, the underlying data and empirical analysis offer further avenues to initiate innovative research on political favoritism within and beyond the agricultural sector.

References

Abman, R. and C. Carney (2020). Agricultural productivity and deforestation: Evidence from input subsidies and ethnic favoritism in Malawi. *Journal of Environmental Economics and Management 103*, 102342.

Afrobarometer (2018). Afrobarometer: Merged rounds 1–6. Technical report, Afrobarometer. Available at http://www.afrobarometer.org.

AidData (2017). World Bank Geocoded Research Release Level 1. Version 1.4.2 Geocoded Dataset. Technical report, Williamsburg, VA and Washington, DC.

Akiyama, T. and D. F. Larson (1994). Adding up problem: Strategies for primary commodity exports in Sub-Saharan Africa. World Bank Policy Research Working Paper 1245.

Arriola, L. R. (2009). Patronage and political stability in Africa. *Comparative Political Studies 42*(10), 1339–1362.

Bartik, T. J. (1991). *Who benefits from state and local economic development policies?* WE Upjohn Institute for Employment Research.

Bates, R. H. (2014). *Markets and states in tropical Africa: the political basis of agricultural policies*. Univ of California Press.

Bates, R. H. and S. Block (2009). Political economy of agricultural trade interventions in Africa. Agricultural Distortions Working Paper 87, World Bank.

Bates, R. H. and S. Block (2010). Agricultural trade interventions in Africa. In K. Anderson (Ed.), *In The Political Economy of Agricultural Price Distortions*. Cambridge University Press.

Berman, N. and M. Couttenier (2015). External shocks, internal shots: The geography of civil conflicts. *Review of Economics and Statistics 97*(4), 758–776.

Besley, T. (2020). State capacity, reciprocity, and the social contract. *Econometrica 88*(4), 1307–1335.

Bluhm, R., A. Dreher, A. Fuchs, B. C. Parks, A. M. Strange, and M. J. Tierney (2025). Connective financing: Chinese infrastructure projects and the diffusion of economic activity in developing countries. *Journal of Urban Economics 145*, 103730.

Bommer, C., A. Dreher, and M. Perez-Alvarez (2022). Home bias in humanitarian aid: The role of regional favoritism in the allocation of international disaster relief. *Journal of Public Economics 208*, 104604.

Bomprezzi, P., A. Dreher, A. Fuchs, T. Hailer, A. Kammerlander, L. C. Kaplan, S. Marchesi, T. Masi, C. Robert, and K. Unfried (2024). Wedded to prosperity? Informal influence and regional favoritism. CEPR DP 18878.

Borusyak, K., P. Hull, and X. Jaravel (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies 89*(1), 181–213.

Bueno De Mesquita, B. (2005). *The Logic of Political Survival.* MIT press.

Burgess, R., R. Jedwab, E. Miguel, A. Morjaria, and G. Padró i Miquel (2015). The value of democracy: evidence from road building in Kenya. *American Economic Review 105*(6), 1817–1851.

Colantone, I. and P. Stanig (2018a). Global Competition and Brexit. *American Political Science Review 112*(2), 201–218.

Colantone, I. and P. Stanig (2018b). The trade origins of economic nationalism: Import competition and voting behavior in Western Europe. *American Journal of Political Science 62*(4), 936–953.

Cruzatti, J., A. Dreher, and J. Matzat (2023). Chinese aid and health at the country and local level. *World Development 167*, 106214.

De Luca, G., R. Hodler, P. A. Raschky, and M. Valsecchi (2018). Ethnic favoritism: An axiom of politics? *Journal of Development Economics 132*, 115–129.

Dickens, A. (2018). Ethnolinguistic favouritism in African politics. *American Economic Journal: Applied Economics 10*(3), 370–402.

Dixit, A. and J. Londregan (1996). The determinants of success of special interests in redistributive politics. *The Journal of Politics 58*(4), 1132–1155.

Dreher, A., V. Z. Eichenauer, and K. Gehring (2018). Geopolitics, aid, and growth: The impact of UN Security Council membership on the effectiveness of aid. *The World Bank Economic Review 32*(2), 268–286.

Dreher, A., A. Fuchs, R. Hodler, B. C. Parks, P. A. Raschky, and M. J. Tierney (2019). African leaders and the geography of China's foreign assistance. *Journal of Development Economics 140*, 44–71.

