Diversity and the World's Endangered Languages

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Ninety percent of the world's languages face extinction within the next century. Many social scientists attribute this to increased trade, despite a lack of empirical work exploring this relationship. This paper empirically tests whether mutual trade incentives affect language vitality for thousands of ethnolinguistic groups. We find that at the language level, groups that are more likely to trade are less likely to face extinction, in contrast to claims that trade is a threat to diversity. In fact, greater mutual trade incentives are significantly associated with more ethnolingusitic fractionalization at the country level.

Keywords: Diversity, economic incentives, language extinction.

JEL Codes: O1, Z1.

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1. Introduction

Ninety percent of the world's languages face extinction within the next century (McWhorter, 2015), and more than a third of currently active languages will not be passed on to the next generation (Simons & Lewis, 2013). Scholars of language usually attribute this looming annihilation of ethnolinguistic diversity to globalization. However, this conclusion is mostly built on case studies of threatened languages, rather than a global empirical investigation. Even among case studies, research rarely tries to identify the particular types of trade that harm diversity. Indeed, it is often taken for granted that trade will only ever quash diversity, despite a positive correlation between diversity and markets in the economics literature (Montalvo & Reynal-Querol, 2021). That said, economic research rarely considers endangered languages. These individually small groups may, collectively, shape economically important measures of ethnolinguistic heterogeneity. Accordingly, the relationship between trade and the survival of ethnolinguistic diversity remains poorly understood.

In this paper we empirically demonstrate that trade affects the vitality of thousands of languages. To do this we rely on data that measures the potential gains from local agricultural trade. This measure (from Blouin and Dyer (2022)) is based only on agricultural suitability and human nutritional needs, so it is plausibly exogenous. It captures how much each ethnolinguistic group gains from trading with each neighbouring group, and how much each of their neighbours gains from trading with them. We use this to identify which groups have large mutual gains from trade with their neighbours. In other words, the data measure where local cross-cultural trade is most likely to occur. After using this data to explore whether trade affects language endangerment, we aggregate to the level of countries, and test whether the dynamics of language vitality are substantial enough to impact the various measures of country-level diversity.

To do this requires two additional types of data, in addition to the trade data mentioned above. First, we rely on data scraped from the Ethnologue (Lewis, 2009) that codes languages according to the Expanded Graded Intergenerational Disruption Scale (EGIDS) of language vitality. Despite the Ethnologue being ubiquitous within economics, this information on the changing status of languages has infrequently been investigated. This has led to an incomplete picture of diversity and economic development, since half of groups in our data are currently undergoing either significant growth or decline. We combine this with oft-used measures of country level diversity that have been linked to important outcomes such as conflict, quality of government, and trust.

We find that language groups that are more likely to trade are less likely to face extinction, in contrast to some of the claims of the market's role in language homogenization. In such situations, trade appears to promote specialization rather than homogenization. This is consistent with work showing that a shared context leads to location-specific human capital and group formation (Michalopoulos, 2012) and that areas of greater ethnic heterogeneity are associated with more markets and economic growth (Montalvo & Reynal-Querol, 2021). However, this average effect hides considerable heterogeneity. In particular, the estimate is driven predominantly by groups who would have been categorized as 'threatened' if they were less likely to trade, and are instead classified as 'non-dominant.' We see little effect of trade on the vitality of official national or provincial languages.

Economic incentives therefore play an important role in the dynamics of language vitality, especially for endangered languages. The next natural question is whether these dynamics, in turn, impact country-level diversity. This is a potentially important issue, given the evidence that ties ethnolinguistic diversity to poor economic development at the country-level. Seminal work, for instance, shows that ethnic fractionalization is negatively related to quality of government and growth (Alesina et al., 2003). We find that greater mutual trade incentives are associated with countries being fractionalized into smaller groups. This is true whether we use the standard Ethnolinguistic Fractionalization measure (Alesina et al., 2003), an alternative measure of Fragmentation (Fearon, 2003), a Cultural Diversity measure (Desmet et al., 2009; Fearon, 2003; Greenberg, 1956),[1] or simply the number of ethnolinguistic groups in a country (Michalopoulos, 2012). Despite trade primarily impacting the vitality of small, endangered language groups, when considered together the survival of these groups significantly increases fractionalization. Understanding the factors that shape fractionalization is crucial both because of its demonstrated close relationship with economic development, and because it is important to understand when and how fractionalization is endogenous.

The same empirical relationship does not, however, hold for measures of diversity that capture polarization. The impact of mutual trade incentives is small and insignificant when we consider outcomes such as Ethnic Polarization (Esteban & Ray, 1994, 2011; Reynal-Querol, 2002). This is true regardless of whether or not we compute polarization using cultural distances (Desmet et al., 2012). The same is true for Peripheral Heterogeneity (Desmet et al., 2009), which captures the sum of differences between the largest group and all others. These measures of heterogeneity have also been shown to affect economic development through various mechanisms. Peripheral heterogeneity is associated with redistribution (Desmet et al., 2009) and polarization with conflict (Esteban et al., 2012; Esteban & Ray, 2011; Reynal-Querol, 2002). Our finding that trade impacts fractionalization but not these measures of heterogeneity is consistent with the language-level finding that trade encourages the survival of endangered languages.

All together, the contribution of this article is to show that economic trade is an important determinant of diversity because it supports the survival of endangered languages. To show this we introduce new data on language vitality, and complement this

[1] Cultural Diversity refers to fractionalization weighted by linguistic distance (Fearon, 2003).

