How Wide is the Ethnic Border?

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In this study, we explore the relationship between ethnic heterogeneity and within- and cross-country barriers to trade. We develop a spatial model of trade in which observable weather shocks affect local productivity. These shocks directly affect local prices and propagate through the trading network differentially depending on unobserved trading frictions. Coupling data describing monthly commodity prices in 230 cities across 42 African counties, remotely sensed weather data, and spatial data describing the locations of ethnic-group homelands, we estimate this model to quantify the costs traders incur when crossing ethnic and national borders. Our results show that ethnic borders induce a friction approximately one quarter the magnitude of national borders, indicating that ethnic heterogeneity is an impediment to the development of efficient national markets. Through counterfactual experiments, we quantify the effect of these frictions on prices and the extent to which colonial-era political borders have hindered African economic integration. In all, our paper suggests that trade impediments caused by ethnic borders are a substantial channel through which ethnic fractionalization impacts development.

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A substantial body of research has found that, across various measures of ethnicity, diversity is negatively associated with economic growth (Easterly and Levine, 1997; Alesina et al., 2003; Collier, 2001; Posner, 2004). While numerous mechanisms linking ethnic diversity to development outcomes have been proposed, the results of empirical scholarship evaluating these channels is considerably less robust (Easterly, 1999; Alesina and Ferrara, 2005). In this paper we provide evidence that diversity impacts growth by retarding the development of efficient national markets.

We accomplish this by estimating a model of trade that identifies the frictions induced by crossing ethnic-homeland and national borders. To estimate the model we couple monthly commodity price data in 42 countries across 230 African cities, remotely sensed weather data, and spatial data on the distribution of ethnic groups. Our estimates indicate that the friction associated with crossing an ethnic-homeland border is approximately one-quarter the size of that associated with crossing a national border.

Through counterfactual experiments we quantify the economic impact of three interventions. First, we estimate the reduction in price levels that would result from removing ethnic borders outright. Our model predicts that the total elimination of ethnic homelands would result in prices between .61 and 1.76 times lower than their factual values. There is, however, considerable heterogeneity in this effect, with substantial cross-national externalities resulting from the removal of internal ethnic barriers.

Second, we simulate the removal of national borders. Consistent with a large literature on the political economy of cross-border trade within Sub-Saharan Africa,[1] national borders are estimated to cause large trade frictions. On average, removing them results in a 2.17-2.58 fold decrease in prices and substantial convergence in prices across locations.

Third, we simulate a redrawing of national borders to eliminate ethnic partitions, e.g. ethnic

[1]See the Appendix for an in-depth discussion

groups that straddle national borders. We find that, on average, prices do not decrease when national borders are moved to ensure national borders do not fragment ethnic homelands. Trade frictions caused by within-country ethnic borders dwarf the role of national borders acting as partitions between coethnic markets. This null effect obtains because there are relatively few partitioned ethnic groups in our data and coethnic markets separated in this way are often at a considerable physical distance from each other, so that there are substantial trade costs between them even after the national border is removed.

In short, we show that ethnic fragmentation leads to market fragmentation. A large literature in trade economics demonstrates that market fragmentation inhibits economic growth (Redding and Venables, 2004; Waugh, 2010; Caliendo and Parro, 2015; Goldberg and Pavcnik, 2016; Pascali, 2017; Sotelo, 2019; Porteous, 2019). Together, this literature and our empirical findings and imply that ethnic homeland boundaries are a substantial impediment to growth, limiting the development of efficient internal markets.

Our results speak to a large body of literature on the impact of ethnic diversity on development. Cross-national growth regressions consistently establish a negative relationship between diversity and growth (Easterly and Levine, 1997; Collier, 2001; Alesina et al., 2003; Posner, 2004). Hypothesized channels for this relationship include ethnic diversity's impact on civil conflict and violence (Fearon and Laitin, 2003; Montalvo and Reynal-Querol, 2005; Cederman, Weidmann and Gleditsch, 2011; Esteban, Mayoral and Ray, 2012), inefficient or inegalitarian public policy (Mauro, 1995; Montalvo and Reynal-Querol, 2005; Desmet, Weber and Ortuño-Ortín, 2009), and in-group favoritism and/or out-group discrimination (Tajfel et al., 1971; Bates, 1973; Alesina, Baqir and Easterly, 1999; Vigdor, 2004; Hjort, 2014).

Our paper addresses a novel channel: the impact of ethnicity on development due to barriers to trade. Coethnicity may faciliate trade by reducing informational problems and search costs

(Gould, 1994; Rauch and Trindade, 2002; Rauch and Casella, 2003). Shared culture, networks, or linguistic similarities make intra-ethnic cooperation more likely (Deutsch, 1966; Hardin, 1997; Besley, Coate and Loury, 1993). Ethnic networks can help resolve problems of incomplete contracting and enforcement (Greif, 1993; Landa, 1994; Melitz and Toubal, 2014). Co-ethnics can more easily construct social norms and sanctioning mechanisms to ensure cooperative behavior (Fearon and Laitin, 1996; Fearon, 1999; Habyarimana et al., 2007). The existence of sharp ethnic barriers allow for intra-ethnic punishment strategies that can promote trade, particularly in the absence of centralized political authority. Our results are especially credible because a wealth of micro-data on grain traders in Africa demonstrates that this trade is carried through a network of small, in-person transactions that rarely span ethnic boundaries.

Ethnic barriers to trade are not a special case of other proposed channels linking diversity to underdevelopment. We find that the width of the ethnic border can not be reduced to the linguistic distance between groups or to the political salience of an ethnic difference. There is evidence that market integration is weakly deeper when trade circulates among politically-favored ethnic regions. However, our counterfactuals imply that markets in politically-favored ethnic homelands would benefit economically from the removal of ethnic trade barriers. Finally, we consider whether the mass violence is responsible for the trade frictions we estimated. Trade costs induced by national and ethnic borders are only slightly attenuated when the potential effects of battles, explosives attacks, violence against civilians, riots, and protests are modelled explicitly.

Econometrically, we develop a novel approach to the measurement of trade costs with sparse data. Standard methods used to identify trade frictions require data on trade flows, price levels, or both (Head and Ries, 2001; Eaton and Kortum, 2002; Anderson and Van Wincoop, 2004; Waugh, 2010; Novy, 2013; Simonovska and Waugh, 2014; Waugh and Ravikumar, 2016). In the case of Sub-Saharan Africa, intra-state trade flow data are, practically, non-existent. Approaches that exploit price gaps require specific geographies of production. In particular, standard methodologies require that the commodity being studied be produced in a single, known location (Atkin and Donaldson, 2015; Donaldson, 2018) or exported from a single, known port (Sotelo, 2019). Then, trade costs along the least cost path to the production source can be identified from data describing market-market price gaps or data describing the extensive margin of trade (Allen, 2014).[2] Since neither of these requirements obtain in our setting, an alternative methodological approach is required.

Our model characterizes how observable weather shocks impact local productivity. These shocks propagate through the trade network differentially depending on unobserved trading frictions. We estimate those frictions from the covariance in prices and observable productivity shocks across disparate market pairs. The logic underlying the model is straightforward. If market A and B are well-connected (they have low trade costs), then shocks to the productivity of A will transmit easily to market B, leading to high covariance between prices in B and shocks in A. Conversely if markets A and B are distant (high trade costs), shocks to the productivity of A will not affect prices in B, leading to low covariance. We derive this theoretical relationship from the equilibrium price index of Eaton and Kortum (2002) and estimate it using data on the observed covariances between weather and commodity prices across all locations.

The remainder of the paper proceeds as follows: In the next section we present our model of trade and describe our estimation strategy. In section 2 we describe our data and in section 3 we provide some reduced-form evidence of ethnicity's impact on trade. In section 4 we give our main model estimates and in section 5 provide results of counterfactual experiments describing ethnic borders' impact on production. Finally, we conclude.

[2]Porteous (2019) simulates this quantity, rendering it observable given data on production.

I Data

Our main outcome data come from Porteous (2019). These describe the monthly price data for four staple cereal crops – Maize, Millet, Rice, and Sorghum – from March of 2003 to April 2013.[3] These are collected by Porteous from the World Food Program's VAM unit, FAO's GIEWS project, and USAID's FEWS NET project and are converted to USD/kg using monthly exchange rates. These data cover 230 locations in 42 countries with the average location-commodity series having 83 observations. In Appendix Table A6 we provide a full set of descriptive statistics by product-location.

Our main independent variable, the presence of an ethnic homeland border, is taken directly from the the Geo-referenced Ethnic Groups (GREG) dataset (Weidmann, Rød and Cederman, 2010). For each location, we identify the ethnic homeland it sits within. With this we construct an indicator of ethnic boundaries as follows. If a pair of locations do not exist within the same homeland our measure take on a value of one, indicating they are separated by an ethnic border. If a pair of locations are contained in the the same ethnic homeland, our indicator takes on a value of zero.

For each pair of ethnic group-locations we calculate two measures of distance. First, we follow the procedure of Müller-Crepon, Pengl and Bormann (2020) to calculate the distance along the language tree of Lewis (2009). For every pair of locations this gives a measure of linguistic similarity, which proxies for cultural distance more generally (Fearon and Laitin, 2003). Second, we calculate travel distance by road between all markets used in our analysis. To do this we query Google Maps' Directions API for all pairs of markets in our data which returns the distance along the shortest road path by expected travel duration.[4]

We determine measure the political relevance of each ethnic-group by linking the GREG data to the Ethnic Power Relations (EPR) dataset (Vogt et al., 2015). Our indicator takes on a value of

[3]The value of local production (in local prices) of these commodities constitutes 8.7 percent of national g.d.p. for the average country in our sample.

[4]The Directions API averages over traffic conditions to compute the fastest route.

one for groups that appear the in the EPR data and zero otherwise. We classify politically relevant ethnic boundaries as those where the ethnic group in either location is in the EPR data. We then construct a more granulated measure using the EPR classification of each ethnic group's position. This indicator takes on a value of one if the group is classified as having a either monopoly of power, a dominant position, or if it is senior and junior partner in power and it takes on zero otherwise. With this classification, we can decompose ethnic borders into those where neither location is in power, where one location is in power, and where both are in power.

Finally, we use weather data from the USAID-FEWS, measured monthly, which provides three features of the weather for each location in our data. First, we capture for each location monthly evapotranspiration, which is the combination of transpiration from vegetation and evaporation from soil. This is derived from the data of (Velpuri et al., 2013). Second, we measure monthly precipitation as derived from the Climate Hazards Groups InfraRed Precipitation with Station (CHIRPS) data archive (Funk et al., 2014). Third, we capture monthly averages of daily maximum air temperatures as taken from (Funk et al., 2019). We use these data to construct a monthly, scalar-valued productivity shock for each market.[5]

Two Patterns in the African Cereal Trade

Our data reveal two patterns that, in conjunction, suggest that both national and ethnic borders serve as barriers to trade. Moreover, they suggest that national borders in Africa induce a friction large enough to virtually eliminate cross-national trade in our four cereal crops.

Production and trade data highlight the dearth of cross-country trade in the cereals we investigate. In Table 2 we present consumption shares for each product from three sources: consumption produced domestically; consumption from crops imported from other African countries; and consumption

[5]The method by which we reduce the dimensionality of these data is described in Section III.

African Agricultural Commodity Consumption Shares

	Within-Country	Within-Africa Imports	World Imports	*Total*
Maize	0.303	0.002	0.004	0.309
Millet	0.145	0.000	0.000	0.146
Rice	0.263	0.004	0.071	0.337
Sorghum	0.205	0.001	0.003	0.208
Total:	0.92	0.01	0.08	1.00

Table 1—*African Agricultural Cereal Consumption Shares:* This table gives the consumption share of each cereal from domestic production, imported from other African countries, and imported from outside of Africa. Data are from BACI, FAO.

from crops imported from outside of Africa. Over ninety-percent of cereal consumption is produced domestically. What is more, less than one percent is derived from within-Africa imports.

Second, price differences are suggestive of ethnic barriers to trade. For each of product in our data, price gaps within ethnic homelands are lower than those across ethnic borders. In Table 2 we present average price gaps for pairs of locations defined by each combination of national and ethnic borders. Whether we focus on within-country or cross-country comparisons of ethnic and non-ethnic borders, within ethnic-group pairs evince lower average price gaps than locations that cross ethnic borders. Similarly, when focusing on within ethnic group or across ethnic group comparisons, locations separated by national borders have larger price gaps than locations within the same country.

Cross National Evidence of Ethnicity's Effect on Trade

Similar patterns obtain in a broader sample of countries. In Table A2 in the supplemental appendix we examine cross-national panel data describing bilateral trade volumes from (Barbieri, Keshk and Pollins, 2009) and provided reduced-form estimates of the correlation between co-ethnicty and trade

Average Price Gap (kg/$) for Cereals

	Within Ethnic Group	Across Ethnic Group	*Total*	Within Ethnic Group	Across Ethnic Group	*Total*
		Maize			*Millet*	
Within Country	0.114	0.142	*0.138*	0.084	0.123	*0.113*
	(0.003)	(0.001)	*(0.001)*	(0.002)	(0.001)	*(0.001)*
Across Country	0.143	0.206	*0.206*	0.127	0.174	*0.173*
	(0.003)	(0.000)	*(0.000)*	(0.003)	(0.001)	*(0.000)*
Total	*0.125*	*0.202*	*0.201*	*0.097*	*0.166*	*0.161*
	(0.002)	*(0.000)*	*(0.00)*	*(0.002)*	*(0.000)*	*(0.000)*
		Rice			*Sorghum*	
Within Country	0.167	0.202	*0.199*	0.118	0.129	*0.126*
	(0.004)	(0.001)	*(0.001)*	(0.003)	(0.002)	*(0.001)*
Across Country	0.191	0.263	*0.262*	0.170	0.208	*0.207*
	(0.005)	(0.000)	*(0.000)*	(0.004)	(0.000)	*(0.000)*
Total	*0.176*	*0.255*	*0.254*	*0.132*	*0.201*	*0.199*
	(0.003)	*(0.000)*	*(0.000)*	*(0.002)*	*(0.000)*	*(0.000)*

TABLE 2—*Average Price Gaps:* THIS TABLE GIVES THE AVERAGE PRICE GAP $|p_j - p_i|$ IN DOLLARS PER KILOGRAM FOR MILLET, MAIZE, RICE, AND SORGHUM, ACROSS COMBINATIONS OF ETHNIC AND NATIONAL BORDERS. DATA ARE FROM (PORTEOUS, 2019).

flows. Patterns in global and within-Africa trade suggest that ethnic differences impede market integration. In the next section, we introduce a model of trade across ethnic and national borders. Married to data, the model quantifies how "wide" these borders are in terms of obstructing trade. By relating these borders to price levels across all locations, the model will allow us to consider how manipulating the spatial distribution of ethnic and national borders would affect the level and dispersion of prices of agricultural commodities in sub-Saharan Africa.