Dreher, A., A. Fuchs, B. Parks, A. Strange, and M. J. Tierney (2021). Aid, China, and growth: Evidence from a new global development finance dataset. *American Economic Journal: Economic Policy 13*(2), 135–174.

Ejdemyr, S., E. Kramon, and A. L. Robinson (2018). Segregation, ethnic favoritism, and the strategic targeting of local public goods. *Comparative Political Studies 51*(9), 1111–1143.

Franck, R. and I. Rainer (2012). Does the Leader's Ethnicity Matter? Ethnic Favoritism, Education, and Health in Sub-Saharan Africa. *American Political Science Review 106*(2), 294–325.

Francois, P., I. Rainer, and F. Trebbi (2015). How is Power Shared in Africa? *Econometrica 83*(2), 465–503.

Gershman, B. and D. Rivera (2018). Subnational diversity in Sub-Saharan Africa: Insights from a new dataset. *Journal of Development Economics 133*, 231–263.

Goemans, H. E., K. S. Gleditsch, and G. Chiozza (2009). Introducing archigos: A dataset of political leaders. *Journal of Peace research 46*(2), 269–283.

Hendrix, C. S. and S. Haggard (2015). Global food prices, regime type, and urban unrest in the developing world. *Journal of Peace Research 52*(2), 143–157.

Hijmans, R., N. Garcia, J. Kapoor, A. Rala, A. Maunahan, and J. Wieczorek (2018). Global administrative areas, Version 2.8.

Hodler, R. and P. A. Raschky (2014). Regional favoritism. *Quarterly Journal of Economics 129*(2), 995–1033.

Hodler, R., M. Valsecchi, and A. Vesperoni (2021). Ethnic geography: Measurement and evidence. *Journal of Public Economics 200*, 104446.

IMF (2018). IMF Primary Commodity Prices. Available at `https://www.imf.org/external/np/res/commod/index.aspx`, last accessed October 2, 2018.

Isaksson, A.-S. and A. Kotsadam (2018). Chinese aid and local corruption. *Journal of Public Economics 159*, 146–159.

Kanyinga, K. (1994). Ethnicity, Patronage and Class in a Local Arena: "High“ and "Low“ politics in Kiambu, Kenya, 1982–92. *The New Local Level Politics in East Africa*, 66.

Kasara, K. (2007). Tax me if you can: Ethnic geography, democracy, and the taxation of agriculture in Africa. *American Political Science Review 101*(1), 159–172.

Klasen, S. (2000). Measuring poverty and deprivation in South Africa. *Review of Income and Wealth 46*(1), 33–58.

Kotsadam, A., G. Østby, S. A. Rustad, A. F. Tollefsen, and H. Urdal (2018). Development aid and infant mortality. Micro-level evidence from Nigeria. *World Development 105*, 59–69.

Kramon, E. and D. N. Posner (2013). Who benefits from distributive politics? How the outcome one studies affects the answer one gets. *Perspectives on Politics 11*(2), 461–474.

Lang, V. (2021). The economics of the democratic deficit: The effect of imf programs on inequality. *The Review of International Organizations 16*(3), 599–623.

McGuirk, E. and M. Burke (2020). The economic origins of conflict in Africa. *Journal of Political Economy 128*(10), 3940–3997.

Miguel, E. and M. K. Gugerty (2005). Ethnic diversity, social sanctions, and public goods in Kenya. *Journal of Public Economics 89*(11-12), 2325–2368.

Monfreda, C., N. Ramankutty, and J. A. Foley (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles 22*(1), 1–19.

Nunn, N. and N. Qian (2014). US Food Aid and Civil Conflict. *American Economic Review 104*(6), 1630–1666.

Öhler, H., M. Negre, L. Smets, R. Massari, and Ž. Bogetić (2019). Putting your money where your mouth is: geographic targeting of World Bank projects to the bottom 40 percent. *PloS one 14*(6), e0218671.

Padró i Miquel, G. (2007). The control of politicians in divided societies: the politics of fear. *The Review of Economic Studies 74*(4), 1259–1274.

Sen, A. (1993). *Capability and Well-Being.* Oxford: Clarendon Press.

Stöcker, A., T. Baskaran, and P. Hufschmidt (2023). *Political favoritism and internal migration in Benin.* Ruhr Economic Papers 1031.