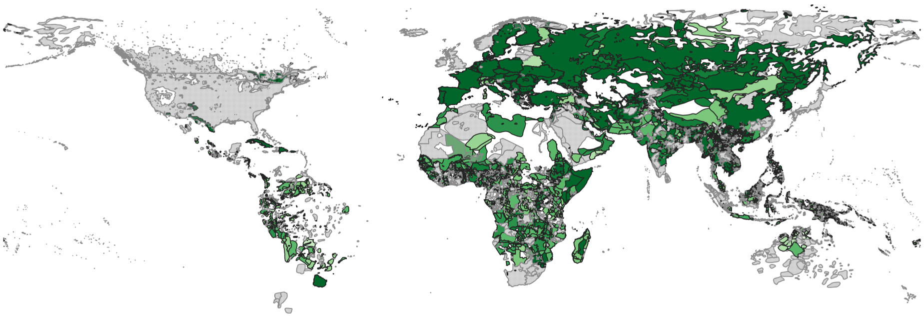
data with the main measures of diversity in the literature. Beyond those mentioned above, work by Alesina et al. (2016) shows that economic inequality determines the *impact* of diversity. They show that a measure of inequality across ethnicities dominates other population-based heterogeneity measures in explaining economic performance. We present evidence that trade incentives positively influence this measure as well, although the fact that the variable combines notions of diversity and inequality (both of which are plausibly influenced by trade) complicates the interpretation. Similarly, we also consider Ethnic Segregation (Alesina & Zhuravskaya, 2011). This measure accounts not only for the population of each group, but also their geographic dispersion. As this measure incorporates mechanisms such as integration and internal migration, interpreting the impact of trade incentives is also less clear. Nevertheless, we show that mutual trade incentives are also positively associated with this type of diversity.

While a large literature documents the economic impact of diversity, there is less work examining the endogeneity of diversity, with a few notable exceptions. The seminal work on the topic demonstrates that variation in elevation and land quality is associated with more diversity (Michalopoulos, 2012). Suggestive evidence points towards one channel being that location-specific human capital accumulation constrains the migration of members of an ethnolinguistic group. Conversely, Dickens (2022) shows that greater geographic heterogeneity between neighbouring groups leads to greater linguistic similarity. Ahlerup and Olsson (2012) show that the relationship between peripheral and core populations in a group leads to the endogenous emergence of new groups. Blouin and Dyer (2022) show that power dynamics within cross-cultural relationships shape the patterns and direction of cultural convergence. Jha (2013) shows that historical incentives for inter-group interaction lead to higher contemporary ethnic tolerance.

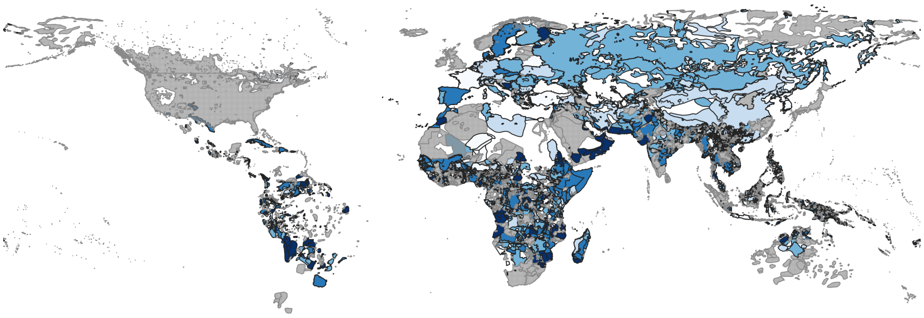
Finally, the investigation into language extinction contributes to a small but growing literature on cultural change, rather than culture as a fixed constraint. Giuliano and Nunn (2021) explore the role of environmental stability in the determining the strength of cultural persistence. Bisin and Verdier (2021) introduce the use of phase diagrams as a tool to explore cultural change over time.

2. Data: Vitality, Diversity, and Trade Incentives

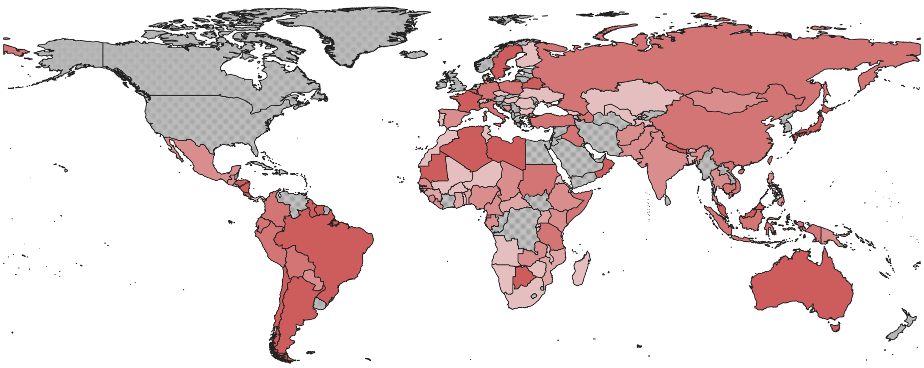
To study dynamics and economic implications of endangered language survival we need three pieces of information. First is whether groups are dwindling or thriving. To measure this, we draw upon the best-practice coding system to classify languages according to their level of intergenerational disruption. Second is how these dynamics shape country-level diversity. To measure this we collect the most common measures in the literature on ethnolinguistic heterogeneity. Third is to measure the incentive for groups to trade with each other. To this end, we use estimated trade incentives, based on plausibly exogenous