II Model

There is a set $\mathcal{N} = \{0, \ldots, N-1\}$ of locations, indexed with i, j, and k, in which goods are produced and sold. There is a set $\mathcal{M} = \{1, \ldots, M\}$ of goods, indexed m, which can be produced in every location. Goods come in a continuum of varieties $\omega \in \Omega_m$. Varieties are produced and sold in discrete periods, $t \in \{0, \ldots, T-1\}$. Markets clear period-by-period.

In order to produce a unit of a given variety, ω, producers must hire $1/Z^t_{i,m}(\omega)$ workers. There is an active outside sector in each location that pays a time-invariant wage w_i. Hiring a worker to produce any product in location i therefore costs w_i. $Z^t_{i,m}(\omega)$ is a measure of location i's productivity in producing good m in period t. We model $Z^t_{i,m}(\omega)$ as the realization of a random variable that depends on features of the location and the good. Following Eaton and Kortum (2002), $Z^t_{i,m}(\omega)$ is distributed Fréchet with c.d.f.

$$F^t_{i,m}(z) = e^{-\tilde{T}^t_i c_m z^{-\theta}}.$$

The global parameter θ controls the variance of these draws. As θ increases, heterogeneity in the distribution of productivity draws increases. $\tilde{T}^t_i$ is a location-period-specific technology shifter – higher values of $\tilde{T}^t_i$ correspond to higher expected productivity in location i across all goods. Notably, technology changes dynamically. In particular, $\tilde{T}^t_i = \eta^t_i T_i$ where T_i is a time-invariant feature of location i and η^t_i is a period-specific productivity shock with $\mathbb{E}[\eta^t_i] = 1$. Below, we model η^t_i as a function of weather-related variables that affect producers' ability to produce agricultural goods, such as rainfall and temperature. Finally, c_m is a good-specific cost shifter. Goods which require more labor to produce on average have smaller values of c_m.

Markets are competitive, resulting in prices that reflect underlying costs of production. Purchasing a variety of good m produced locally costs $p^t_{ii,m}(\omega) = \frac{w_i}{Z^t_{i,m}(\omega)}$. Varieties can be shipped and sold in other markets, incurring iceberg transit costs d_{ji} en route from location i to destination j. Inclusive of these costs, the price of a variety of good m produced in i and sold in j is $p^t_{ji,m}(\omega) = d_{ji} p^t_{ii}(\omega)$. We impose the normalization $d_{ii,m} = 1$ for all locations, i, and goods, m.

Each location consumes every variety of every good and searches for the cheapest source of each. Equilibrium prices are

$$p^t_{j,m}(\omega) = \min_{i \in \mathcal{N}} \left\{ p^t_{ji,m}(\omega) \right\}.$$

The distribution of prices for good m in location j across all varieties has c.d.f.

$$G^t_{j,m}(p) = 1 - e^{-p^\theta \Phi^t_{j,m}}$$

where

$$\Phi^t_{j,m} = \sum_k c_m \tilde{T}^t_k (w_k d_{jk})^{-\theta}$$

is a measure of the competitiveness of the market for good m in location j. In the Appendix, we show that expected prices in market j for good m (expecting over varieties ω) can be written as a function of this competitiveness metric. Specifically,

$$\mathbb{E}_\omega \left[p^t_{j,m}(\omega) \right] = C(\theta) \left(\Phi^t_{j,m} \right)^{-\frac{1}{\theta}} \tag{1}$$

where $C(\theta)$ is a constant.[6] This expected price depends in intuitive ways on the deep parameters of the model. Prices in market j fall when technology improves or wages fall in any location k. However, the extent to which these changes affect location j depend on d_{jk}. If j is closer to k (d_{jk} small), then changes to the productivity of k have a larger effect on prices in j.

Transforming equation 1, the competitiveness index can be expressed in terms of a constant, the

[6]Specifically,

$$C(\theta) = \Gamma \left(\frac{1+\theta}{\theta} \right)$$

where Γ is the Gamma function.

productivity dispersion parameter θ, and our data moment – the average price level of good m in location j

$$\Phi^t_{j,m} = C(\theta)^\theta \mathbb{E}_\omega \left[p^t_{j,m}(\omega)\right]^{-\theta}.$$

Then, using the competitiveness metric in a base location-period ($t = 0$, $m = 0$) as numeraire ($\Phi^0_{0,m} = 1$) for all m, we can write

$$\Phi^t_j = \frac{\Phi^t_{j,m}}{\Phi^0_{0,m}} = \mathbb{E}_\omega \left[p^t_{j,m}(\omega)\right]^{-\theta} = \sum_k \tilde{T}^t_k (w_k d_{jk})^{-\theta}.$$

where the good-specific cost shifter and the constant drop out of the equation. This feature of the model allows us to pool over all cereal crops in our data in the analysis to follow.

It is noteworthy that our approach requires us to take no stance on consumers' tastes. In our competitive economy, prices reflect the costs of producing goods and getting them to market. These are the fundamentals of interest here.

Identification

Our goal is to estimate location-location trade frictions d_{ji}. Our identification strategy exploits the relationship between local productivity shocks, η^t_i and prices elsewhere implied by the model. It is instructive to first consider the case of uncorrelated shocks. Suppose location i experiences a positive productivity shock. Local prices fall as a result and traders may encounter arbitrage opportunities in other markets, *so long as trade frictions are small enough.* If trade frictions between a given location j and location i are small, then prices in location j will respond strongly to the shock in location i. Conversely, if trade frictions between the two locations are large, prices in location j will remain relatively unchanged.

In other words, the covariance between shocks in location i and prices in location j, relative to the covariance between the same shocks and prices in location i, identifies the trade friction. When shocks are independent, then the covariance between prices in location i and shocks in location i can be written

$$\mathrm{Cov}[\Phi_i^t, \eta_i^t] = T_i \left(w_i\right)^{-\theta} \mathrm{Var}\left[\eta_i^t\right]$$

and the covariance between prices in a second location j and the same shock in location i is given by

$$\mathrm{Cov}[\Phi_j^t, \eta_i^t] = T_i \left(w_i d_{ji}\right)^{-\theta} \mathrm{Var}\left[\eta_i^t\right].$$

Taking the ratio of these two quantities yields

$$\frac{\mathrm{Cov}[\Phi_j^t, \eta_i^t]}{\mathrm{Cov}[\Phi_i^t, \eta_i^t]} = d_{ji}^{-\theta}$$

which tells us that magnitude of the trade friction between j and i is identified up to θ when the aforementioned covariances are observed. The responsiveness of prices in location j to shocks in location i, relative to the responsiveness of prices in i to local shocks, reveals the magnitude of the trade friction between the two markets.

This intuition can be extended to the case of interrelated shocks. Here,

$$\mathrm{Cov}[\Phi_j^t, \eta_i^t] = \sum_k T_k \left(w_k d_{jk}\right)^{-\theta} \mathrm{Cov}\left[\eta_k^t, \eta_i^t\right]$$

or

$$\mathrm{Cov}[\Phi_j^t, \eta_i^t] = \sum_k \mu_k d_{jk}^{-\theta} \mathrm{Cov}[\eta_k^t, \eta_i^t] \tag{2}$$

where we will refer to

$$\mu_k = T_k w_k^{-\theta}$$

as a "location fixed effect" capturing time-invariant technological and labor market conditions prevailing in location k. Equation 2 accounts for the covariance between shocks in location i and prices in location j due to correlation between the shocks in location i and shocks elsewhere. Suppose locations j and i experience large trade frictions but locations j and k are closely connected. If shocks to the productivity of location j covary with shocks in location k, prices in location j will (spuriously) covary with productivity shocks in location i through correlated productivity shocks in location k. The spatial covariance in shocks, $\text{Cov}[\eta_k^t, \eta_i^t]$, acts as weights on the economic fundamentals connecting location j and k, determining whether or not shocks to location i spuriously transmit to other locations.

Given panel data on prices and weather variation, the empirical analogues to $\text{Cov}[\Phi_j^t, \eta_i^t]$ and $\text{Cov}\left[\eta_k^t, \eta_i^t\right]$ are observed. We calibrate $\theta = 1$,[7] leaving a set of N^2 equations defined by equation 2 to identify N^2 unknowns – N location fixed effects $\boldsymbol{\mu}$ and $(N^2 - N)$ trade frictions $\boldsymbol{d}$.[8]

III Estimation

We reduce the dimensionality of this estimand by modeling d_{ji} as an exponential function of the observed potential trade barriers, with

$$d_{ji}(\boldsymbol{X}_{ji}; \boldsymbol{\beta}) = e^{\boldsymbol{\beta}^T \boldsymbol{X}_{ji}}.$$

[7] In principle, θ could be estimated from variation in some observable component of trade costs, such as freight rates, or a richer set of price data, as in Eaton and Kortum (2002) and Simonovska and Waugh (2014). Because these such data are unavailable in our setting and because θ acts only to scale our primary estimand, τ_{ij}, we leave this exercise for future research.

[8] Recall that $d_{ii} = 1$ for all i.

$\boldsymbol{X}_{ij}$ are observed dyadic features of locations j and i, such as the distance between these locations, and $\boldsymbol{\beta}$ is a vector of parameters governing the relationship between these features and trade costs.

We assume observed covariances, $\widetilde{\mathrm{Cov}}[\Phi_j^t, \eta_i^t]$ and $\widetilde{\mathrm{Cov}}[\eta_k^t, \eta_i^t]$ are measured with mean-zero error, ϵ_{ji} and ξ_{ki}, respectively. These can therefore be written

$$\widetilde{\mathrm{Cov}}[\Phi_j^t, \eta_i^t] = \mathrm{Cov}[\Phi_j^t, \eta_i^t] + \epsilon_{ji}$$

and

$$\widetilde{\mathrm{Cov}}[\eta_k^t, \eta_i^t] = \mathrm{Cov}[\eta_k^t, \eta_i^t] + \xi_{ki}.$$

We construct an estimator that minimizes the Euclidean distance between the model's predictions and the data, holding the value of θ fixed. Our estimates satisfy

$$\left(\hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\mu}}\right) = \arg\min_{\boldsymbol{\beta},\boldsymbol{\mu}} \sum_i \sum_j \left(\widetilde{\mathrm{Cov}}[\Phi_j^t, \eta_i^t] - \sum_k \left(\mu_k d_{jk}^{-\theta} \widetilde{\mathrm{Cov}}\left[\eta_k^t, \eta_i^t\right] \right) \right)^2 . \tag{3}$$

We then construct uncertainty intervals surrounding our estimates through nonparametric bootstrap. We sample with replacement our set of $T-1$ periods, recompute $\widetilde{\mathrm{Cov}}[\Phi_j^t, \eta_i^t]$ and $\widetilde{\mathrm{Cov}}[\eta_k^t, \eta_i^t]$, and re-run our estimator.

Constructing Weather Shocks

It remains to populate values for the weather shocks, η_i^t. We store the data on weather variation in location j in period t (discussed above) in the vector $\boldsymbol{Z}_j^t$. To transform this data into a scalar-valued weather shock, we model local prices as a function of local weather variation

$$\Phi_j^t = f(\boldsymbol{Z}_j^t) + \zeta_j^t.$$

We fit this model via Multivariate Adaptive Regression Splines (MARS) (Friedman, 1991). This method searches over the subsets of all linear combinations of a set of basis functions and fits the model to each subset. It chooses which subset of basis functions to include via cross validation. We then set $\eta_i^t = \hat{f}(\boldsymbol{Z}_j^t)$. The importance of each of our weather predictors in this model is shown in Figure 1. After fitting the model, our constructed weather shock covaries positively with local prices in 80 percent of locations.

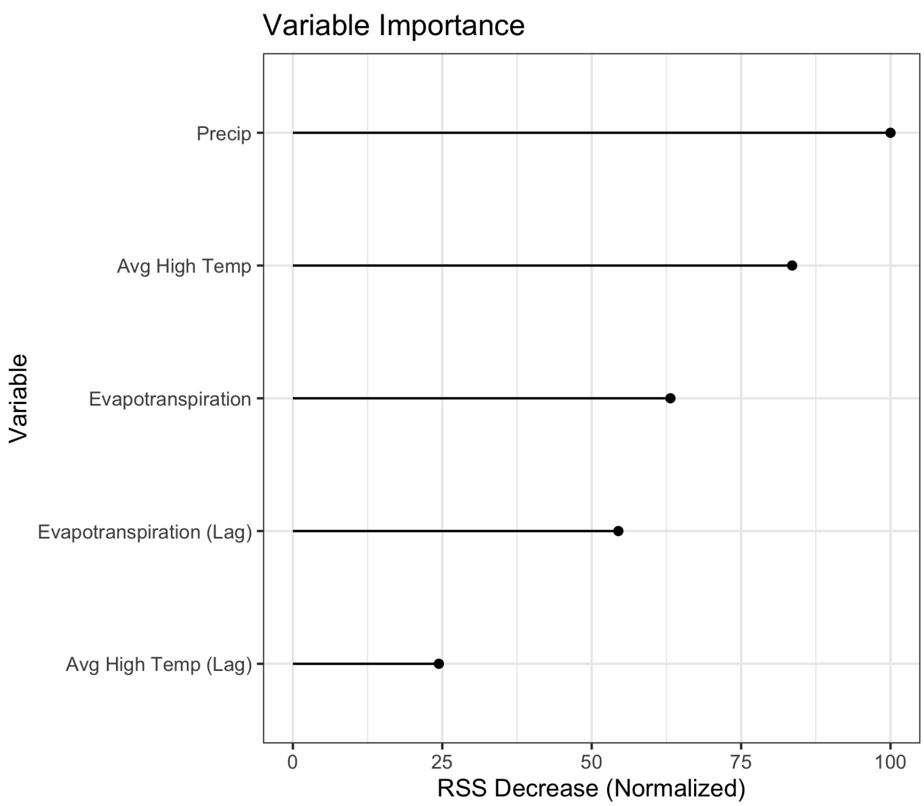


Figure 1. Importance of each weather predictor, measured by the relative change in the residual sum of squares when the predictor is removed from the model.

