Teacher Absenteeism and the Salience of Local Ethnic Diversity: Evidence from African Districts

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Abstract

The rate of teacher absenteeism is over five times higher in Uganda than it is in New York. In India, it is two and a half times higher than the rate of absenteeism for private sector factory workers. One potential explanation for these observations is that, in the presence of weak formal institutions—such as those found in many less developed countries—the likelihood of punishment for absent teachers may be lower. In these settings, other forms of local collective action are often required to produce public goods and prevent free-riding. However, a growing literature has shown that local collective action outcomes are often adversely affected by ethnic divisions. In this paper, I identify the impact of a new measure of ethnic divisions on teacher absenteeism using two datasets: one collected from random, unannounced school visits in Uganda, and another collected from over 20,000 survey respondents in 16 sub-Saharan African countries. In light of growing empirical support for constructivist theories of ethnicity, I allow the effect of diversity to vary by the salience of ethnic identification in each district. I find that, at high levels of ethnic salience, a one standard deviation increase in ethnic diversity increases the observed absenteeism rate in Uganda by between 3.8 and 9.3 percentage points, or 0.08 and 0.21 standard deviations. In the multi-country survey data, the same change increases perceived absenteeism by 0.08 standard deviations. At low levels of ethnic salience, diversity has no positive effect on absenteeism in either dataset. Consistent with the recent literature on the limitations of participatory programs on public service delivery, I provide suggestive evidence that social capital in the form of within-school teacher networks, rather than community-level monitoring, may explain the findings. The results offer one explanation for why substantial recent investment in education does not seem to be leading to improved test-score outcomes for children in many poor and ethnically diverse countries. The analysis also has implications for the measurement of ethnic divisions.

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1 Introduction

Despite the unprecedented expansion of primary school access over the past decade, standardized test results in many less developed countries reveal that basic numeracy and literacy skills are not improving.[1] Evidence from Chaudhury et al. (2006) and Duflo et al. (2012) strongly suggests that teacher absenteeism may be significantly contributing to this observation. The former study found that 19% of teachers were absent during unannounced visits to nationally representative samples of schools in Bangladesh, Ecuador, India, Indonesia, Peru and Uganda in 2002 and 2003,[2] while Duflo et al. (2012) show that a reduction of the absenteeism rate in Udaiper, India, from 36% to 18% led to an improvement in test scores of 0.17 standard deviations.

In this analysis, I show that ethnic divisions at the district and school levels are associated with significantly higher rates of teacher absenteeism. I design a new measure of ethnic divisions to capture what are sometimes called the 'evolutionary' and the 'constructivist' components of ethnic identity.[3] Traditional measures of ethnic diversity, or 'ethnolinguistic fractionalization', are based on the composition of ethnic groups in a given area. This is to a large extent the product of long-term cultural drift, itself caused by historical settlement duration (Ashraf and Galor, forthcoming; Ahlerup and Olsson, 2012) and geographic variability (Michalopoulos, 2012). However, the extent to which this diversity is manifested in collective action problems or political cleavages depends on the salience of ethnic identification, which can vary across countries and over time due to nation-building policies (Miguel, 2004), political competition (Posner, 2004a; Eifert et al., 2010) or other historical and contextual factors (Dunning and Harrison, 2010; Glennerster et al., 2012). In order to capture these 'constructivist' conditions, I create a district-level term that represents ethnic divisions by interacting ethnic diversity with the salience of ethnic identification. The diversity component is based on a Herfindahl concentration index of Afrobarometer survey respondents, while the salience component is based on respondents' propensity to identify themselves along ethnic lines rather than

[1] See Uwezo (2011, 2012) for East African cases, and Pratham (2006) for Indian cases.

[2] This is a conservative estimate. The inclusion of 'tea-drinkers'—teachers who were present but were not teaching as scheduled—increases the figure from 25% to almost 50% for India alone.

[3] These are often described as 'primordial' and 'instrumentalist' respectively.

national lines.