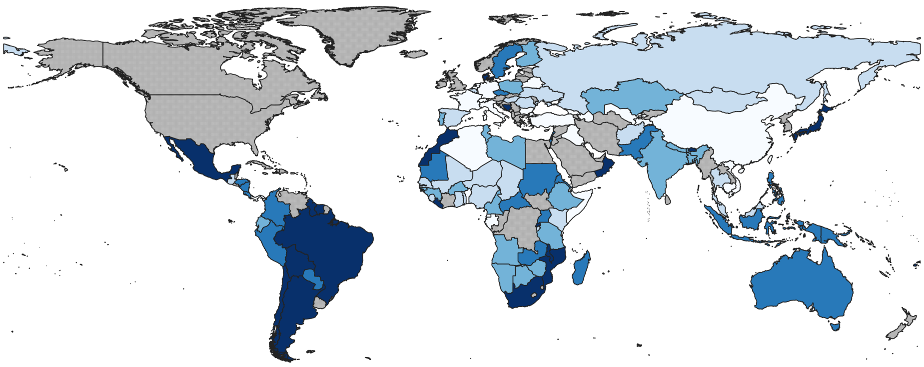
(a) Language Vitality Score



(b) Language-Level Mean Trade Incentives



(c) Country-Level Share of Languages that are Threatened



(d) Country-Level Mean Trade Incentives

Figure 1: Global Language Vitality and Mutual Trade Incentives

Description: These maps show, in panels a) and b) mean pairwise mutual trade incentives across the world, and the vitality of different language groups. In panels c) and d) we show what these measures look like when aggregated to the country level.

complementarity of geographic endowments.

Summary statistics are in table A1,[2] and the geographic distribution of both trade and ethnolinguistic diversity can be seen in figure 1. We next give a detailed discussion of each of these three types of data.

2.A. Measuring Language Vitality

There is a vast and growing literature on ethnolinguistic diversity. However, the survival of individual ethnolinguistic groups has so far received little attention from economists. We address this by compiling the meticulous work carried out by linguists to classify languages according to their vitality and disruption along a standardized scale.

The data that we introduce (to economics) in this article categorize the vitality of each language. Specifically, we extract EGIDS scores, developed by Lewis and Simons (2010), and assigned to each language in the Ethnologue database (Lewis, 2009). These EGIDS scores are assigned on a 13 point scale, ranging from languages of 'International,' 'National,' or 'Provincial' importance, through to languages that are 'Nearly Extinct,' 'Dormant,' or 'Extinct.'[3]

The process of categorizing languages into one of these groupings followed four steps. First, Lewis and Simons (2010) reviewed the academic literature covering each language, and categorized any languages where there was enough academic work to do so. Second, in cases where this information was not available, they consulted UNESCO's *Atlas of the World's Languages in Danger* (Moseley, 2010), which also provides statistics on language use that allow for categorization. From these two steps, about two thirds of languages could be categorized. For the remaining one-third, they imputed an initial categorization of 'Vigorous Oral Use,' which is the modal category across the world. Finally, they then sent this first-draft of the data to a panel of 43 regional-experts. Based on the expertise of the panel, many updates and corrections were implemented.

Conceptually, we are interested in three types of languages. First are the dominant languages that drive many measures of diversity, like ethnolinguistic polarization. Second, the stable languages whose survival is not under threat but who are not dominant at the national or regional level. Finally, the groups whose survival is under threat, and are at greatest risk of being absorbed by other groups. To this end, we group languages into three intuitive categories *dominant*, *non-dominant*, and *threatened*.[4]

The first stylized fact that should be stressed is that language groups are dynamic. We present the distribution of languages in figure B1. This histogram shows that roughly a third of languages are listed as *Threatened*, while just under a third are *Shifting*. In

[2]Balance tests are in table A2.

[3]Supplementary information on the original construction of categories is in section B2.

[4]The definition of each category in the EGIDS is in table B1, which also shows the groupings into dominant, non-dominant and threatened.

short, the majority of the world's languages are in flux. This is particularly pertinent given the tendency within the economics literature to treat the existence and distribution of languages as static (Bisin & Verdier, 2014). Further inspection of the distribution shows that, in fact, a very small share of the world's languages are dominant nationally, provincially, or regionally.

2.B. Measuring Country-level Diversity

We measure the ethnolinguistic diversity of countries using standard measures in the economics literature. These roughly fall into two categories: those that measure the degree to which a country is fragmented into many small groups (which we will call fractionalization-style measures) and those that measure to what degree a country is partitioned into competing blocks (which we will refer to as polarization-style measures).

The first type of country-level diversity measure captures the concept of fractionalization. This group of variables measures the degree to which a country is split into many different ethnolinguistic groups. We consider a number of standard fractionalization measures that are commonly used in the literature.[5] First, we use the Ethnolinguistic Fractionalization measure (henceforth ELF), first introduced in Alesina et al. (2003). Second, we explore the Fragmentation index (F), taken from Fearon (2003). F and ELF are computed in the same way - both capture the probability that if two random people from the country meet, they are from different groups. That said, they are not close to being perfectly correlated (table A5a). The difference between them is that Fearon (2003) goes to considerable lengths to base F on an underlying data set that captures how much people actually identify with a particular ethnic group, in a particular country. Conversely, ELF is based on the ethnographies of outsiders.

We also explore two other related measures. Inspired by work on cultural distance (Desmet et al., 2012; Fearon, 2003; Greenberg, 1956), we construct Cultural Diversity (CD). CD is a fractionalization measure that is weighted by cladistic language distance (i.e. the extent of overlap in the branches of a language tree).[6] Lastly, building off of Michalopoulos (2012), we also look at the logarithm of the number of ethnolinguistic groups in a country. All of these measures share the characteristic that they are largest when a country's population is split into a large number of groups.

To complement this, we consider polarization-style measures of diversity that tend to place greater weight on the distribution of the population that belongs to the larger, more dominant ethnic groups in a country.[7] If the survival of potentially threatened languages has a negligible impact on the population of large influential groups, it is possible that

[5] See supplementary details from original source in table A3.

[6] This approach is used in a number of other applications (Blouin, 2021; Desmet et al., 2009; Greenberg, 1956).

[7] See supplementary details from original source in table A4.

the impact of mutual trade incentives on fractionalization may differ markedly from the impact of trade on these other measures.