IV Results

We flexibly explore the effect of various observable features on trade frictions by modifying the dyadic features included in the matrix $\boldsymbol{X}$. Our baseline set of models includes three dyadic features:

road distance, national borders, and ethnic borders. We consider two alternative measures of road distance. The first measure is simply the distance along the fastest road path in kilometers. The second converts this measure into ordinal bins, as in Eaton and Kortum (2002).[9]

We present our baseline set of parameter estimates in Table 3 to quantify the implied frictions incurred by trading across these observable obstacles. First, we account for the friction induced by travel distance between locations using both our continuous (Model 1) and ordinal (Model 2) measures. As expected, both measures indicate that distance induces a positive and statically significant impediment to trade. Next we account for the impact of national borders. Again, as expected, national borders induce a positive and statistically significant trade-friction. When we condition on the presence of national borders the impact of travel distance is attenuated and statistically indistinguishable from zero when distance is operationalized continuously (Model 3) and roughly two-thirds smaller (but still positive and significant) when distance is treated ordinally (Model 4). Finally, we estimate the relative impact of ethnic homeland boundaries. In each specification we come to the same conclusion: ethnic borders induce a positive and statistically significant impediment to trade. What is more, across each model, the relative magnitude of ethnic and national borders are nearly identical. When we treat distance continuously (Model 5) and ordinally (Model 6) the ethnic border friction equals 24% of the friction induced by a national border.

Model Fit

Patterns of correlation between prices and weather shocks across space identify the model's parameters. But expected price levels (over product varieties and weather shocks) and can be readily computed given estimates of market fixed effects ($\hat{\mu}$) and the magnitude of frictions induced by

[9]We consider the following set of bins: 1 – $<$ 50km, 2 – 50 – 250km, 3 – 250 – 1000km, 4 – 1000 – 5000km, 5 – $>$ 1000km

Baseline Parameter Estimates of Border Frictions

	1.	2.	3.	4.	5.	6.
Distance	10.587	1.588	-0.608	0.574	-0.453	0.360
	[1.340, 23.486]	[1.035, 9.384]	[-0.935, 3.235]	[0.222,1.132]	[-3.115,4.991]	[-0.834,0.782]
National Border			9.244	4.283	10.430	4.433
			[4.030, 19.195]	[2.159, 18.671]	[2.752, 41.289]	[1.952, 33.492]
Ethnic Border					2.485	1.081
					[0.349, 28.099]	[0.089, 4.695]
Distance Measure:	Continuous	Ordinal	Continuous	Ordinal	Continuous	Ordinal

Table 3—This table gives parameter estimates when accounting for travel distance, national, and ethnic borders. Bootstrap ninety-five percent confidence intervals presented in brackets.

observable dyadic features ($\hat{\beta}$). To see this, note that expected competitiveness in market j is

$$\mathbb{E}_\eta\left[\Phi_j^t\right] = \sum_k T_k(w_k d_{jk})^{-\theta}$$

and $\Phi_j^t = \mathbb{E}_\omega\left[p_{j,m}^t(\omega)\right]^{-\theta}$. We therefore recover estimated average price levels as

$$\hat{p}_j = \left(\hat{\Phi}_j\right)^{-\frac{1}{\theta}} = \left(\sum_k \hat{\mu}_k\left(d_{jk}(\boldsymbol{X}_{jk};\hat{\boldsymbol{\beta}})\right)^{-\theta}\right)^{-\frac{1}{\theta}}.$$

In Figure 2 we compare model-predicted average prices levels to observed average prices in the data.[10] Even though observed average price levels were not used to fit the model, model-predicted and observed price levels are highly correlated ($\rho = .499$), indicating our model is fitting the data well.

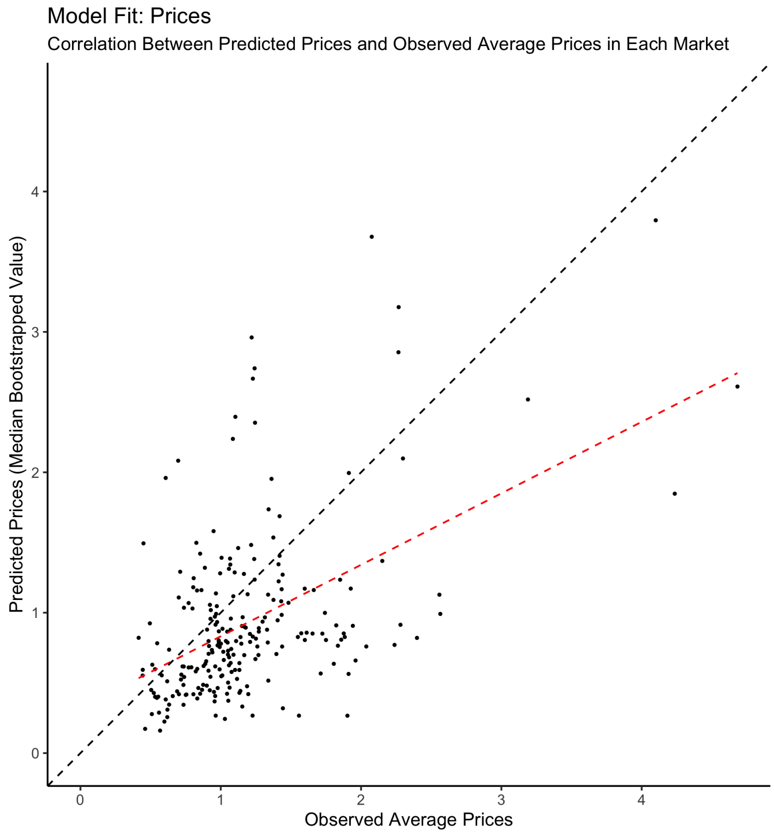


Figure 2. Model fit. Each observation is a market. Average price levels (across goods and periods) are plotted on the x-axis. Model-predicted price levels are plotted on the y-axis.

Ethnic Trade Frictions and Ethnic Politics in Africa

How well does our model correspond with observed features of ethnic politics in Africa? To gauge this we calculate the average within-country trade friction for every country. For every pair of locations in each country we compute the trade friction implied by our model as[11]

$$d_{ji}(\boldsymbol{X}_{ji}; \hat{\boldsymbol{\beta}}) = e^{\hat{\boldsymbol{\beta}}^T \boldsymbol{X}_{ji}}.$$

[10] We include all three baseline features in this mode:, (ordinal) distance, national borders, and ethnic borders.
[11] We use the baseline model with all dyadic features to produce these.

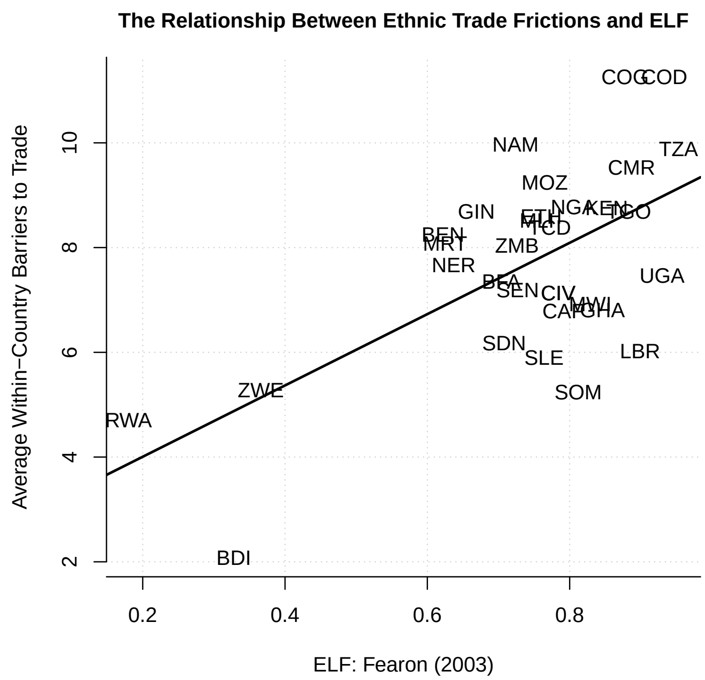


Figure 3. Correlation between estimated within-country trade friction and Fearon's (2003) index of Ethno-Linguistic Fractionalization.

Then, for each country we simply take the average of these dyadic frictions between within-country locations. We show that this is correlated with various measures of ethnic diversity.

In Table 4 we present the correlation between our measure of within-country trade friction, estimated from Model 5 in Table 3, and seven measures of ethnic fractionalization. Across these measures our estimates of trade frictions has a fairly strong correlation with diversity. All but one of these measures (Posner 2004) has a correlation above .5 and three have a correlation above .6. To visualize this, in Figure 3 we plot the ELF score of Fearon (2003) against our measure of average within-country trade friction. They are correlated at $\rho = .621$ indicating that more ethnically fractionalized societies exhibit more internal trade barriers.

In addition, we show that our measure is also associated with a key determinant of within-country ethnic heterogeneity in Africa: the construction of artificial states by European colonialists. In the

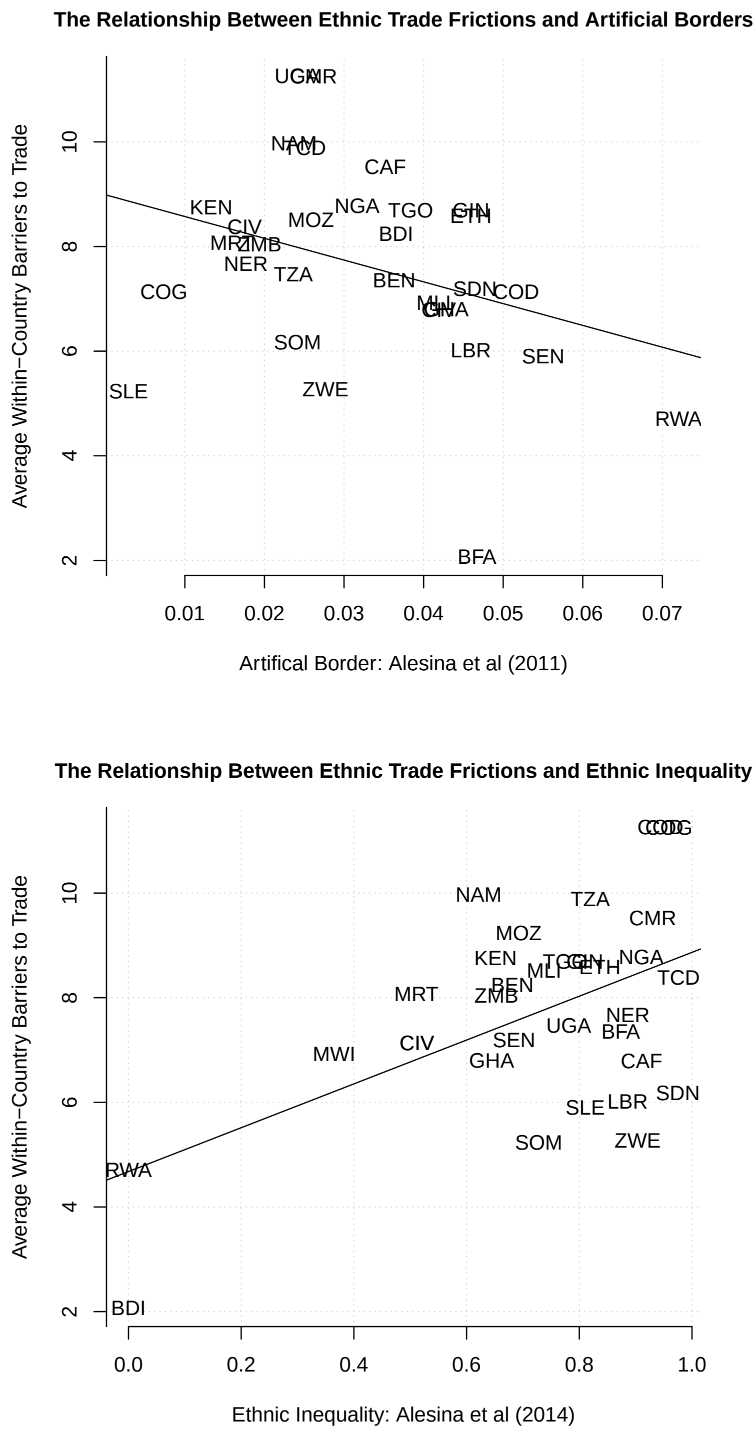


Figure 4. Correlation between estimated within-country trade friction and Alesina et al's (2011) measure of border artificiality and Alesina et al's (2014) measure of ethnic inequality.

Correlation Between Ethnic Fractionalization and Ethnic Trade Frictions

Index	Ethnic Trade Friction	Morrison et al. (1989)	Fearon (2003)	Taylor & Hudson (1972)	Drazanova (2019)	Roeader (2001)	Alesina et al. (2003)
Morrison et al. (1989)	*0.666*						
Fearon (2003)	*0.621*	0.688					
Taylor and Hudson (1972)	*0.625*	0.930	0.696				
Drazanova (2019)	*0.541*	0.738	0.645	0.766			
Roeader (2001)	*0.546*	0.898	0.648	0.972	0.768		
Alesina et al (2003)	*0.538*	0.641	0.868	0.723	0.597	0.649	
Posner (2004)	*0.366*	0.468	0.358	0.628	0.397	0.619	0.393

Table 4—This table gives the correlation between our measure of the average within-country trade friction and seven commonly measures of ethnic fractionalization.

top panel of Figure 4 we plot our estimated within-country trade friction against Alesina et al's (2011) fractal measure of border artificiality. Simply, Alesina et al's measure captures the straightness of a given country's border, the intuition being that comparatively straight borders were determined by exogenous forces, external to on-the-ground politics. Lower values of Alesina's measure indicate straighter borders. This measure is correlated at $\rho = -.331$ with our average trade friction measure, meaning less artificial states – states with less straight borders – have more efficient internal markets.

Finally, we provide suggestive evidence that the internal barriers to trade that our model identifies may limit economic mobility across ethnic groups. In the lower panel of Figure 4 we plot the ethnic inequality measure of Alesina et al (2014) against our estimate of average within-country trade barriers. This measure of inequality is a gini coefficient that, using night-time luminosity as a proxy for development and the same ethnic homeland data we exploit, captures the degree of inequality across ethnic groups. It is correlated at $\rho = .537$ with our measure of average internal trade friction, indicating that in countries with less integrated national markets ethnic groups are less equal.

Mechanisms Linking Ethnic Borders to Trade Frictions

Linguistic Similarity

To start, we explore the possibility that our baseline ethnic-border effect is driven by groups' linguistic differences, evaluating the possibility that cultural or linguistic differences may inhibit trade across ethnic groups. In other words, we ask if our baseline effect is driven by the mere existence of distinct groups or if it is driven by groups' relative similarity. In this sense, we seek to evaluate the intensive margin of ethnic borders. We provide estimates treating the mean and minimum distance between ethnic groups on the language tree as our measures of linguistic similarity.