Strange, A. M., A. Dreher, A. Fuchs, B. Parks, and M. J. Tierney (2017). Tracking underreported financial flows: China's development finance and the aid–conflict nexus revisited. *Journal of Conflict Resolution 61*(5), 935–963.

Svensson, J. (2000). When is foreign aid policy credible? Aid dependence and conditionality. *Journal of Development Economics 61*(1), 61–84.

Van de Walle, D. and R. Mu (2007). Fungibility and the flypaper effect of project aid: Micro-evidence for Vietnam. *Journal of Development Economics 84*(2), 667–685.

Widmer, P. and N. Zurlinden (2022). Ministers engage in favoritism too. *Journal of Public Economics 213*, 104707.

World Bank (2015). Management's discussion & analysis and financial statements. Available at `https://ida.worldbank.org/sites/default/files/images/ida_financial_statements_jun_15.pdf`, last accessed September 27, 2018.

World Bank (2018). Global Economic Monitor (GEM). Available at `https://data.world/worldbank/global-economic-monitor`, last accessed September 30, 2018.

Appendix A.1 Data Appendix

Table B.1: Sampled Countries and Years

Afrobarometer Round	Years	Sampled Countries
Round 3:	2005-2006	Benin, Botswana, Ghana, Lesotho, Madagascar, Malawi, Mali, Mozambique, Namibia, Nigeria, Senegal, South Africa, Tanzania, Uganda, Zambia, Zimbabwe
Round 6:	2014-2015	Algeria, Benin, Botswana, Burkina Faso, Cameroon, Egypt, Gabon, Ghana, Guinea, Ivory Coast, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Morocco, Mozambique, Namibia, Niger, Senegal, Sierra Leone, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe
Round 7:	2016-2018	Algeria, Benin, Botswana, Burkina Faso, Cameroon, Gambia, Gabon, Ghana, Guinea, Lesotho, Liberia, Madagascar, Mali, Mauritius, Morocco, Mozambique, Namibia, Niger, Senegal, Sierra Leone, South Africa, Tanzania, Togo, Uganda, Zambia, Zimbabwe

Table B.2: Data Sources

Variable Name	Description	Years Available	Source
Poverty	Aggregate of five individual poverty assessments ranging each from 1 "Never" to 5 "Always."	1999-2018	Afrobarometer (2018)
Leader Ethnicity	Information on leader's ethnicity combined with information on individual ethnicity from Afrobarometer Round 3-7: "What is your tribe? You know, your ethnic or cultural group."	2005-2018	Own data collection, Bomprezzi et al. (2024) & Afrobarometer (2018)
Leader	Binary indicator if administrative region was the leader birth region.	1980-2018	Own data collection, Bomprezzi et al. (2024)
PPI	Self-constructed index of agricultural producer and consumer prices using prices and production capacity data.	1980-2018	IMF (2018), World Bank (2018), Monfreda et al. (2008)
WB Aid	log of WB Aid disbursements per region-year	2000-2012	AidData (2017)
Chinese Aid	log of Chinese Aid disbursements per region-year	2000-2012	Strange et al. (2017)
btrspre	Binary indicator distinguishing low (not at all;just a little) and high (somewhat;a lot) agreement to item "How much do you trust the president, or haven't you heard enough about her/him to say?"	1999-2018	Afrobarometer (2018)
Administrative Boundaries	Boundaries of subnational administrative divisions.	1980-2015	Hijmans et al. (2018)
Socio-economic indicators	Gender, Age, Education (four categories), Urban/Rural.	1999-2015	Afrobarometer (2018)

Appendix A.2 Analytical Appendix

Table B.3: Descriptives - Main Variables

	N	Mean	SD	Max	Min
Poverty Index	202,384	10.9	4.8	25.0	0.0
Producer Price Index	202,384	2.3	4.9	36.8	0.0
Democracy	202,384	0.5	0.5	1.0	0.0
Leader Region	202,384	0.1	0.3	1.0	0.0
Leader Ethnicity	135,930	0.3	0.5	1.0	0.0
Age	200,357	34.4	15.7	130.0	0.0
Education	201,703	2.4	1.0	4.0	1.0
Urban Residence	201,504	0.6	0.5	1.0	0.0

Note: Survey items on tax support and ethnicity were not collected across all rounds.