We first consider Ethnic Polarization (EP) (Esteban & Ray, 1994, 2011; Reynal-Querol, 2002). EP takes into account each group's size, and versions of it also consider the linguistic distance between them and another group. This measure, which has been associated with greater conflict (Esteban & Ray, 2011; Reynal-Querol, 2002; Reynal-Querol & Montalvo, 2005), is maximized (holding distances constant) when a country is divided into two equally large groups. Following Desmet et al. (2012) we consider variations of this measure considering group cleavages occurring at different depths of the linguistic family tree. We also examine Peripheral Heterogeneity (PHI) (Desmet et al., 2009), which takes the sum of the distance between the central (largest) group and all peripheral (other) groups, weighted by group sizes.[8]

Finally, we also consider two complex measures of diversity that are not solely population based, but incorporate other aspects of integration.[9] For this reason, the interpretation is not as straightforward as with the measures discussed above. Ethnic Inequality (EI) (Alesina et al., 2016) is a measure of fractionalization that accounts for wealth inequality. Ethnic Segregation (ES) (Alesina & Zhuravskaya, 2011) captures the degree to which the populations of different groups are segregated across sub-regions of a country. This is maximized when a country has groups living in separate sub-regions. Since both wealth and migration may also be linked to trade incentives, it is not clear that any relationship with mutual trade incentives is driven solely by the survival of threatened languages. The analysis of these outcomes, therefore, is more suggestive in nature.

2.C. Estimating Local Agricultural Trade Incentives

To measure the incentive for each language-group to trade with each other, we use pairwise language-group data on welfare gains from agricultural trade. This measure is generated based upon a combination of the methodological approach of Costinot and Donaldson (2012) and the insight that groups aim to maximize nutrients consumed, in the spirit of Galor and Özak (2016). In particular, we use the measure in Blouin and Dyer (2022), who introduce this data in greater detail and carry out a number of validation exercises. Importantly, gains from trade in this model are plausibly exogenous, as they arise from complementarity in geographic characteristics.

More specifically, Blouin and Dyer (2022) estimate the welfare gains from local agricultural trade that each group receives via trade with each other group. The data is restricted to language group pairs that are geographic neighbours, and for each of these pairs we observe the incentives for one group to trade with the other, and vice-versa. These need not be the same, and often are not. Trade incentives are structurally esti-

[8] The correlations among fractionalization and polarization measures are in table A5a and A5b.
[9] See supplementary details from original source in table A6.

mated using a rudimentary model of Ricardian trade in agricultural products, based on Costinot and Donaldson (2012). The model in Costinot and Donaldson (2012) is augmented with nutrititional data - building on Galor and Özak, 2015 - who model caloric suitability instead of simple agricultural suitability. Inspired by this insight, utility is modeled as a function of meeting the necessary nutritional requirements for survival. In short, complementarity in geographically-determined potential production of calories and sixteen essential nutrients generates the incentive to trade across ethnolinguistic groups.

The data used to estimate gains from trade are based on production suitability for forty-nine crops covering the entire world, from the Global Agro-Ecological Zones (GAEZ) data-set (IIASA/FAO, 2012).[10] These data determine the production potential of each crop for each ethnolinguistic group, and therefore allow for estimation of the supply-side of the model. Nutritional information is used to model demand for agricultural goods. This demand function generates estimates of equilibrium prices, and ultimately gains from trade. This information is based on the nutrients that are known to be essential in the diet (Chipponi et al., 1982) and the Dietary Reference Intakes (DRI) (compiled by the NAS Institute of Medicine (2006)) as the target amounts of each nutrient.

The model produces a few key pieces of information. Most importantly, it delivers the consumption utility of each group. We include this as a control throughout the analysis and also use to construct gains from trade. In particular, to compute the gains to one group (i) from trading with another (j), we take the utility of group i when they are able to trade with the entire region (U_i^{FT}), and compare this to their utility under the counterfactual when j is not in the region (U_i^{FT-j}). This captures gains from exchange between i and j, as follows:

$$
\begin{aligned}
\gamma_{ij} &= \frac{U_i^{FT} - U_i^{FT-j}}{U_i^{FT-j}} \\
\iota_{ij} &= \frac{U_j^{FT} - U_j^{FT-i}}{U_i^{FT-i}}
\end{aligned}
\tag{1}
$$

Because the trade incentives are not symmetric, we are able to compute the extent to which group i gains from trading with group j (γ_{ij}) as well as the extent to which group j benefits from trading with i. When both i benefits from trading j, and j benefits from trading with i, we will say that there exist mutual gains from trade. We interpret these mutual gains from trade as a measure of the likelihood of trade.

[10]Estimates are based on the potential yield for rain-fed crops using low levels of inputs, as in Galor and Özak (2016).

3. How trade impacts the survival of languages

In this section we explore the dynamics of language survival. We first describe the language-level empirical strategy, and then review the resulting empirical estimates.

3.A. Empirical Specification

For analysis at the language level we regress language vitality on trade incentives, controlling for country fixed effects and a variety of additional variables. Our main variables of interest capture the incentives for a group to trade with each of their J neighbours.

$$\gamma_i = \sum_j^J \frac{\gamma_{ij}}{J} \qquad (2)$$

$$\iota_i = \sum_j^J \frac{\iota_{ij}}{J}$$

$$\mu_i = \sum_j^J \frac{\gamma_{ij} \times \iota_{ij}}{J}$$

We interpret these variables as the group's average gain from trade (γ_i), the average gains from trade for their neighbours (ι_i), and the mutual gains from trade (μ_i). The idea behind μ_i is that it represents the likelihood that trade takes place. A trading relationship is more likely when both parties find it beneficial to trade with the other, and is unlikely if either party does not find it beneficial. The interpretation of μ_i as proportional to the likelihood of trade stems from the fact that the gains from trade variables assume frictionless trade, which does not seem realistic in reality. Because of this, the larger is interaction in the two gains from trade, the more likely it is that the benefit of trade for both parties exceeds their respective trade costs. We include all three of these variables in a regression as follows:

$$v_i = \beta_0 + \beta_1 \mu_i + \beta_2 \gamma_i + \beta_3 \iota_i + \mathbf{X}_i' \Gamma + \alpha_c + \epsilon_i \qquad (3)$$

where $\mathbf{X}$ is a vector of controls,[11] and α_c represents country (c) fixed effects. The outcome, v_i, is the vitality of language i.[12]

[11] This includes the mean and the standard deviation of the group's area share in their neighbourhood, the share of their land that is arable, the diversity of a group's land, as well as their level of utility under trade and their mean level of neighbours' utility under trade.