Results from this exercise are given in Table 5. Across specification, we find that linguistic distance is statistically indistinguishable from zero. However, when included with the continuous distance measure (Models 1 and 3) the language-distance coefficient is comparatively large relative to the national border effect, but is noisily estimated. Nevertheless, when the discrete ethnic border measure is simultaneously included (Models 5 and 6), the linguistic distance coefficient is substantially attenuated, while the coefficient on the discrete ethnic border retains its magnitude. In sum, we find little evidence that our measures of linguistic similarity explain the ethnic border effect.

Differences in Political Power

Next, we consider the possibility that our ethnic border effect is driven by differences in political power across ethnic groups. That is, we consider the possibility that in-power or politically important groups may be able to implement market-distorting policies that drive our baseline finding. We consider two related measures to capture this. First, we simply record whether or not each group in our data are present in the Politically Relevant Ethnic Groups database and treat each within-

Linguistic Diversity and Trade Frictions

	1.	2.	3.	4.	5.	6.
Distance	-0.636 [-2.540, 5.541]	0.509 [-0.289, 8.545]	-0.585 [-1.637, 6.076]	0.510 [0.106, 9.248]	-1.212 [-3.344,4.886]	0.330 [-0834, 1.863]
National Border	14.127 [2.755, 59.431]	3.788 [-3.118, 39.531]	9.538 [3.411, 21.483]	3.576 [-2.961, 46.290]	10.829 [1.892, 29.799]	4.214 [1.524, 93.818]
Ethnic Border					6.371 [-0.322, 30.114]	1.589 [-3.571, 5.323]
Linguistic Distance	5.833 [-0.901, 205.579]	0.397 [-3.764, 9.964]	2.355 [-0.844, 15.474]	0.414 [-3.406,6.904]	0.849 [-8.639, 8.606]	-0.558 [-3.324,9.807]
Linguistic Distance: Distance Measure:	Minimum Continuous	Minimum Ordinal	Mean Continuous	Mean Ordinal	Minimum Continuous	Minimum Ordinal

Table 5—This table gives parameter estimates when accounting for two measures of linguistic distance. We consider linguistic difference as both an alternative and complementary channel to the existence of ethnic borders. Bootstrap ninety-five percent confidence intervals presented in brackets.

country dyad with at least one politically relevant ethnic group as a politically relevant ethnic border. Second, we use more refined data from the PREG data that describes whether or not a given ethnic group is in power or not. This allow us to decompose the set of politically relevant borders into those where neither group is in power, one group is in power, or both groups are in power.

Results describing the impact of differences in group power are presented in Table 6. First, when we just include the indicator for politically relevant ethnic borders (Models 1 and 2) we observe that the parameter describing this friction is nearly identical to those we recover in our baseline analysis. However, when we compare this to the friction induced by politically irrelevant ethnic borders (Models 3 and 4) the estimated frictions are statistically indistinguishable from each other. Nevertheless, the point estimates on the politically irrelevant ethnic borders are smaller.

Finally, we decompose politically relevant ethnic borders based upon groups' relative political power (Models 5 and 6). Here, the set of parameters describing the differences across politically relevant groups are indistinguishable from politically irrelevant groups. Moreover, in only one model (Model 6) is any of the politically relevant frictions, that associated with both groups being politically relevant but out of power, statistically distinguishable from zero. Again, these point estimates are noisily estimated but suggest that differences in political power do not explain our baseline ethnic border effect.

Political Power and Ethnic Group Trade Frictions

	1.	2.	3.	4.	5.	6.
Distance	-0.666 [-0.976,1.184]	0.422 [0.179, 1.053]	-0.519 [-2.477, 4.534]	0.356 [-0.930, 0.774]	-0.385 [-2.139, 6.666]	0.364 [-0.943, 1.010]
National Border	10.089 [4.136, 24.772]	3.818 [2.500, 33.563]	11.648 [4.608,46.934]	4.598 [2.676, 33.671]	13.380 [4.856,41.941]	5.012 [2.666,33.127]
Politically Relevant Ethnic Border	5.824 [0.559,32.244]	1.955 [-0.946, 17.216]	3.241 [-0.677, 32.138]	2.438 [0.188,16.235]		
Politically Irrelevant Ethnic Border			2.096 [0.041,7.534]	0.710 [-0.367, 4.631]	1.940 [-0.185,7.203]	0.583 [-0.617,5.182]
Neither in Power					9.672 [-0.220, 48.308]	13.459 [0.591, 37.934]
One in Power					2.762 [-1.016,19.681]	1.855 [-.459, 19.065]
Both in Power					1.301 [-2.037, 10.056]	3.323 [-1.195, 27.314]
Distance Measure:	Continuous	Ordinal	Continuous	Ordinal	Continuous	Ordinal

Table 6—This table gives parameter estimates when accounting for various measures of the distribution of political power across ethnic groups. We consider politically-relevant (within country) versus cross-national ethnic borders separately, and categorize politically-relevant borders according to the political power of the group on either side of the border. Bootstrap ninety-five percent confidence intervals presented in brackets.

Violence and Protest

Next we consider the impact of violence. Here, we use data from the the Armed Conflict Location & Event Data Project (ACLED) to construct the count of violent events (battles, violence against civilians, explosions/remote violence, riots, and protests) taking place within a 100 kilometer radius of the road path between each pair of locations over the course of our study. We reproduce this measure removing riots and protests from the count total. Results from this exercise are presented in columns 3-6 of Table 7. We find no evidence that political violence confounds our estimated ethnic border effect.

Customs Unions

Our results could be biased if cross national co-ethnic groups are more likely to establish formal or institutional relationships that foster trade. To account for this possibility we distinguish between national borders that are within a customs union and those national borders that separate locations outside of customs unions. These data are obtained from the database of Larch (2008). Results are presented in the first two columns of Table 7. Here, we find that our estimated ethnic border friction remains unchanged. Somewhat counter-intuitively we estimate national borders within customs unions impose a *greater* trade friction than those outside of them. This comports with the intuition that there exist substantial non-tariff barriers to trade inhibiting the flows of goods and services in Africa, even in the presence of formal commitments to reduce them.

V Quantifying the Impact of Borders

Besides recovering parameters that describe the average relative friction of national and ethnic homeland borders, we use our model to conduct counterfactual experiments that quantify their impact on prices. We conduct three experiments. First, we consider the impact of removing national borders, effectively constructing a continent-wide economic union. Second, we consider the effect of removing ethnic-homeland borders, making Africa ethnically homogeneous. Finally, we consider the impact of partitioned of ethnic groups. Here, we hold the number of national borders fixed and reassign ethnic groups that are currently partitioned by national borders to the country where the group's population is largest. Across our experiments we use our baseline model with all features

Custom Unions, Violence, and Ethnic Group Trade Frictions

	1.	2.	3.	4.	5.	6.
Distance	-0.381 [-2.948,4.699]	0.363 [-0.791,1.708]	-0.283 [-2.733, 7.697]	0.484 [0.067, 14.107]	-0.326 [-2.755, 6.6734]	0.477 [0.062, 10.848]
National Border			5.214 [1.904, 31.924]	2.999 [-1.776, 36.005]	6.128 [3.036, 41.384]	2.840 [-0.916, 16.584]
Ethnic Border	2.393 [0.918, 24.620]	1.038 [0.035, 4.739]	2.254 [-0.014, 19.371]	0.501 [-5.473, 2.921]	2.138 [-.193, 25.396]	0.482 [-6.358,3.010]
National Border (Within Customs Union)	10.900 [2.283, 42.990]	15.223 [2.228, 78.567]				
National Border (Outside Customs Union)	5.145 [1.864, 31.802]	2.614 [0.292, 51.565]				
Violence (Total)			-0.003 [-0.160, 7.910]	- 0.032 [-0.878, 0.008]		
Violence (Excluding Protests/Riots)					-0.003 [-0.208, 19.935]	-0.034 [-0.638,0.008]
Distance Measure:	Continuous	Ordinal	Continuous	Ordinal	Continuous	Ordinal

TABLE 7—THIS TABLE GIVES PARAMETER ESTIMATES WHEN ACCOUNTING FOR VIOLENT EVENTS ALONG THE ROAD PATH BETWEEN A GIVEN PAIR OF MARKETS AS WELL AS THE EXISTENCE OF CUSTOMS UNIONS BETWEEN GOVERNMENTS. BOOTSTRAP NINETY-FIVE PERCENT CONFIDENCE INTERVALS PRESENTED IN BRACKETS.

included and employ our ordinal measure of distance.[12]

The effects of each of these scenarios on prices in each location can be computed given estimates of trade frictions ($\hat{\boldsymbol{\beta}}$ and location fixed effects ($\hat{\boldsymbol{\mu}}$). Recall from above that estimated price levels are

$$\hat{p}_j = \left(\hat{\Phi}_j\right)^{-\frac{1}{\theta}} = \left(\sum_k \hat{\mu}_k \left(d_{jk}(\boldsymbol{X}_{jk}; \hat{\boldsymbol{\beta}})\right)^{-\theta}\right)^{-\frac{1}{\theta}}.$$

We compare these price levels to those that would prevail under counterfactual dyadic features $\boldsymbol{X}'$,[13] given by

$$p'_j = \left(\Phi'_j\right)^{-\frac{1}{\theta}} = \left(\sum_k \hat{\mu}_k \left(d_{jk}(\boldsymbol{X}'_{jk}; \hat{\boldsymbol{\beta}})\right)^{-\theta}\right)^{-\frac{1}{\theta}}.$$

Removing observable barriers between location j and k reduces d_{jk}, lowering prices. The extent to which prices fall depends on location k's market fixed effect, μ_k, as well as the state of other features in $\boldsymbol{X}_{jk}$. As μ_k increases, changes to the dyadic features describing markets j and k have larger effects on prices.

In each counterfactual we focus upon two quantities. First we are interested in the impact of each intervention on prices for the average consumer. To gauge this we estimate the following quantity $\log(\frac{\bar{p}'}{\hat{\bar{p}}}) = \sum_{n=1}^{N} w_n \log(\frac{p'_n}{\hat{p}_n})$, where $\hat{p}_n$ is the estimated price level in location n, p'_n is the price level in location n under our counter factual intervention, and w_n equals the population weight (the ratio of each location's population to the total population). Second, we are interested in the impact of each intervention on price dispersion. That is, we want to know the degree to which each intervention reduces the variance in prices across consumers. To evaluate this, we estimate $1 - \frac{\sigma'^2}{\hat{\sigma}^2}$ Where σ'^2 is the population weighted variance under the counterfactual and $\hat{\sigma}^2$ is the model estimated population weighted variance. We provide estimates of these quantities in Table 8.

[12] Focusing on the ordinal distance metric provides more plausible counterfactual results because our point estimate for this trade friction is positive. This ensures that geographically distant location exert little influence on prices in a given location, even when national borders (for example) are removed.

[13] For example if feature 1 describes the presence of national borders between all locations, then $X^1_{jk} = 0$ for all j, k when national borders are removed.

The Removal of National Borders

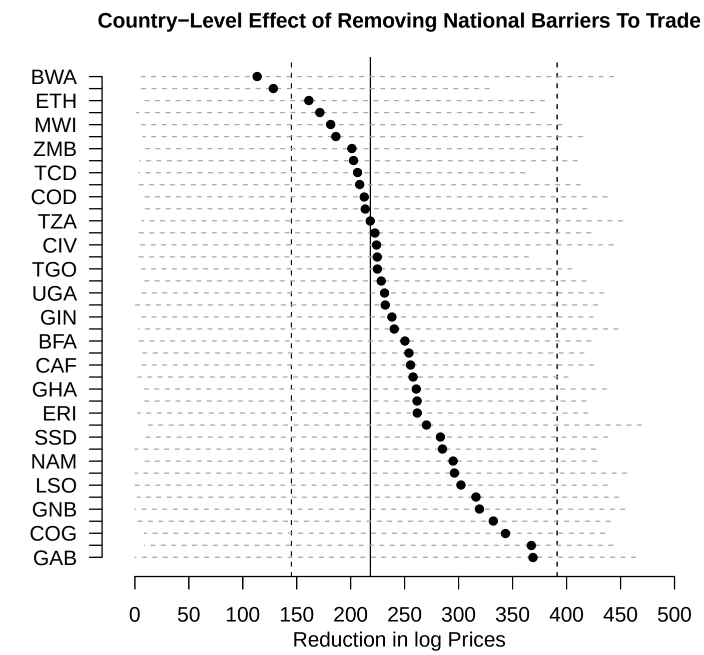
The average effect of removing national borders is summarized in the middle two columns of Table 8. Under complete economic unification, our model indicates that the average consumer would see a reduction in prices of between 217 and 257%. Moreover, the estimated average reduction in price variance, which we estimate to be between 97 and 99%, suggests the removal of national borders will lead to near uniform prices across the continent.

Nevertheless, our model uncovers substantial cross-national variation in the impact of removing national political borders on. Generated from Model 5 in Table 3, estimates of the impact on prices for the average consumer in each country are provided in the top panel of Figure 5. The vertical lines gives the overall (population weighted average) impact and ninety-five percent confidence interval, corresponding to the estimate presented in the third column of Table 8. Each point and horizontal bar give the average reduction in prices and its ninety-five percent confidence interval for each country in our sample. These estimates range from a 113 to 369% reduction in average prices.

In the lower panel of Figure 5 we plot our counterfactual estimates of the reduction in prices for the average consumer in each country against that country's (logged) population in 2017 as derived from the Penn World Tables. Consistent with theoretical expectations (Ades and Glaeser, 1999), these measures are negatively correlated at $\rho = -.49$, indicating that larger countries benefit least from market integration and smaller countries benefit most.

Removing Ethnic Homelands

The average effect of removing ethnic homeland borders is summarized in the first two columns of Table 8. While the effects of removing ethnic homelands are smaller than those of removing national borders, they are nevertheless sizeable. Our model indicates that the average consumer would see a reduction in prices of between 61 and 176%. In addition we find the estimated average reduction in



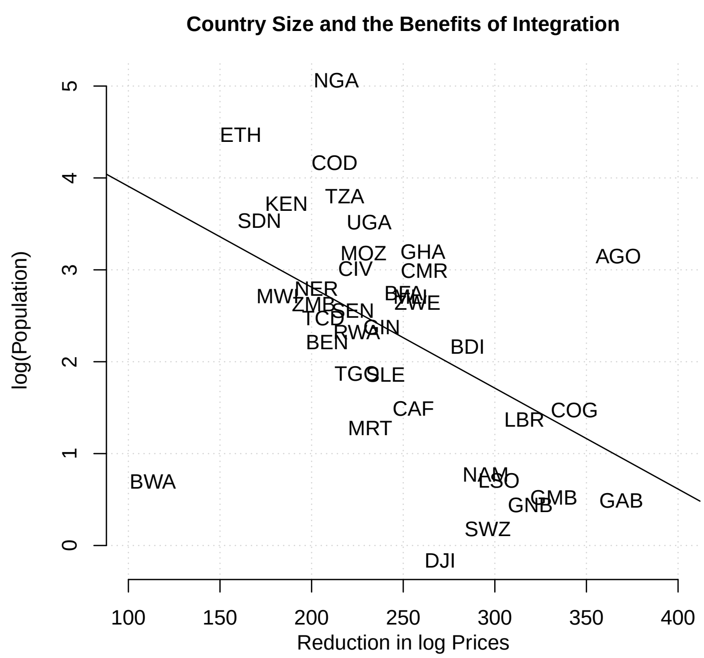


FIGURE 5. CAPTION

price variance is between 12 and 14%.