I combine this new interpretation of ethnic divisions with data on (i) observed teacher absences collected from random visits to almost 100 schools in 10 Ugandan districts;[4] and (ii) perceived teacher absenteeism amongst over 20,000 survey respondents in 16 African countries. At high levels of ethnic salience,[5] I find that an increase of one standard deviation in local ethnic diversity increases the rate of observed teacher absenteeism in the Ugandan dataset by between 3.8 and 9.3 percentage points, or 0.08 and 0.21 standard deviations. In the multi-country survey data, the comparable increase in perceived teacher absenteeism amongst respondents is 0.08 standard deviations.[6] At low levels of ethnic salience, however, I find no positive effect of ethnic diversity on absenteeism in either dataset: in the multi-country data there is no significant effect; while in the Ugandan data there is a significantly negative effect, which I suggest may be explained by residential sorting. In addition, I find that including the diversity component alone, and by implication ignoring the role of salience, would lead to the erroneous conclusion that ethnicity does not have any significant effect on absenteeism.

I also replicate the Ugandan analysis using school-level alternatives to the district-level measure of ethnic divisions. In each of the 94 schools, head teachers are asked to estimate the shares of the three most commonly spoken mother tongues amongst pupils in that school. I use this information to construct a measure of ethnic diversity, and interact it with the salience measure from the Afrobarometer. In addition, I create a range of teacher-specific proxies based on their linguistic, ancestral and regional origins. Across a broad range of specifications, the results are consistent with those reported above.

Having robustly established the link between ethnic divisions and teacher absenteeism, I take a step towards identifying the channels of causation that may explain the relationship. This is facilitated by the richness of the Ugandan data, which includes information on teacher-level characteristics as well as school-level infrastructural and management characteristics. In order to establish a

[4]These data were collected in a project led by Habyarimana (2010) and Chaudhury et al (2006).

[5]High (low) ethnic salience is defined as the mean plus (minus) one standard deviation.

[6]This is a subjective measure based on a four-point scale, hence there is no meaningful percentage point change to report for comparison.

conceptual framework for this exercise, I draw on the literature on both ethnic diversity and teacher incentives. In simple terms, ethnic diversity is most commonly purported to affect social capital and cooperation in three ways. First: through a 'taste' for discrimination between coethnics and non-coethnics (Becker 1957, 1974; Hjort 2012). This may increase absenteeism if 'outsider' teachers simply care less about non coethnic students, parents or other teachers. Second: through its impact on the effectiveness of social sanctions (Miguel and Gugerty, 2005; Habyarimana et al., 2007, 2009). In this case, ethnic divisions may lead to higher absenteeism for two reasons: (i) it may reduce the capacity for collective action necessary to form local monitoring institutions, such as parent teacher associations; and (ii) outsiders may not face the same credible threats of informal sanctioning by parents, head teachers or other teachers that apply to coethnics. Third: ethnic divisions may have a negative impact on group formation and social participation (Alesina and La Ferrara, 2000). This could affect the cooperation of teachers within schools, which may ultimately impact attendance decisions.

Against this background, I conduct three groups of tests to explain the association between ethnic divisions and teacher absenteeism. First, using a range of measures, I reject the altruism channel by identifying no statistical difference between 'native' and 'outsider' teachers' attendance decisions. Second, I find that neither parent teacher associations, school inspections nor the sanctioning history of head teachers can explain the main result. This is consistent with a growing literature on teacher incentives in developing countries.[7] Evidence from Banerjee et al. (2010), de Laat et al. (2008), and Duflo et al. (2012) indicates that participatory programs designed to empower the beneficiaries of public services—in this case parents—by providing them with information and access to educational authorities are unlikely to substantially affect teacher attendance. This is largely due to a combination of weak demand amongst parents and their relative lack of power to enforce accountability mechanisms. Moreover, evidence from Kremer and Chen (2001) suggests that head teachers are also unlikely to incentivize attendance.[8]

[7] In addition to Banerjee and Duflo (2006), Kremer and Holla (2009) present a particularly comprehensive overview.

[8] The successful intervention evaluated by Duflo et al. (2012) was based on an objective and external monitoring and reward system that was facilitated by tamper-proof cameras.

Instead, I find that the strength of social networks between teachers within schools, characterized by their social activities outside of official hours, can explain most of the reduced form relationship. The finding is consistent with Alesina and La Ferrara (2000), who show theoretically and empirically how social participation is lower in heterogenous communities. The result suggests that non-pecuniary incentives to attend work may partially derive from a teacher's colleagues rather than the wider local community.