[12] We estimate this as a linear regression, and semiparametrically using the Verardi and Debarsy (2012) implementation of the Robinson (1988) estimator. An overview (drawn heavily from Verardi and Debarsy (2012)) is in appendix C3.

Our primary interest is in β_1, which can be interpreted as the average effect of an increased likelihood of trade, on language vitality. Capturing the correct counterfactual is slightly tricky. In equation 3, β_1 is the estimate of trade likelihood relative to the case where neither a group nor their neighbours have any incentive to trade. However, this is not the only relevant counterfactual. Consider the four possible scenarios: (I) trade incentives are high for both, so trade is likely; two scenarios (II and III) where trade incentives are high for one party but low for the other, so trade is unlikely; and (IV) the scenario where trade incentives are low for both parties, so trade is unlikely.

β_1 captures the difference between (I) and (IV), while β_2 and β_3 capture the difference between (II) or (III) and (IV). The inclusion of γ_i and ι_i in equation 3 can make a difference to the estimate of β_1 if, in scenario (II) or (III), the group that finds trade more profitable has the option to strategically assimilate to reduce trade costs, and facilitate trade with the other groups. In this case, if we only included the variable μ_i, and not γ_i and ι_i, the estimate would reflect a comparison between (I) and all three scenarios where trade was unlikely (the combination of II-IV). However this estimate would be impossible to interpret because trade incentives would be influencing both the treatment group and the control group, but for different reasons. Accordingly, the cleanest estimate is the effect of likely trade (I) relative to the scenario where there are no trade incentive effects at all (IV). This, as we have already mentioned, is reflected by the parameter β_1 in equation 3.

That said, other comparisons may also be of interest, but they can be recovered from equation 3 as well. Most obviously, the more nuanced potential homogenizing effect of trade incentives when trade is unlikely could also be of interest. This would be captured by β_2 and β_3. Furthermore, the effect of mutual trade incentives relative to the other cases when trade is unlikely could be of interest. These effects can be recovered by examining the difference between β_1 and either of β_2 or β_3. We will consider each of these as we discuss the results that follow.

3.B. Results: Trade Incentives and Language Vitality

We turn now to the relationship between mutual trade incentives and the survival of languages. In particular, the results highlight that when mutual trade incentives are high, languages become less likely to be threatened, and more likely to be stable. This can be seen most clearly in table 1.[13] Column 1 suggests that larger mutual trade incentives are associated with a higher language vitality score, implying that trade makes languages more stable.

This overall relationship between mutual trade incentives and vitality score, however, obscures the details of what exactly happens to the languages that are under threat of

[13]The analogous semiparametric relationship is in figure A1.

Table 1: Trade Incentives and Language Vitality

		Status Groupings (1/0)		
	(1) Vitality Score	(2) Dominant Language	(3) Non-Dominant Language	(4) Threatened Language
Trade is Likely: Mutual Benefits (μ_i, Mutual Trade Incentives)	1.916 (0.499)***	0.055 (0.041)	0.284 (0.156)*	-0.338 (0.157)**
Trade is Unlikely: Neighbour Doesn't Gain (γ_i, Mean Trade Incentives)	-1.040 (0.319)***	-0.025 (0.027)	-0.156 (0.092)*	0.182 (0.094)*
Trade is Unlikely: Only Neighbour Gains (ι_i, Partner Trade Incentives)	-0.827 (0.288)***	-0.011 (0.025)	-0.122 (0.092)	0.133 (0.092)
Arable Land Share	✓	✓	✓	✓
Land Diversity	✓	✓	✓	✓
Utility Level under Trade	✓	✓	✓	✓
Area Share Controls	✓	✓	✓	✓
Country Fixed Effects	✓	✓	✓	✓
Num. Observations	2530	2530	2530	2530
R^2	0.341	0.363	0.243	0.242

Note: The unit of observation is a language-group. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table presents the impact of trade incentives on language vitality with the Vitality Scale as the first outcome, ranging from 1-12 with a higher number indicating greater vitality. We next break this scale into three intuitive categories in columns 2-4.

extinction. To see this more clearly, we present results on the likelihood of a language falling into each of our three groupings of vitality categorizations: dominant languages, non-dominant languages, and threatened languages. We find that mutual trade incentives reduce the likelihood that a language is threatened, and increase the likelihood that it is non-dominant. Meanwhile, there is no effect on dominant languages.

This result appears to be quite robust. For instance, in table A7 we show robustness to different ways of constructing mutual gains from trade. The relationship is also significant, separately, for three of the four regions that make up the bulk of the sample (table A8). It is also robust to adjusting the thresholds that define the categories of vitality (table A9). Finally, in table A10 we drop the category *Vigorous* because it was used as a default category during data construction, and doing so increases the precision of the estimates.

While our focus is on mutually beneficial trade, it is also worth noting that in table 1 the coefficient on γ_i typically follows the opposite pattern to mutual trade incentives. This suggests that, when a group has high gains from trade with their partners – but that this is not reciprocated – this group's language is more likely to be threatened. One reason for this could be that the endangered language group simply fully integrates with the group they would like to trade with. In other words, trade *incentives* in the absence of *actual* trade tend to be a force for assimilation, while mutual trade incentives (i.e. actual inter-group trade) tends to preserve diversity.