Again, there is substantial heterogeneity across countries in the effect of removing ethnic homeland borders. The average reduction in prices for consumers in each country is plotted in the top panel of Figure 6. The overall price reduction for the average consumer and its ninety-five percent confidence interval are given by the vertical lines and correspond with the first column of Table 8. Each point and horizontal bar gives the average reduction in prices and ninety-five percent confidence interval for every country in our sample. These estimated country-level reductions range from 32 to 103%.

In the lower panel of Figure 6 we plot Fearon (2003)'s measure of ELF against our predicted reduction in prices from the removal of ethnic homelands. Unsurprisingly, these measures are positively correlated, with a correlation coefficient of .38, indicating that more diverse societies benefit most from the removal of ethnic homelands.

Removing Ethnic Partitions

The average effect of removing ethnic partitions is given in the last two columns of Table 8. Here, the effect are small and indicate an increase in average prices, rather than an increase. However, especially when distance is measured continuously, these point estimates are noisily estimated and are statistically indistinguishable from zero.

In Figure 7 we give the location-by-location estimates of the price reduction associated with the removal of ethnic partitions for non-partitioned and partitioned locations, e.g. those locations whose country remains constant and locations whose country is changed by the counterfactual. In both cases, the average reduction in prices (the thick vertical line in both panels) is statistically indistinguishable from zero, with the average effect in the not partitioned locations equal to an increase of 13% with a ninety-five percent confidence interval of [32%,-73%] and an average effect in the partitioned locations of 0% with a ninety-five percent confidence interval of [25%, 137%]. In sum, we

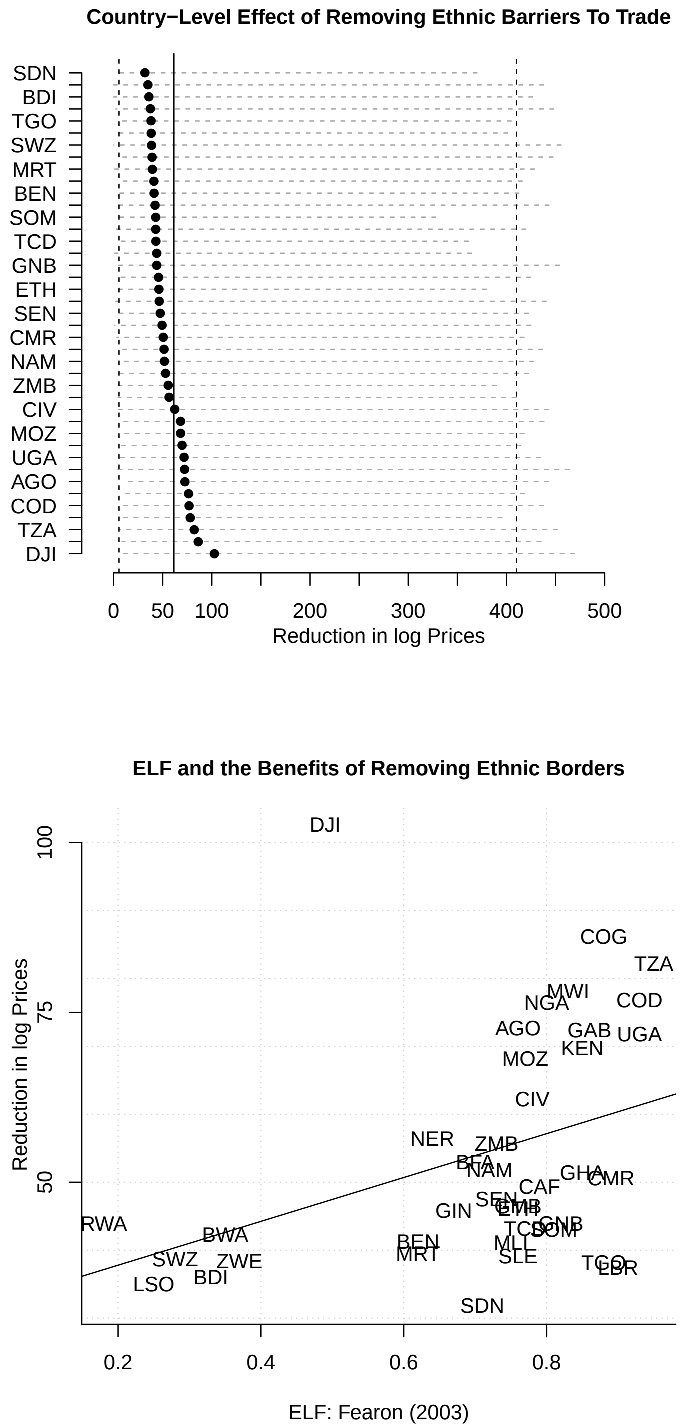


Figure 6. Average national price reductions from removing internal ethnic borders and correlation of average price reductions with Fearon's (2003) ethno-linguistic fractionalization index.

find no evidence that the partitioning of ethnic groups across national borders has a negative effect on trade.

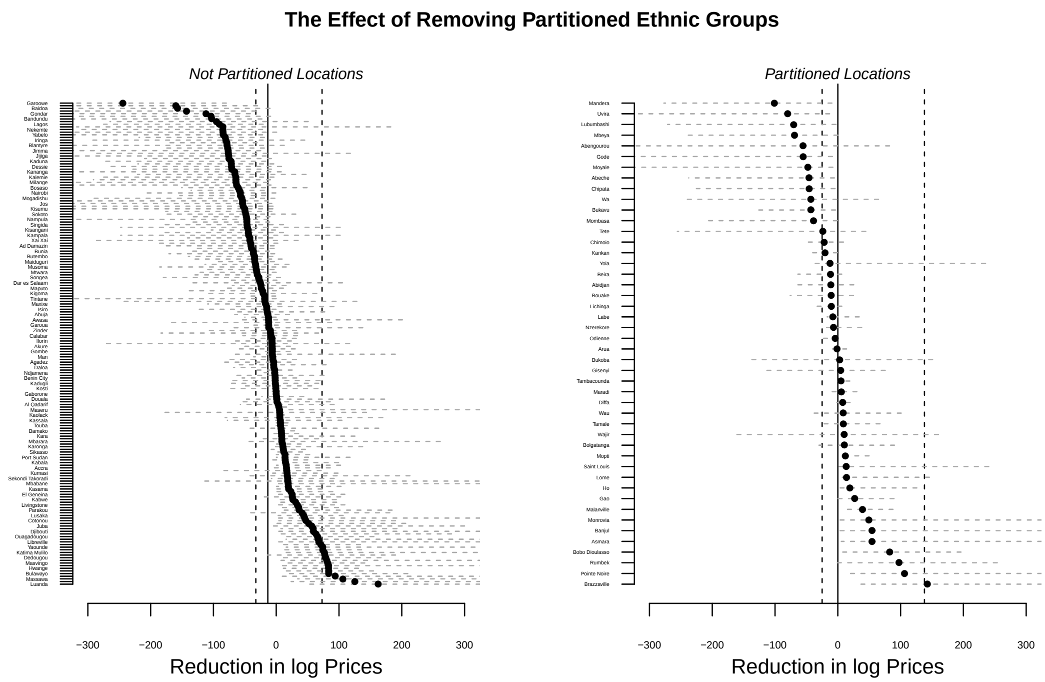


FIGURE 7. REDUCTION IN PRICES FROM ELIMINATING ETHNIC-HOMELAND PARTITIONS, DISAGGREGATED AT THE LOCATION AND ETHNIC GROUP-LEVEL.

VI Conclusion

Why do country-level measures of ethnic fragmentation consistently predict low economic growth? Despite the persistence of this empirical finding, debate persists as to *why* ethnic heterogeneity might retard economic growth. Here, we have provided evidence that ethnic heterogeneity serves as an impediment to the development of integrated national agricultural commodity markets. This evidence connects a large "micro-level" literature on the effects of co-ethnicity on interpersonal trust and cooperation to the "macro-level" literature on ethnic heterogeneity and economic growth. The

Summary of Counterfactual Experiments

	Ethnic Borders		National Borders		Partitioned Groups	
$\log\left(\frac{p'}{\hat{p}}\right)$	-0.615	-1.761	-2.176	-2.583	0.118	0.027
	[-4.08,-0.056]	[-5.73,-0.291]	[-3.774, -1.448]	[-4.045,-1.185]	[-0.358, 0.243]	[-0.393, 1.628]
$1-\frac{\sigma'^2}{\hat{\sigma}^2}$	0.119	0.142	0.976	0.995	0.085	0.614
	[0.013, 0.692]	[0.002, 0.939]	[0.626, 0.999]	[0.360, 1.00]	[-1.754, 0.726]	[-1.014, 0.618]
Distance:	Ordinal	Continuous	Ordinal	Continuous	Ordinal	Continuous

Table 8—This table gives the average change in prices & average reduction in variance. Bootstrap ninety-five percent confidence interval in brackets.

trust gaps identified by the first set of studies plausibly hamper economic exchange between members of different ethnic groups (Greif, 1993), providing a microfoundation for our main empirical finding. Traders purchase goods from co-ethnic sources when there exist cheaper alternatives across ethnic borders. These trade frictions almost certainly inhibit economic growth by preventing efficient specialization, a phenomenon consistently documented in a large literature on the development consequences of fragmented markets. Our quantitative exercises demonstrate that prices and spatial price gaps fall substantially and when these trading frictions are counter-factually eliminated, reflecting the benefits of economic specialization facilitated by increased trade. Together, these findings account for the correlation between ethnic fragmentation and economic growth documented by the second set of studies. Why these frictions persist in the face of enormous efficiency gains that would result from their elimination remains a puzzle to be tackled by future research.

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Background information on agriculture in Sub-Saharan Africa

The political economy of cash crops in Sub-Saharan Africa

Until the late-1980s agricultural markets were heavily regulated in Africa. Export crops were the primary source of tax revenue and foreign exchange for many African countries. The producers of export crops were taxed by governments in three ways: direct levies, underpayment for their crops by government export boards, and an overvalued exchange rate (Kasara, 2007).

Bates (1981) argues that the heavy burden on cash crop producers reflected the pro-urban bias of African governments, which feared unrest in their capitals above all else. The direct and indirect taxation of cash crops provided the foreign exchange necessary to ensure low-priced food in urban areas. Governments depended on imports—and, by extension, the supply of foreign exchange—to keep food prices in urban areas low. This dependence reflected limited integration of domestic food markets and urban demand for rice and wheat over other cereals that are more readily produced domestically (Poulton, Kydd and Dorward, 2006).

State intervention and cereal markets in Sub-Saharan Africa

State intervention in food crop markets varied by country and was not uniformly anti-rural. For example, the government of Malawi used proceeds from tobacco exports to support a minimum price for maize up until the mid-1990s (Fafchamps, Gabre-Madhin and Minten, 2005). Under other pro-agriculture regimes, including in Kenya, Zambia and Zimbabwe, the government subsidized inputs, credit and transportation to bolster small farmer incomes. Private trade in food crops was banned in countries including Malawi, Ethiopia, Guinea, Madagascar, and Mozambique; in some instances the government's procurement prices were a subsidy to farmers and, in other cases, an indirect tax (Kherallah et al., 2000). Finally, "countries with few colonial settlements and no single dominant crop, such as Ghana and Cameroon, hardly intervened in food markets" (Kherallah et al., 2000, 8). For example, in Benin government purchasing accounted for a maximum of 5% of the trade in cereals prior to deregulation.

Common features of deregulation of agricultural markets in the 1990s were elimination or reduction of input subsidies, price controls, and restrictions on private trade. Parastatal firms and marketing boards were disbanded or given a smaller role in in crop procurement, retail distribution, and control of imports and exports. Deregulation measures were more fully implemented with respect to food crops compared to export crops (Kherallah et al., 2000). African food markets have become more integrated domestically and internationally in the 15 years, in part because world food prices were historically high (Jayne, Chamberlin and Benfica, 2018).

Despite the trend toward deregulation, government intervention in non-export crops persists. Deregulation was superficial or temporary in some cases (Jayne et al., 2002). In most countries in eastern and southern Africa, agricultural boards and parastatal retail outlets defend both a floor and ceiling price for food grains (Tschirley and Jayne, 2010). Input subsidies are still found in countries in all regions of Africa (Kherallah et al., 2000) and have proven to be very difficult to cut. On the other hand, the direct cost of these subsidies is a modest expense in many government budgets (Ghins, Mas Aparisi and Balié, 2017).

High barriers to international trade

As of 2007, there were 30 Regional Trade Arrangements (RTA) among African countries. Tariffs were lower in the major trading areas compared to the mid-1990s. Intra-region agricultural trade has expanded since that period.

Average tariffs on in-Africa trade were nonetheless above the rates found in other developing countries (Yang and Gupta, 2007) and regional trade flows are relatively low (Badiane and Odjo, 2016). In the period our data covers, multiple countries imposed temporary bans on food grain imports

(Sitko et al., 2017) and wheat imports were government monopolies in Ghana, Kenya, Madagascar, and Zimbabwe. Non-tariff barriers to within-Africa trade are well documented (Teravaninthorn and Raballand, 2009; Karugia et al., 2009; Seck et al., 2010). These include lengthy stops for customs, quality inspection and immigration, and restrictions on international freight carriers.

International trade barriers persist for at least three reasons. First, taxes on international trade account for about 30% of African government revenues (Yang and Gupta, 2007). Second, controls over food imports and exports are the primary lever for manipulating domestic prices in some cases. Third, food imports can create balance of payment problems. 43 of 51 African countries (including north Africa) are net food importers (Rakotoarisoa, Iafrate and Paschali, 2011). The size of the deficit is small—about 5% of GDP—but it is consequential for the subset of African countries that earn limited foreign exchange through non-food and non-agricultural exports. Fear of foreign exchange shortages motivates regimes of import licensing and foreign exchange rationing (Poulton, Kydd and Dorward, 2006).