Alternative measures of well-being

Three alternative data sources come to mind to assess poverty on the subnational level. First, DHS data offers information on assets and ethnicity and allows for a comparable analysis. However, it is questionable that assets respond quickly to volatile cash crop price movements. Second, the Living Standard Measurement Surveys (LSMS) offer information on per capita expenditure for a limited subsample of countries (Malawi, Niger, Nigeria, Tanzania). However, those data are not well suited for the main analysis of interest as the LSMS do not provide information on individuals' ethnicity and analysis is, thus, confined to leader birth regions. Third, another potential indicator for regional economic well-being considered in recent scholarly work is night-light output. Although regional light intensity is arguably a viable measure for local economic activity, it is again hard to discern intra-group heterogeneity with this measure. Moreover, while lights are well-suited to measure industrial productivity, its suitability for agricultural output is questionable. In order to test, if the poverty measure based on Afrobarometer data corresponds to other survey-based indicators, Tables B.4, B.5 and B.6 report correlations.

Regions with a higher poverty index show indeed a negative correlation with per capita expenditure, the asset-based wealth index and nightlights. For the main results, I thus rely on the Afrobarometer data.

Table B.4: Correlation of Poverty Index and Expenditure

Dep. Variable: Regional average of Poverty Index (0-25)		
	(1)	(2)
$Expenditurep.c._{\mathrm{c,r,t}}$	-0.0021***	-0.0017**
	(0.0000)	(0.0001)
N	75	75
Country FE:	No	Yes
Year FE:	No	Yes

Note: Expenditure data is based on LSMS. Standard errors clustered by country in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Correlations - DHS

Average of Wealth Quintile in country-region cr in period t		
	(1)	(2)
$PovertyIndex$	-0.0341***	-0.0941*
	(0.0076)	(0.0447)
N	271	269
Country FE:	No	Yes
Year FE:	No	Yes

Note: Standard errors clustered by country in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Instrumental Variable Approach for Development Aid

For the aid variable, I consider the log of development aid disbursed by the World Bank's lending arm the International Development Association. As development aid disbursements are usually correlated with need (Kotsadam et al., 2018) and, thus, endogenous, I apply an instrumental variable approach to address this issue.

Table B.6: Correlations - Lights

Log of night light emission in country-region cr in period t		
	(1)	(2)
PPI	-0.0066	
	(0.0042)	
$PovertyIndex$		-0.0018
		(0.0016)
N	1088	1088

Note: All regressions include period and regional (province) level fixed effects. Standard errors clustered by region and by country-period in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Along the lines of (Dreher et al., 2021), I construct my instrument by using the interaction between exogenous temporal variation in the WB's IDA liquidity and the regional probability to receive development aid by the World Bank. Variation in the funding position, defined as "the extent to which IDA can commit to new financing of loans, grants, and guarantees given its financial position" (World Bank, 2015), can be caused by repayments by large borrowers including India or the timing of shareholders' timing of payments.

For China, I follow a similar logic: I construct the instrument by using the the regional probability to receive Chinese development aid interacted with the production of Chinese construction materials from Bluhm et al. (2025) – China is known for using development aid to reduce its oversupplies in its production of construction materials (Dreher et al., 2021).

As Afrobarometer does not provide a panel, but only repeated cross-sections, the instrument would suffer from a weak instrument issue. In order to achieve sufficient strength of my instrumental variable, I employ an out of sample prediction based on 1677 sub-national regions from 1995-2012. Results of the first stage are depicted in

Table B.7 and indicate that the interacted instrument $IDA\,Position \times Prob_{t-1}$ is a significant positive predictor of more development aid.

Table B.7: First Stage – IDA Position and World Bank Aid

Dep. Variable: Log of WB Aid and Log of Chinese Aid in region r in country c		
	(1)	(2)
$Prob\,IDA_{i,t-1}$	-1.22e+06	
	(1.91e+06)	
$IDA\,Position \times Prob\,IDA_{i,t-1}$	2.86e+06	
	(2.04e+06)	
$Prob\,CHN_{i,t-1}$		-1.29e+08
		(9.71e+07)
$CHN\,Material_{t-1} \times Prob\,CHN_{i,t-1}$		-4.28e+07
		(4.27e+07)
N	26896	20004

Note: Estimates include country, year and sub-national region fixed effects. p-values refer to two-way clustered standard errors by country-year and subnational region: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.