Figure 2 dis-aggregates the effect even further. The figure plots the coefficients for mutual trade incentives for each of the individual language categorizations in the EGIDS, in order from most threatened to the most vital. This is an important robustness check given the way that the EGIDS data was initially constructed by Lewis and Simons (2010). In particular the category 'Vigorous Oral Use' was initially imputed prior to being reviewed by regional experts. It may therefore reflect that there is very little information that is known about a language. Accordingly it would be a concern if estimates were primarily driven by this category, or were sensitive to how the category was treated empirically.

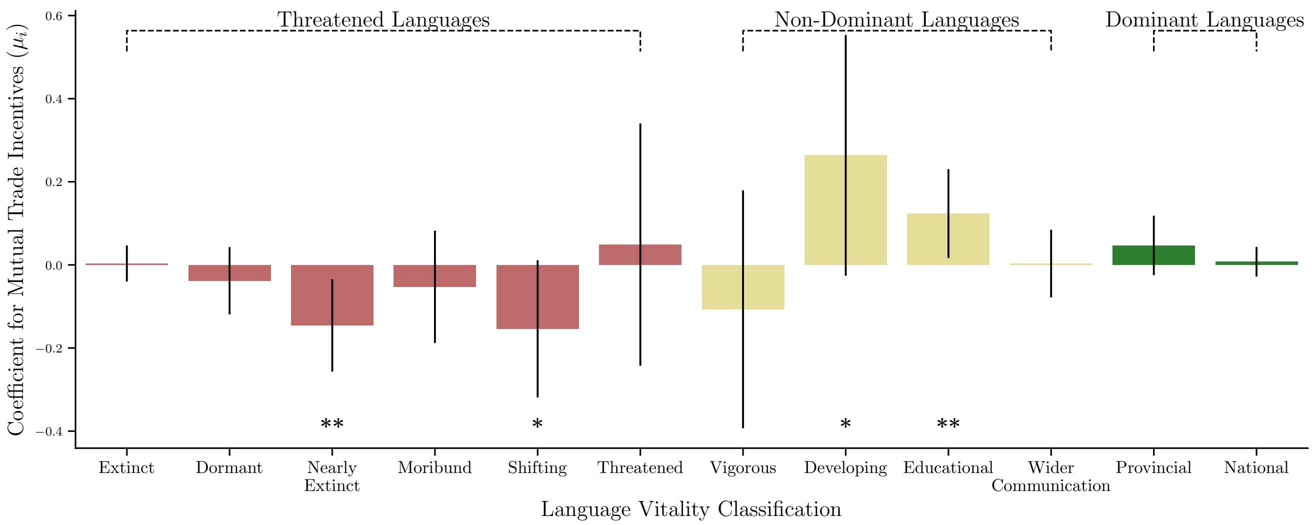


Figure 2: Regression Coefficients by Language Vitality Class

Note: Error bars represent estimates of μ_i (Mean Mutual Trade Incentives), from equation 3, where the outcome is a binary indicator variable for a language belonging to each EGIDS classification in turn. 95% confidence intervals presented. *** p<0.01, ** p<0.05, * p<0.1.

In the figure, each bar plots the value of β_1 (the coefficient on μ_i) from a regression where the outcome is an indicator variable for a language being assigned the given classification. The results reinforce the pattern in the aggregated categories. Mutual trade incentives make it less likely that a language falls into one of the threatened categories and more likely to be non-dominant. Interestingly, most of the effect seems to come from the 'Nearly Extinct' category, which is far less common when mutually beneficial trade is more prevalent. These languages instead appear to be categorized as either 'Developing' or 'Educational' when trade is mutually beneficial. Once again, we do not find much evidence that trade influences categorization into either the 'Provincial' or 'National' language categories. Importantly, results do not appear to be driven at all by the 'Vigorous Oral Use' category, which may contain a combination of legitimately vigorously used languages and missing data.

4. How trade impacts country-level diversity

The results above show that trade incentives impact the survival prospects of potentially endangered languages. We now explore whether the dynamics of trade incentives and threatened languages are large enough to impact common measures of country-level heterogeneity. As before, we begin by describing our empirical specification and how we generate the country-level data. We then review the results, first for the fractionalization-style measures, and then for the polarization-style measures.

4.A. Empirical Specification

For analysis at the country level we take the means of our key variables across groups in a country (c). The set of country-level variables are constructed as follows:

$$\bar{x_c} = \sum_{i \in c}^{I_c} \frac{x_i}{I_c} \quad \forall \ x \in \{\gamma, \iota, \mu\} \tag{4}$$

Which aggregate from the language-level (i) to the country level (c) by taking the mean over all language-groups in each country (I_c), for each of mutual trade incentives ($\bar{\mu_c}$), gains from trade ($\bar{\gamma_c}$), and trade influence ($\bar{\iota_c}$).