Integration of domestic cereal markets

Analyses of cereal price data across African markets show that integration of domestic markets has increased in the last three decades (Rashid, 2004; Moser, Barrett and Minten, 2009; Negassa, Myers and Gabre-Madhin, 2003; Dillon and Dambro, 2017; Campenhout, 2007). Trade in cereals is competitive and the profit margins of intermediaries are modest (Fafchamps, Gabre-Madhin and Minten, 2005; Dillon and Dambro, 2017; Minten et al., 2016). Nonetheless, barriers to cereals trade persist due to shortcomings in market infrastructure, “both institutional (e.g., contract law, police protection, uniform grades and standards) and physical (e.g., roads, electricity)” (Barrett, 2008, 311).[14] Shortfalls in this infrastructure increase search and transport costs, make contracts more

[14]Panel studies have demonstrated that these bottlenecks are meaningful by showing improved agricultural productivity and market integration when marketing costs fall (Berg, Blankespoor and Selod, 2018; Aker and Fafchamps, 2014).

difficult to specify and enforce, and contribute to price volatility.

Most cereal farmers do not produce large enough crops to justify internalizing the costs of transportation to market. If they sell any of their crop, they conduct this trade through an intermediary. Such private traders proliferated in African grain markets after deregulation (Fafchamps, Gabre-Madhin and Minten, 2005). These traders are numerous and under-capitalized, driving up marketing costs and discouraging investment in on-farm productivity. Traders face high search costs because relatively few farmers sell their crops and because quality-control requires most purchases be made in person. Most transactions are too small to justify the expense of using the formal justice system to enforce contracts (Rashid et al., 2010; Fafchamps, Gabre-Madhin and Minten, 2005, Table 6). Surveys of grain traders find that their disputes are virtually always settled through direct negotiation (Fafchamps and Minten, 1999; Gabre-Madhin, 2001). Interpersonal relationships are necessary to lower search costs, resolve disputes, and facilitate trust. Therefore, trading networks are "personalized [or] kin-based" (Jayne et al., 2002, 1980) and transactions on credit are rare (Fafchamps and Minten, 1999; Gabre-Madhin, 2001).

A typical grain trader resells merchandise within a short time period because they do not own or rent storage facilities. Few have access to storage.[15] Grain travels in a series of small trips between dealers instead of a single dealer moving product from farmer to consumer. Transportation costs accumulate as goods travel circuitous paths and are loaded and unloaded repeatedly (Rashid et al., 2010).

This characterization is based on trader surveys concerning various countries, eras, and crop (Table A1. However, there are caveats. First, this kind of micro-date is not available at all for many markets. Some of the most recent trader surveys find relatively streamlined trading systems (Minten et al.,

[15]Storing grain requires (a) keeping it at low enough humidity to prevent rotting or germination and (b) protecting it from insects and rodents. On farms, grain can be stored in clay, stone, or metal silos and receptacles. To transport grain economically, it needs to be in something lighter, usually a sack. Sacks of grain will mold or be breached by animals unless they are stored in buildings with special ventilation and pest control. See Proctor (1994).

2016, e.g.). For example, the first survey of maize markets in Nigeria since the 1970s, found short transaction chains moving maize throughout that very large country (Liverpool-Tasie et al., 2017). Sitko, Burke and Jayne (2018) document a boom in private investment in agricultural trading due to high food prices in mid-2000s. Personalized networks of small grain traders may be on their way out in at least some countries.

Networks and ethnicity

Where private cereal trade runs through small traders and personal networks, there are likely to be ethnic barriers to trade. If traders are more likely to have network ties with coethnics, trade flows more readily within than between ethnic groups. That pattern would hold even if coethnics were no more likely to cooperate or trust each other when interacting outside a shared network. Fafchamps (2003) surveyed food traders in Madagascar, Benin, and Malawi, gathering detailed information about who they traded with and the details of the transactions. He did not find differences in how likely traders were to offer or receive credit according to ethnicity, although traders with larger social networks[16] were more likely to use credit. Network ties rather than coethnicity facilitated trust and trade.

Are there rents from limited internal trade in cereals?

Does the limited integration of cereals markets generate rents that could explain why integration is limited?

Some federal countries, such as India and the United States, have subnational governments that are able to impose barriers to trade on behalf of constituent producers. Comparable powerful subnational governments are not present in most African countries and local powers of protection are limited.

[16] Instrumented with "start-up working capital, numbers of suppliers and clients known at start-up, the number of relatives, and the average association membership in each district" (23).

Table A1—Studies that use trader and/or farmer surveys to characterize food trade networks in Sub-Saharan Africa

Country, Year(s)	Crop(s)	Citation
Benin, 1999	Grains, legumes, tubers	Fafchamps, Gabre-Madhin and Minten (2005); Fafchamps (2003)
Democratic Republic of Congo (formerly Zaire), 1990	Maize	Minten and Kyle (1999)
Ethiopia, 2012	Cereal	Minten, Stifel and Tamru (2014)
Ethiopia, 2012	Teff	Minten et al. (2016)
Ethiopia, 2002	Food grain	Rashid et al. (2010); Negassa, Myers and Gabre-Madhin (2003)
Ethiopia, 1995-1996	Grain	Gabre-Madhin (2001)
Ghana, 2013-2014	Grain	Kornher and Asante (2016)
Kenya, 2008	Maize	World Bank (2009)
Kenya, 2007	Maize	Karugia et al. (2009)
Madagascar, 2001	Grain, legumes, tubers	Fafchamps, Gabre-Madhin and Minten (2005); Fafchamps (2003)
Madagascar, 2000-2001	Rice	Moser, Barrett and Minten (2009)
Madagascar, 1997	Grain, legumes, tubers	Fafchamps and Minten (1999)
Malawi, 1999-2000	Grain, legumes, tubers	Fafchamps, Gabre-Madhin and Minten (2005); Fafchamps (2003)
Niger, 2000-2007	Grain	Tack and Aker (2014); Aker and Mbiti (2010)
Nigeria, 2011-2016	Maize	Liverpool-Tasie et al. (2017)
Tanzania, 2008	Maize	World Bank (2009)
Tanzania, 2007	Maize	Karugia et al. (2009)
Uganda, 2000-2002	Maize	Nkonya (2002)
Uganda, 2012	Rice	Kikuchi et al. (2016)
Uganda, 2008	Maize	World Bank (2009)
Uganda, 2007	Maize	Karugia et al. (2009)
Uganda, 2000-2002	Grain	Rashid (2004)

A national government might, in theory, have the incentive to provide trade protection to some regions of the country if support for the government were regionally concentrated. This hypothetical runs contrary to Bates' thesis that African governments are preoccupied with low food prices in urban areas for consumers. Internal protectionism is also less plausible in light of the fact that most African farmers are net buyers of cereals (Barrett, 2008; Bos, Lutz and Bassolet, 2020).[17] Farmers in low-productivity agricultural regions are particularly likely to be net buyers of cereal, so that protectionism on their behalf would be self-defeating.

Could subnational protectionism be implemented on behalf of the relatively small set of farmers who control larger landholdings? This scenario would be possible in a case where lucrative urban market(s) for cereals were located in a relatively-low productivity agricultural region and there were nonetheless a handful of farms in that low-productivity region producing cereal for the market rather than own consumption. This constellation of circumstances may capture the political economy of some countries. However, we find ethnic barriers to the integration of cereal markets in most African countries, despite variation in the location of urban areas relative to more and less productive agricultural zones.

Although protection rents for farmers are an unlikely explanation for poorly integrated markets, some of the high marketing costs that cereal producers face are related to rent-seeking in other sectors. For example, the cost of bribes paid to police or government officials at road blocks or market facilities contributes to high marketing costs (Seck et al., 2010). Teravaninthorn and Raballand (2009) argue that high transport prices in western and central Africa reflect rent-seeking in the trucking industry. They estimate that the costs to freight operators moving goods on major western and central African corridors is similar to the costs of similar transport within China. Trucking firms charge much higher prices along these routes in Africa versus China, however. Legal regulations create de facto trucking

[17] Lowder, Skoet and Raney (2016) quantify the distribution of farm sizes for nine Sub-Saharan African countries. They find 80% of farms, accounting for 40% of farmland, were less than 2 hectares. The FAO benchmark for a "smallholder" farm is 10 hectares. The same review identified 15 countries in Sub-Saharan Africa where farm sizes decreased between 1960 and 2000, 3 countries where average farm size increased in that period and 1 country with unchanged farm sizes.

Most smallholders consume rather than sell all or most of their own cereal crop and purchase additional cereal as needed when their own stores are exhausted. Money for these purchases comes from non-cereal crops or non-farm employment.

cartels which can charge elevated prices and enjoy the associated rents.

Observable Dyadic Features

Figures A1 and A2 visualize how our dyadic measures are constructed. Figure A1 shows shortest road path from each location in our sample to Lagos, Nigeria. We use these routes to construct our continuous and ordinal distance measures. Figure A2 shows all ethnic homelands in our data. A pair of locations is considered to face an ethnic-homeland border if they do not inhabit the same homeland.

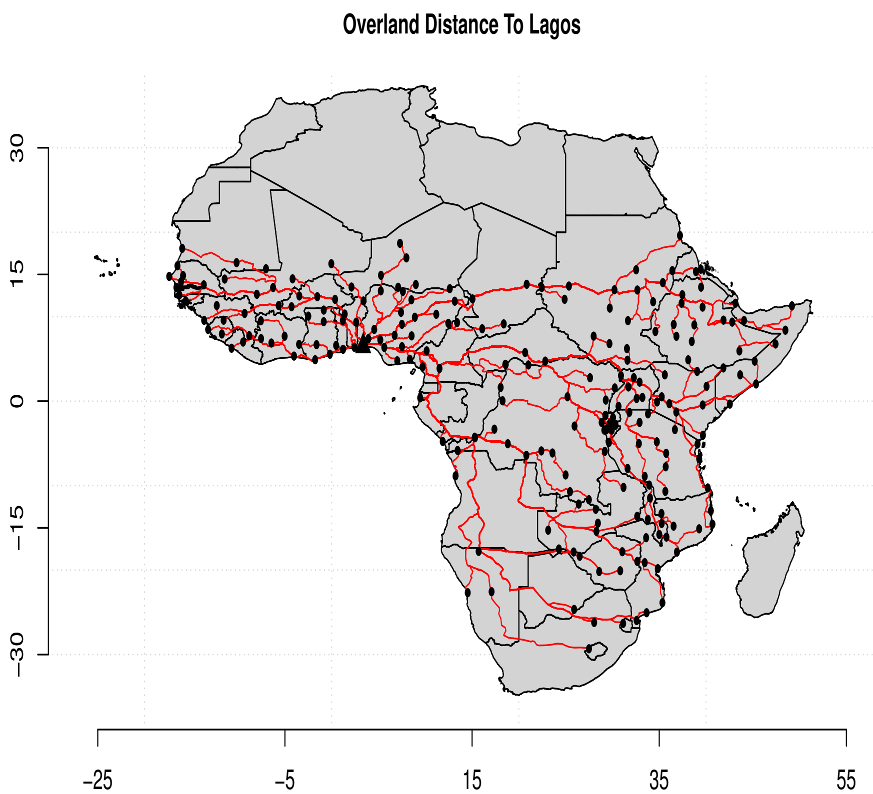

FIGURE A1.

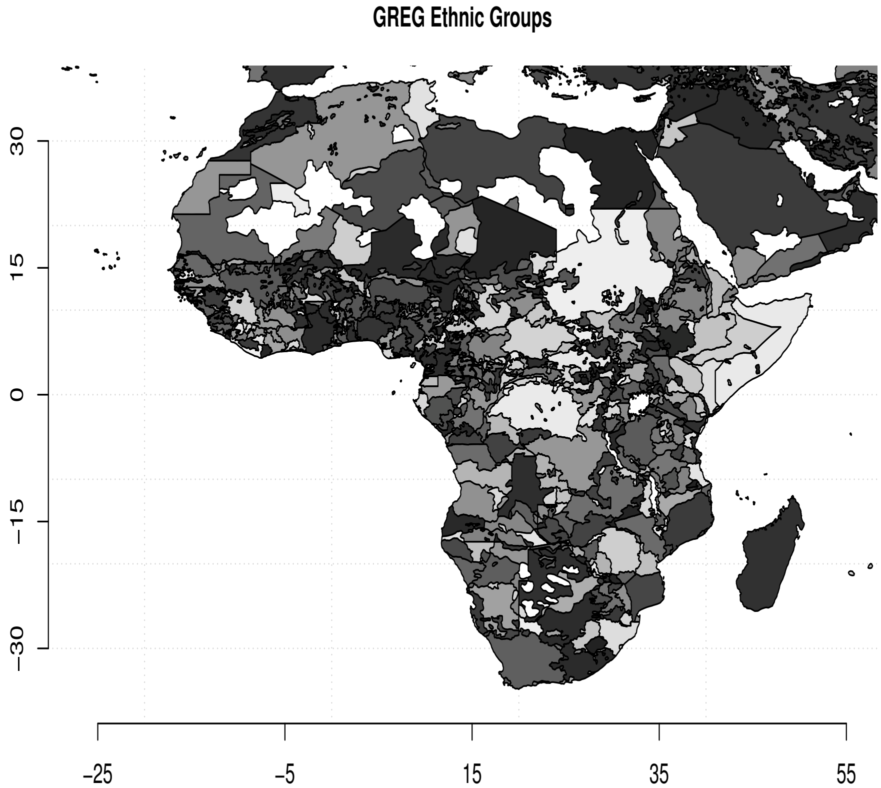

Figure A2.

Cross-National Estimates of Co-Ethnicity's Impact on Trade

We estimate a gravity model of the form:

$$F_{i,j,t} + 1 = G_t \frac{M_i M_j}{\tau_{i,j}^{\alpha}} \eta_{i,j,t} \tag{A1}$$

Where $\tau_{i,j} = D_{i,j} \exp(\gamma \text{Shared Ethnic Group}_{i,j})$, where $D_{i,j}$ is the distance in kilometers between country i and j, Shared Ethnic $\text{Group}_{i,j}$ is an indicator for a shared ethic group in countries i and

j, and where $F_{i,j,t}$ is trade flow from country i to country j in year t. We estimate the log-linear version of this model.

$$\text{(A2)} \qquad ln(F_{i,j,t}+1) = g_t + m_i + m_j - \beta_1 ln(D_{i,j}) - \beta_2 \text{Shared Ethnic Group}_{i,j} + \epsilon_{i,j,t}$$

We derive our measure of Shared Ethnic Groups from the Transborder Ethnic Kin dataset (Cederman et al., 2013) which records all politically relevant ethnic groups living in at least two countries. We construct two measures from these data. First, for each dyad we take a count of the shared ethnic groups. Then, we construct a dummy variable that takes on a value of one for dyads that have a shared ethnic group and zero otherwise.

Results are presented in Table A2. In the first four columns we use the count of shared ethnic groups as our main independent variable of interest. In columns 1 and 2 our sample is all country-dyads and in columns 3 and 4 we restrict the sample to African dyads. Finally, in columns 2 and 4 we include as additional regressors the natural logarithm of importer and exporter GDP, respectively. Across specification we find that the coefficient on number of shared ethnic groups is positive and statistically significant at conventional levels. In the global sample an additional shared ethnic group is associated with an (approximately) 30-33% increase in trade. In the African sample this coefficient is attenuated by about one-third, now ranging from .19 to .21, and is again statistically significant at conventional levels. In the next four columns (5-8) we repeat this analysis, now using the dummy measure of shared ethnic group. The results remain qualitatively unchanged.

Reduced Form Results of the Association of Ethnicity and Price Correlations Across Space.

Shared Ethnicity and International Trade

	1.	2.	3.	4.	5.	6.	7.	8.
Sample:	Global		Africa		Global		Africa	
Shared Ethnic Groups (Count)	0.298	0.327	0.208	0.187				
	(0.022)	(0.025)	(0.053)	(0.058)				
Shared Ethnic Group (Dummy)					0.443	0.492	0.356	0.326
					(0.029)	(0.031)	(0.063)	(0.066)
ln(Distance KM)	-0.718	-0.812	-0.539	-0.551	-0.72	-0.813	-0.533	-0.545
	(0.01)	(0.011)	(0.029)	(0.031)	(0.01)	(0.011)	(0.028)	(0.03)
ln(Importer GDP)		0.442		0.135		0.442		0.135
		(0.014)		(0.023)		(0.014)		(0.023)
ln(Exporter GDP)		0.363		0.077		0.363		0.078
		(0.013)		(0.024)		(0.013)		(0.024)
Importer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.648	0.696	0.380	0.396	0.648	0.696	0.382	0.399
N	177	158	50	46	177	158	50	46
T	145	65	87	65	145	65	87	65
Total Obs	1,155,777	909,176	94,032	81,560	1,155,777	909,176	94,032	81,560

Table A2—This table provides estimates of the relationship between shared ethnic groups and trade. The unit of observation is the country-dyad-year. Shared Ethnic Groups (Count) is the number of shared ethnic groups within a dyad. Shared Ethnic Group (Dummy) is an indicator taking on 1 if a dyad shares at least one common ethinc group and zero otherwise. Distance is measured in kilometers from the centroids of each paired country. GDP per capita is taken from the Penn World Tables. All models include importer, exporter, and year fixed effects. Standard errors clustered by dyad in parentheses.

We explore how prices are transmitted across national and ethnic boundaries through the following regression framework:

(A3)

$$\begin{aligned} ln(Price_{ipt}) =& \rho_0 ln(Price_{jpt}) + \rho_1 ln(Price_{jpt}) \cdot EthnicBorder_{ij} + \rho_2 ln(Price_{jpt}) \cdot ln(Distance_{ij}) \\ &+ \rho_3 ln(Price_{jpt}) \cdot NationalBorder_{ij} + \lambda_1 EthnicBorder_{ij} + \lambda_2 ln(Distance_{ij}) \\ &+ \lambda_3 National_{ij} Border + \phi_i + \theta_j + \alpha_t + \epsilon_{ijtp}. \end{aligned}$$

Results are shown in Table A3. This table provides the correlation between cross-city prices across Ethnic and National borders. The unit of observation is the city-product-month. Ethnic Border is a dummy for gross an ethnic group border as described the GREG dataset. Standard errors clustered by city-dyad in parentheses. Consistent with our structural empirical results, the coefficients associated with the interaction of prices in a second market with the presence of ethnic borders, national borders, and distance are generally negative and statistically significant. This suggests that these features serve as a barrier to the transmission of prices across space.

The Correlation of Prices Across Ethnic Borders

	1.	2.	3.	4.	5.	6.	7.
$\ln(\text{Price})_j$	0.652	0.253	0.383	-0.031	0.571	0.515	0.421
	(0.026)	(0.042)	(0.033)	(0.06)	(0.028)	(0.028)	(0.014)
$\ln(\text{Price})_j$ x Ethnic Border	-0.07	0.026	-0.068	-0.169	-0.068	-0.065	-0.07
	(0.013)	(0.015)	(0.014)	(0.018)	(0.011)	(0.011)	(0.008)
$\ln(\text{Price})_j$ x $\log(\text{Distance}_{ij})$	-0.036	-0.015	-0.018	0.017	-0.03	-0.029	-0.02
	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)
$\ln(\text{Price})_j$ x National Border	-0.074	-0.09	-0.075	-0.105	-0.055	-0.054	-0.04
	(0.007)	(0.008)	(0.009)	(0.012)	(0.006)	(0.006)	(0.003)
Ethnic Border	-0.065	0.009	-0.072	-0.145	-0.082	-0.075	-0.063
	(0.015)	(0.004)	(0.016)	(0.015)	(0.013)	(0.012)	(0.008)
$\ln(\text{Distance}_{ij})$	-0.041	-0.009	-0.019	0.018	-0.012	-0.013	-0.018
	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)
National Border	-0.089	-0.01	-0.086	-0.101	-0.068	-0.066	-0.037
	(0.008)	(0.002)	(0.01)	(0.011)	(0.006)	(0.005)	(0.003)
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Month FE	Yes	Yes	Yes	Yes	Yes	No	Yes
Product FE	No	No	No	No	Yes	No	No
Product-Month FE	No	No	No	No	No	Yes	No
Product-Market FE	No	No	No	No	No	No	Yes
Sample:	Maize	Rice	Sorghum	Millet	All	All	All
R^2	0.734	0.721	0.781	0.801	0.777	0.785	0.831
Total Obs	1781190	688328	632116	263332	3364966	3364966	3364966

TABLE A3—

Price Level Derivation

The distribution (c.d.f.) of prices in j is

$$G^t_{j,m}(p) = 1 - e^{-p^\theta \Phi^t_{j,m}}$$

with associated p.d.f.

$$g_{j,m}^{t}(p) = e^{-p^{\theta}\Phi_{j,m}^{t}} p^{\theta-1} \theta \Phi_{j,m}^{t}$$

Then, the expected price in market j is

$$\mathbb{E}_{\omega}[p_{j,m}^{t}(\omega)] = \int_{0}^{\infty} e^{-p^{\theta}\Phi_{j,m}^{t}} p^{\theta} \theta \Phi_{j,m}^{t} dp$$

With the change of variables $x = p^{\theta}\Phi_{j,m}^{t}$ $(dx = \theta p^{\theta-1}\Phi_{j,m}^{t})$ this can be written

$$\begin{aligned}
\mathbb{E}[g_{j,m}^{t}(p)] &= \int_{0}^{\infty} e^{-x} x^{\frac{1}{\theta}} \left(\Phi_{j,m}^{t}\right)^{1-\frac{1+\theta}{\theta}} dx \\
&= \left(\Phi_{j,m}^{t}\right)^{1-\frac{1+\theta}{\theta}} \int_{0}^{\infty} e^{-x} x^{\frac{1}{\theta}} dx \\
&= \left(\Phi_{j,m}^{t}\right)^{-\frac{1}{\theta}} \Gamma\left(\frac{1+\theta}{\theta}\right)
\end{aligned}$$

where

$$\Gamma(z) = \int_{0}^{\infty} e^{-x} x^{z-1} dx$$

is the Gamma function.

Differences in Prices by Size and Type of City

	Maize	Rice	Sorghum	Millet	Mean Price	$log(\hat{p})$	$log(p'_{nat}/\hat{p})$	$log(p'_{eth}/\hat{p})$
log(pop)	0.015	-0.031	-0.013	0.017	-0.010	0.005	-0.044	0.097
	(0.026)	(0.031)	(0.035)	(0.021)	(0.018)	(0.027)	(0.057)	(0.060)
Largest City	-0.003	-0.068	-0.060	0.032	-0.010	0.000	-0.053	0.030
	(0.056)	(0.070)	(0.072)	(0.037)	(0.038)	(0.017)	(0.035)	(0.037)
Capital	0.012	0.019	-0.026	0.054	0.000	-0.007	-0.043	0.075
	(0.06)	(0.071)	(0.074)	(0.040)	(0.04)	(0.023)	(0.049)	(0.052)

Table A4—This table gives the results of 24 regressions. Each cell in gives the coefficient from the regression of the log price or log ratio of prices given in each column on the independent variable given in each row. Population data are from Porteous (2019). Largest city is an indicator taking on a value of one if a given location is the largest city within each country and zero otherwise. Capital is an indicator taking on a value of one if a location is a capital city and zero otherwise. Each specification includes the full set of country fixed effects. Results without country fixed effects are qualitatively similar and are available on request. Standard errors clustered by country are in parentheses.

Location Price Levels: Descriptive Statistics

Descriptive Statistics By Location-Commodity

	Maize $\overline{p}$ (σ_p)	Millet $\overline{p}$ (σ_p)	Rice $\overline{p}$ (σ_p)	Sorghum $\overline{p}$ (σ_p)
Market	N	N	N	N
Angola				
Luanda	1.797			
	(0.053)			
	11			
Market				
Cotonou	0.398		0.833	
	(0.015)		(0.015)	
	142		142	
Malanville	0.279			0.327
	(0.016)			(0.016)
	122			122
Natitingou	0.301		0.843	0.405
	(0.015)		(0.015)	(0.018)
	140		140	94
Parakou	0.322		0.999	

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
	(0.016)		(0.024)	
	114		53	
Gaborone	0.262			
	(0.023)			
	57			
Burkina Faso				
Bobo-Dioulasso		0.379		0.297
		(0.025)		(0.025)
		48		48
Dedougou		0.341		0.293
		(0.021)		(0.021)
		71		71
Fada-Ngourma		0.344		0.31
		(0.021)		(0.021)
		71		71
Ouagadougou		0.341		0.29
		(0.018)		(0.018)
		95		95
Burundi				
Bujumbura	0.419			0.466
	(0.018)			(0.018)
	98			98
Gitega	0.35			0.396
	(0.018)			(0.018)
	98			98
Muyinga	0.362			0.342
	(0.018)			(0.018)
	97			98
Cameroon				
Bamenda	0.478		0.719	
	(0.017)		(0.017)	
	105		105	
Douala	0.562		0.723	
	(0.017)		(0.017)	
	105		105	
Garoua	0.389		0.854	
	(0.017)		(0.017)	
	105		105	
Yaounde	0.537		0.826	
	(0.017)		(0.017)	
	105		105	

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
Central African Republic				
Bambari	0.654		0.718	
	(0.03)		(0.03)	
	34		34	
Bangassou	0.288		0.62	
	(0.036)		(0.036)	
	24		24	
Bangui	0.494		1.218	
	(0.017)		(0.017)	
	104		104	
Côte d'Ivoire				
Abengourou	0.745		0.775	
	(0.034)		(0.033)	
	27		28	
Abidjan	0.567		0.815	
	(0.032)		(0.033)	
	30		29	
Bouake	0.303		0.697	
	(0.017)		(0.018)	
	103		92	
Daloa	0.491		0.804	
	(0.033)		(0.034)	
	28		27	
Man	0.362		0.716	
	(0.017)		(0.019)	
	105		81	
Odienne	0.258		0.733	
	(0.024)		(0.024)	
	52		52	
Chad				
Abeche		0.392		0.267
		(0.016)		(0.016)
		121		121
Moundou		0.373		0.302
		(0.016)		(0.016)
		121		121
Ndjamena	0.429	0.441	0.806	0.347
	(0.016)	(0.016)	(0.016)	(0.016)
	121	121	121	121
Sarh		0.394		0.334

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
		(0.016)		(0.016)
		121		121
Republic of Congo				
Brazzaville			1.17	
			(0.034)	
			27	
Djibouti				
Djibouti			0.729	
			(0.016)	
			119	
Democratic Republic of Congo				
Bandundu	0.392		1.19	
	(0.022)		(0.022)	
	66		66	
Bukavu	0.629		1.207	
	(0.022)		(0.022)	
	66		65	
Bunia	0.596		1.235	
	(0.022)		(0.022)	
	66		66	
Butembo	0.506		1.111	
	(0.022)		(0.022)	
	66		66	
Gbadolite	0.498		1.386	
	(0.022)		(0.022)	
	66		66	
Goma	0.437		1.266	
	(0.022)		(0.022)	
	66		66	
Isiro	0.651		1.198	
	(0.025)		(0.025)	
	50		50	
Kalemie	0.52		1.155	
	(0.022)		(0.022)	
	66		66	
Kamina	0.396		1.398	
	(0.026)		(0.026)	
	46		46	
Kananga	0.734		0.942	
	(0.022)		(0.022)	

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
	66		66	
Kikwit	0.391		0.982	
	(0.022)		(0.022)	
	65		65	
Kindu	0.661		0.846	
	(0.022)		(0.022)	
	66		66	
Kinshasa	0.673		1.212	
	(0.022)		(0.022)	
	66		66	
Kisangani	0.297		0.819	
	(0.022)		(0.022)	
	66		66	
Kolwezi	0.739		1.233	
	(0.022)		(0.022)	
	66		66	
Lubumbashi	0.713		1.112	
	(0.022)		(0.024)	
	66		52	
Matadi	0.616		1.313	
	(0.022)		(0.022)	
	66		63	
Mbandaka	0.341		0.972	
	(0.022)		(0.022)	
	66		66	
MbujiMayi	0.496		1.31	
	(0.022)		(0.022)	
	66		66	
Tshikapa	0.69		1.542	
	(0.022)		(0.022)	
	66		66	
Uvira	0.519		0.873	
	(0.022)		(0.022)	
	66		66	
Zongo	0.35		1.082	
	(0.022)		(0.022)	
	66		65	
Eritrea				
Asmara				0.925
				(0.044)

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
				16
Ethiopia				
Addis Ababa	0.223			0.446
	(0.015)			(0.022)
	143			64
Awasa	0.494			0.41
	(0.026)			(0.022)
	46			66
Bahir Dar	0.215			0.326
	(0.015)			(0.022)
	143			65
Dessie	0.272			0.407
	(0.018)			(0.022)
	92			66
Dire Dawa	0.257			0.452
	(0.015)			(0.022)
	135			66
Gambela	0.301			0.439
	(0.062)			(0.04)
	8			19
Gode	0.348			0.362
	(0.019)			(0.021)
	82			69
Gondar	0.274			0.323
	(0.018)			(0.019)
	99			85
Jijiga	0.348			0.341
	(0.019)			(0.02)
	83			76
Jimma	0.24			0.384
	(0.018)			(0.022)
	99			66
Mekele	0.256			0.389
	(0.015)			(0.022)
	140			64
Nekemte	0.265			0.262
	(0.033)			(0.022)
	29			66
Yabelo	0.308			
	(0.019)			