We then regress the diversity measures on the country-level trade variables as follows:

$$ELF_c \;=\; \beta_0 + \beta_1 \bar{\mu_c} + \beta_2 \bar{\gamma_c} + \beta_3 \bar{\iota_c} + \mathbf{X}_c' \Theta + \epsilon_c \tag{5}$$

This specification is analoguous to the language-level specification in equation 3. In this case, $ELF_{c,r}$ is the measure of diversity for country c in region r. $\mathbf{X}_c$ is a set of country level controls.[14]

4.B. Results: Fractionalization-style measures of diversity

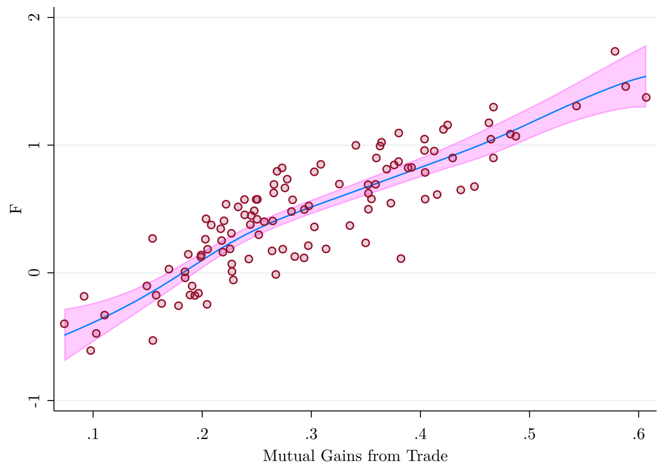
We first tackle the country-level relationship between trade and the fractionalization-style measures of ethnolinguistic heterogeneity. As already discussed, these measures are maximized in countries with a large number of small language groups. The language-level results showed that mutual trade incentives are associated with fewer endangered languages. Endangered languages tend to be small but are quite numerous. It is therefore not clear how much impact they would have on country-level measures of diversity, but if they did, we would expect fractionalization to be greater when mutually beneficial trade is more prevalent.

The results can most easily be seen in figure 3. For each of ELF (panel a), F (panel b), the number of groups (panel c), and CD (panel d) we see a strong positive association with trade incentives, which is reflected in the linear regressions as well (table A11).[15] There may be some concerns about country-level measures of fractionalization being endogenous to the impact of the size of states, artificial borders, the partitioning of ethnic groups,

[14]These include ethnic inequality in area, the log area of the country, and the log population of the country. We also include the mean of the language-level controls and the area share controls in equation 3.

[15]A version of this table with an alternate set of additional controls is in table A12.

(a) Ethnolinguistic Fractionalization (ELF)



(b) Ethnic Fragmentation (F)

(c) Log. Number of Ethnic Groups

(d) Cultural Diversity (CD)

Figure 3: Trade Incentives and Fractionalization

These figures present the semiparametric relationship (estimated using the Verardi and Debarsy (2012) implementation of Robinson (1988)) between trade incentives and various country-level measures of diversity. Shaded area represents 95% confidence intervals. For ease of comparison these figures are truncated at the same level of automatic trimming above which data is sparse ($\mu_i = 0.65$) in the figures for distribution measures of diversity. The analogous linear regressions are presented in table A11.

or other national institutions. To address these concerns we conduct a supplementary robustness exercise in appendix D4 and show that this positive relationship is robust to using synthetically constructed countries using grid cells of various sizes, in the spirit of Montalvo and Reynal-Querol (2021).

For the four main measures of fractionalization, the pattern in the country-level data echoes the results from the language level. Mutual trade incentives impact the survival of individual languages, and the aggregate effect of this has an influence on country-level diversity. This endogeneity implies that caution is in order when interpreting estimates of the impact of fractionalization on economic outcomes as causal. In addition, simply understanding the factors that contribute to maintaining diversity is a concern for many scholars. In particular, the idea that economic trade can support linguistic diversity is certainly not the consensus, so the estimates help to improve our understanding of when linguistic diversity is truly under threat.

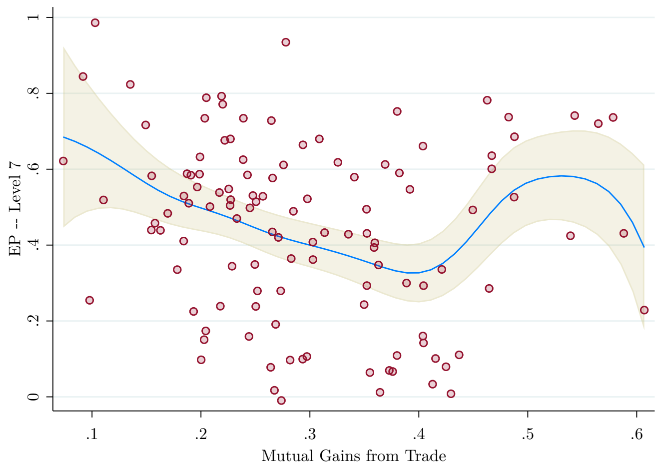
4.C. Results: Polarization-style measures of diversity

While there is evidence of a strong positive relationship between mutual trade incentives and fractionalization, in this section we argue that no similar relationship holds for the polarization-style measures that tend to place greater weight on larger, more influential ethnolinguistic groups.

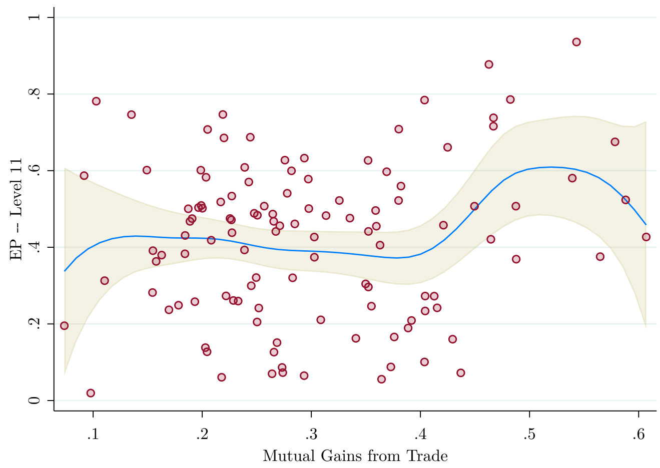
This is quite important, because for many outcomes that are crucial for economic growth, such as conflict, the evidence has shown that the most important aspect of diversity is the distribution of population across large groups. In this case it is EP that matters, which captures how close the distribution of population among ethnicities is to two equal-sized groups.