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
	(82)			
Gabon				
Libreville			1.072	
			(0.019)	
			82	
The Gambia				
Banjul	0.535	0.526	0.578	0.506
	(0.02)	(0.019)	(0.02)	(0.02)
	78	83	80	78
Guinea Bissau				
Bissau	2.078	1.193	0.966	1.239
	(0.021)	(0.02)	(0.02)	(0.021)
	71	74	74	72
Ghana				
Accra	0.408	0.64	0.946	0.519
	(0.018)	(0.018)	(0.018)	(0.018)
	93	93	90	93
Bolgatanga	0.307	0.456	0.813	0.33
	(0.018)	(0.018)	(0.018)	(0.018)
	93	93	90	93
Ho	0.399		0.82	
	(0.022)		(0.023)	
	64		60	
Kumasi	0.375	0.549	0.782	0.406
	(0.018)	(0.018)	(0.019)	(0.018)
	93	93	89	92
Sekondi-Takoradi	0.502		0.874	
	(0.022)		(0.022)	
	64		64	
Tamale	0.276	0.502	0.576	0.333
	(0.018)	(0.018)	(0.019)	(0.018)
	93	93	89	93
Wa	0.284	0.476	0.794	0.36
	(0.018)	(0.018)	(0.019)	(0.018)
	93	92	89	93
Guinea				
Conakry			0.995	
			(0.026)	
			44	
Kankan			0.859	

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
			(0.023)	
			59	
Labe			0.832	
			(0.023)	
			57	
Nzerekore			0.941	
			(0.023)	
			58	
Kenya				
Eldoret	0.245			
	(0.015)			
	139			
Garissa	0.393			
	(0.015)			
	141			
Kisumu	0.288			
	(0.015)			
	143			
Lodwar	0.503			
	(0.015)			
	143			
Mandera	0.461			
	(0.015)			
	143			
Mombasa	0.266			
	(0.015)			
	131			
Moyale	0.277			
	(0.015)			
	133			
Nairobi	0.277			
	(0.015)			
	143			
Nakuru	0.323			
	(0.021)			
	72			
Wajir	0.419			
	(0.015)			
	(135)			
Lesotho				

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
Maseru	0.305 (0.026) (45)			
Liberia				
Gbarnga			0.642 (0.022) 63	
Monrovia			0.57 (0.023) 57	
Malawi				
Blantyre	0.271 (0.018) 92			
Karonga	0.239 (0.016) 127			
Lilongwe	0.254 (0.018) 100			
Mangochi	0.243 (0.016) 121			
Mzuzu	0.233 (0.016) (123)			
Mali				
Bamako		0.333 (0.017) 107	0.664 (0.018) 95	0.307 (0.018) 95
Gao		0.365 (0.022) 66	0.795 (0.024) 54	0.336 (0.023) 57
Kayes		0.377 (0.018) 95	0.77 (0.018) 95	0.335 (0.018) 95
Mopti		0.368 (0.021) 71	0.713 (0.021) 71	0.346 (0.021) 71
Segou		0.319	0.666	0.311

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
		(0.021)	(0.021)	(0.021)
		71	71	71
Sikasso		0.354	0.696	0.293
		(0.021)	(0.021)	(0.021)
		71	71	71
Mauritania				
Adel Bagrou			0.683	0.505
			(0.027)	(0.27)
			43	43
Nouakchott			0.682	0.844
			(0.025)	(0.24)
			49	53
Tintane			0.775	1.1
			(0.053)	(0.055)
			11	10
Mozambique				
Beira	0.232		0.648	
	(0.018)		(0.018)	
	100		92	
Chimoio	0.287		0.93	
	(0.024)		(0.024)	
	52		52	
Cuamba	0.246		1.02	
	(0.025)		(0.025)	
	48		48	
Lichinga	0.214		0.959	
	(0.015)		(0.016)	
	129		127	
Maputo	0.347		0.63	
	(0.015)		(0.015)	
	129		129	
Maxixe	0.317		0.812	
	(0.025)		(0.024)	
	48		52	
Milange	0.23		0.807	
	(0.019)		(0.021)	
	88		70	
Nacala	0.273		0.765	
	(0.027)		(0.027)	
	43		43	
Nampula	0.25		0.649	

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
	(0.015)		(0.015)	
	129		129	
Pemba	0.278		0.719	
	(0.016)		(0.016)	
	121		120	
Quelimane	0.281		0.828	
	(0.028)		(0.025)	
	38		48	
Tete	0.295		1.01	
	(0.024)		(0.024)	
	52		52	
Xai-Xai	0.336		0.86	
	(0.028)		(0.028)	
	39		39	
Namibia				
Katima Mulilo	0.477			
	(0.038)			
	21			
Oshakati	0.603			
	(0.04)			
	19			
Swakopmund	0.539			
	(0.038)			
	21			
Windhoek	0.535			
	(0.038)			
	(21)			
Niger				
Agadez		0.37		0.351
		(0.016)		(0.016)
		124		122
Arlit		0.501		0.482
		(0.024)		(0.024)
		52		52
Diffa		0.465		0.432
		(0.025)		(0.025)
		51		50
Maradi		0.291		0.28
		(0.016)		(0.016)
		124		122
Niamey		0.385		0.388

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
		(0.016)		(0.016)
		124		124
Tahoua		0.517		0.465
		(0.025)		(0.025)
		51		51
Zinder		0.296		0.28
		(0.016)		(0.016)
		124		124
Nigeria				
Abuja	0.368	0.401	0.72	0.385
	(0.019)	(0.019)	(0.019)	(0.019)
	88	88	88	88
Akure	0.421	0.5	0.708	0.483
	(0.018)	(0.019)	(0.019)	(0.019)
	90	87	88	89
Benin City	0.541	0.566	0.786	0.594
	(0.019)	(0.019)	(0.019)	(0.019)
	89	89	88	89
Calabar	0.516	0.627	0.659	0.653
	(0.019)	(0.019)	(0.019)	(0.018)
	87	86	88	90
Enugu	0.503	0.555	0.694	0.509
	(0.019)	(0.019)	(0.019)	(0.019)
	88	88	88	88
Gombe	0.309	0.306	0.557	0.3
	(0.019)	(0.019)	(0.019)	(0.019)
	86	86	86	86
Ibadan	0.363	0.419	0.714	0.394
	(0.019)	(0.019)	(0.019)	(0.019)
	88	87	88	88
Ilorin	0.339	0.373	0.638	0.348
	(0.019)	(0.019)	(0.019)	(0.019)
	87	87	87	87
Jos	0.332	0.396	0.668	0.402
	(0.018)	(0.018)	(0.018)	(0.018)
	91	91	91	91
Kaduna	0.313	0.351	0.646	0.333
	(0.019)	(0.019)	(0.019)	(0.019)
	88	88	88	88
Kano	0.328	0.307	0.598	0.317
	(0.019)	(0.019)	(0.019)	(0.019)

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
	89	89	89	89
Katsina	0.302	0.308	0.573	0.278
	(0.019)	(0.019)	(0.019)	(0.019)
	88	88	88	88
Lagos	0.494	0.558	0.833	0.598
	(0.019)	(0.019)	(0.023)	(0.019)
	88	88	57	87
Lokoja	0.439	0.484	0.728	0.469
	(0.019)	(0.019)	(0.019)	(0.019)
	88	88	88	88
Maiduguri	0.329	0.296	0.672	0.328
	(0.019)	(0.019)	(0.019)	(0.019)
	87	87	87	87
Makurdi	0.408	0.422	0.712	0.387
	(0.019)	(0.019)	(0.019)	(0.019)
	89	89	89	89
Port Harcourt	0.571	0.558	0.919	0.558
	(0.018)	(0.019)	(0.018)	(0.019)
	90	89	90	89
Sokoto	0.345	0.333	0.644	0.342
	(0.019)	(0.019)	(0.019)	(0.019)
	89	89	89	89
Yola	0.345	0.389	0.674	0.349
	(0.019)	(0.019)	(0.019)	(0.019)
	87	87	87	87
Rwanda				
Butare	0.418			0.429
	(0.023)			(0.022)
	58			62
Gisenyi	0.41			0.448
	(0.028)			(0.031)
	39			31
Kigali	0.38			0.422
	(0.024)			(0.024)
	54			54
South Africa				
Johannesburg	0.197			
	(0.015)			
	(143)			
Senegal				

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
Dakar	0.413 (0.026) 45	0.393 (0.015) 134	0.609 (0.047) 14	0.373 (0.017) 101
Kaolack	0.377 (0.02) 79	0.37 (0.02) 79	0.554 (0.175) 1	0.393 (0.02) 77
Saint Louis	0.438 (0.021) 72	0.46 (0.02) 73	0.557 (0.023) 58	0.462 (0.02) 73
Tambacounda	0.38 (0.02) 78	0.407 (0.02) 78	0.572 (0.078) 5	0.39 (0.02) 74
Touba	0.373 (0.023) 56	0.375 (0.02) 75	0.515 (0.027) 41	0.366 (0.022) 61
Ziguinchor	0.475 (0.024) 53	0.459 (0.024) 53	0.697 (0.101) 3	0.472 (0.024) 52
Sierra Leone				
Bo			0.71 (0.026) 44	
Freetown			0.691 (0.034) 27	
Kabala			0.603 (0.039) 20	
Somalia				
Baidoa	0.218 (0.015) 132			0.153 (0.015) 133
Beledweyne	0.283 (0.015) 136			0.209 (0.018) 94
Bosaso	0.381 (0.017) 101			0.534 (0.015) 142
Galkayo	0.411 (0.015)			0.357 (0.015)

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
	131			133
Garoowe	0.59			0.638
	(0.016)			(0.016)
	127			126
Hargeisa	0.429			0.394
	(0.015)			(0.017)
	135			112
Kismayo	0.318			0.252
	(0.018)			(0.026)
	91			45
Mogadishu	0.253			0.201
	(0.015)			(0.015)
	143			139
South Sudan				
Bor	0.727			1.041
	(0.023)			(0.022)
	56			61
Juba	0.674			0.798
	(0.021)			(0.018)
	72			90
Malakal	1.855			0.748
	(0.045)			(0.019)
	15			85
Rumbek	1.439			1.855
	(0.027)			(0.027)
	41			43
Wau	0.762			0.87
	(0.025)			(0.02)
	48			76
Sudan				
Ad-Damazin		0.487		0.352
		(0.018)		(0.018)
		91		93
Al Fashir		0.505		0.442
		(0.015)		(0.019)
		130		82
Al Qadarif		0.453		0.307
		(0.015)		(0.015)
		140		143
El Geneina		0.401		0.268
		(0.016)		(0.016)

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
		125		120
El Obeid		0.454		0.324
		(0.016)		(0.016)
		126		126
Kadugli		0.608		0.349
		(0.017)		(0.017)
		106		111
Kassala		0.449		0.316
		(0.016)		(0.016)
		126		127
Khartoum		0.499		0.347
		(0.015)		(0.015)
		143		143
Kosti		0.436		0.284
		(0.017)		(0.017)
		110		110
Nyala		0.559		0.363
		(0.015)		(0.015)
		129		129
Port Sudan		0.633		0.437
		(0.017)		(0.017)
		102		107
Swaziland				
Mbabane	0.266			
	(0.018)			
	(97)			
Tanzania				
Arusha	0.258		0.784	
	(0.018)		(0.018)	
	93		92	
Bukoba	0.279		0.678	
	(0.019)		(0.019)	
	82		82	
Dar es Salaam	0.277		0.811	
	(0.018)		(0.018)	
	92		92	
Dodoma	0.278		0.851	
	(0.018)		(0.018)	
	92		92	
Iringa	0.227		0.778	
	(0.018)		(0.018)	

Continued...

Descriptive Statistics By Location-Commodity

	Maize	Millet	Rice	Sorghum
	$\overline{p}$	$\overline{p}$	$\overline{p}$	$\overline{p}$
	(σ_p)	(σ_p)	(σ_p)	(σ_p)
Market	N	N	N	N
	92		92	
Kigoma	0.27		0.694	
	(0.021)		(0.02)	
	69		74	
Mbeya	0.226		0.757	
	(0.018)		(0.018)	
	91		91	
Mtwara	0.276		0.785	
	(0.018)		(0.018)	
	91		92	
Musoma	0.28		0.74	
	(0.019)		(0.019)	
	87		87	
Mwanza	0.305		0.719	
	(0.019)		(0.018)	
	89		90	
Singida	0.262		0.774	
	(0.018)		(0.018)	
	92		92	
Songea	0.197		0.771	
	(0.02)		(0.022)	
	80		64	
Sumbawanga	0.202		0.691	
	(0.02)		(0.019)	
	80		81	
Tabora	0.267		0.659	
	(0.02)		(0.018)	
	74		91	
Tanga	0.262		0.771	
	(0.019)		(0.019)	
	89		89	
Togo				
Kara	0.269		0.733	0.334
	(0.015)		(0.015)	(0.015)
	143		143	143
Lome	0.377		0.787	0.515
	(0.015)		(0.015)	(0.015)
	143		143	143
Uganda				
Arua	0.223			

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
	(0.016) 120			
Gulu	0.378 (0.032) 30			0.26 (0.032) 30
Jinja	0.294 (0.032) 30			0.314 (0.032) 30
Kampala	0.362 (0.032) 30			0.368 (0.032) 30
Lira	0.311 (0.032) 30			0.263 (0.032) 30
Masindi	0.176 (0.017) 107			0.233 (0.071) 6
Mbarara	0.537 (0.032) 30			0.676 (0.032) 30
Zambia				
Chipata	0.217 (0.015) 130			
Kabwe	0.194 (0.015) 129			
Kasama	0.229 (0.015) 130			
Kitwe	0.233 (0.015) 130			
Livingstone	0.224 (0.016) 122			
Lusaka	0.24 (0.015) 129			
Mongu	0.195			

Continued...

Descriptive Statistics By Location-Commodity

Market	Maize $\overline{p}$ (σ_p) N	Millet $\overline{p}$ (σ_p) N	Rice $\overline{p}$ (σ_p) N	Sorghum $\overline{p}$ (σ_p) N
	(0.016) 126			
Solwezi	0.221 (0.015) (130)			
Zimbabwe				
Bulawayo	0.312 (0.026) 44			
Harare	0.307 (0.026) 44			
Hwange	0.378 (0.033) 29			
Masvingo	0.354 (0.026) 45			
Mutare	0.323 (0.026) 45			