However, EP does not appear to be influenced by trade incentives. This can be visualized in figure 4a, and the analogous regression results are in table A13. We explore the effect using different cultural distance thresholds to define different groups in panels b and c, and results look similar. Table A13 presents the difference between estimates for polarization, and corresponding estimates for fractionalization (i.e. computed using the same group-defining thresholds). In each case the fractionalization estimate is significantly larger. Overall, the effect of trade incentives on group survival does not seem to correspond to how the population is distributed among the large groups. Other measures of heterogeneity - that are not necessarily maximized with a large number of small groups - look similar. For instance, consider the PHI, which captures the aggregate linguistic distance between the central group and other smaller groups. As with EP, we find no effect on this outcome (figure 4d).

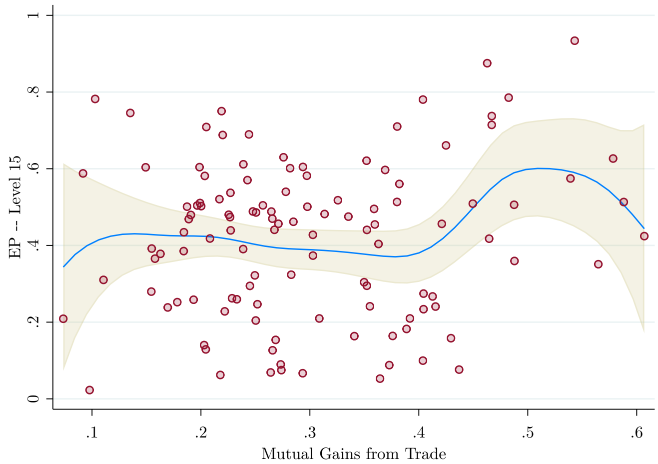
Overall, even though trade increases the vitality of potentially-threatened languages, it has no effect on measures of heterogeneity that place greater emphasis on the distribution of larger groups in society. One plausible explanation that is consistent with all three measures is that when languages die, those who would have otherwise spoken the now dead language instead speak other small, regional languages. This explanation is also consistent with the estimates from the language-level analysis, which highlighted opposite effects for the likelihood of being non-dominant and threatened, but no effect on dominant languages. This suggests some substitute-ability between non-dominant languages. Further, people who would have otherwise spoken now extinct languages do not



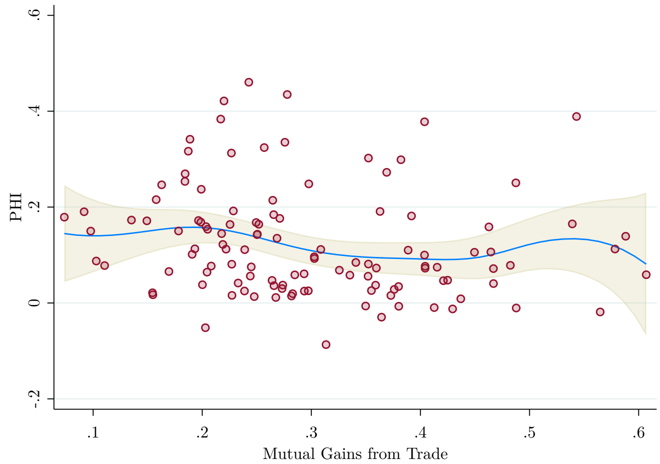
(a) Polarization, calculated using 7 levels of the language family tree



(b) Polarization, calculated using 11 levels of the language family tree



(c) Polarization, calculated using 15 levels of the language family tree



(d) Peripheral Heterogeneity Index (PHI)

Figure 4: Trade Incentives and Distribution Measures of Diversity

These figures present the semiparametric relationship (estimated using the Verardi and Debarsy (2012) implementation of Robinson (1988)) between trade incentives and various country-level polarization-style measures of diversity. Shaded area represents 95% confidence intervals. For ease of comparison these figures are truncated at the same level of automatic trimming above which data is sparse ($\mu_i = 0.65$) in the figures for distribution measures of diversity. The analogous linear regressions are in table A13.

necessarily adopt the regional *lingua franca*.[16]

[16] A country-level version of this analysis is in table A14 where the outcomes are the *share* of languages in a country falling into different categories. We find that countries with greater mutual trade incentives have a greater share of non-dominant languages. Mutual trade incentives are also associated with a lower share of dominant languages, though this may be largely mechanical, due to the greater number of threatened language groups surviving.

4.D. Results: Complex Measures of Diversity

The two measures of fractionalization that we have not yet highlighted are Ethnic Inequality (EI) and Ethnic Segregation (ES). While EI would increase with a larger number of groups, it is also weighted by wealth inequality, which is also plausibly linked to trade. Similarly, while ES would increase with a larger number of groups, it is weighted by population mixing and migration, which is also plausibly linked to trade. Accordingly any relationship between mutual trade incentives and these two outcomes may not be solely due to the improved survival of threatened languages. Nevertheless, we show the relationship between mutual trade incentives and both EI and ES in figures A2a and A2b respectively. As with the other fractionalization-style measures, there appears to be a positive and significant relationship.

5. Discussion

While economic interaction and exchange are often taken to be a homogenizing force, we argue that when neighbouring groups trade with each other, these incentives can actually sustain diversity. In fact, the effect is large enough that it has a significant effect on country level measures of fractionalization. This suggests caution when making causal assertions about the relationship between fractionalization and economic development. We do not, however, find a similar effect on polarization.

Moreover, we show that economic incentives play a significant role in shaping the survival prospects of individual language groups. In particular, where trade between two groups is mutually beneficial, this helps potentially threatened groups to survive. This encouraging insight suggests that it is essential to consider the type of incentives created by economic changes. Rather than entirely avoiding economic interaction, survival depends on shaping the right economic incentives. Since globalization seems largely impossible to avoid, this observation may offer some aid to those seeking to sustain the thousands of languages facing extinction in the near future.

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