The analysis contributes to a growing literature on the negative association between ethnic diversity and the local provision of public goods in sub-Saharan Africa (Miguel and Gugarty, 2005; Habyarimana et al., 2007, 2009) and elsewhere (Alesina et al., 1999; Vigdor, 2004). This association has particularly acute consequences for countries that lack the strong formal institutions required to implement many government policies—like India, Uganda and most of the 16 countries under analysis—where informal collective action methods at the local level are required instead to provide public goods. To illustrate, Chaudhury et al. (2006), show that teachers in their sample of less developed countries are rarely sanctioned formally for not attending school. In India, for example, only one head teacher in a sample of nearly 3,000 public schools reported a case in which a teacher was dismissed for absenteeism, despite an absenteeism rate of 25%; in the Ugandan data, the comparable figure is just under 1.5% of head teachers, despite an absenteeism rate of 28%.[9] Indeed, as the authors venture (pp. 93):

> [...] the mystery for economists may not be why absence from work is so high, but why anyone shows up at all. For many providers, the answer must be that important intrinsic and non-pecuniary motivations - such as professional pride or concern for the regard of peers - affect attendance decisions.

[9] Accordingly, absenteeism is rarely as grave an issue either in countries with strong formal institutions or in private sector industries with high monitoring: administrative data from New York school districts in the mid-1980s revealed a teacher absenteeism rate of around 5% (Ehrenberg et al., 1991); while the Indian Ministry of Labour Industrial Survey 2001-2002 shows that absenteeism amongst factory workers is 10.5%, despite the existence of rigid labour laws. As I note above, the rate of teacher absenteeism in India is estimated (conservatively) by Chaudhury et al. (2006) to be 25%.

This sentiment is reflected by Duflo et al. (2012), who find a large role for the non-pecuniary costs of absenteeism in the decision-making process of teachers using a structural model. Identifying the nature and source of these costs is an open area of research;[10] the literature suggests that, in this clear absence of formal monitoring and enforcement, ethnic diversity may well provide a partial explanation.[11]

Of course, the characterization of ethnic divisions that I present brings with it considerable challenges for the empirical estimation strategy. Ethnic diversity is not a random accident, nor, especially, is the salience of ethnic identity. To account for the potential effect of omitted variables on teacher absenteeism, I construct an extensive set of controls for inclusion in the econometric models. For the multi-country sample, I include controls for a wide set of respondent- and district-level characteristics, as well as fixed effects for regions, ethnicity, and pre-colonial ethnic boundaries. I also control for the temporal and spatial proximity to recent armed conflict events and fatalities by combining information on the geographic coordinates of each district in the Afrobarometer with those in the Armed Conflict Location Event Database (ACLED). In addition, I show that the inclusion of controls for endogenous sorting (based on pre-colonial ethnic boundaries) and historical settlement patterns have no effect on the model in the presence of such an extensive set of fixed effects. For the Ugandan teacher-level dataset, I can control comprehensively for teacher characteristics and school-level covariates based on the specification of Kremer et al., (2005), who use an almost identical dataset in their study of the determinants of teacher absence in India.[12]

An additional methodological challenge inherent in the multi-country section of the analysis is the reliability of subjective assessments of teacher absenteeism. While it is likely to be measured with some stochastic error, Olken (2009) suggests also that an error component may be specifi-

[10] In their review article on teacher absenteeism, Banerjee and Duflo (2006) reach the conclusion that "most attempts to boost the the presence of teachers [...] have not been particularly successful."

[11] Revisiting the Chaudhury et al. (2006) data with this in mind, it is interesting to note that Bangladesh has only the fourth highest absenteeism rate, despite being the second poorest of the six countries. This is likely to be at least partially explained by the fact that it has by far the most homogeneous population, as measured by both ethnolinguistic and cultural diversity from Fearon (2003). Absenteeism in Bangladesh is lower than in Indonesia, which is over twice as wealthy but three times more diverse.

[12] Indeed both are component datsets for the six-country Chaudhury et al (2006) study. As such, they are based on very similar methodologies. The Ugandan dataset is analyzed separately by Habyarimana (2010).

cally correlated with ethnic diversity. He finds that people in ethnically diverse villages tended to overestimate significantly the level of corruption in a road-building project in Indonesia. The implication for this study is that ethnic diversity may be associated with disproportionately negative perceptions of public goods delivery in general, as a result in part of feedback mechanisms over time. Although the obvious mitigation of this concern lies in the replication with objective data from Uganda, I also run a large set of falsification tests to show that the results are highly unlikely to be driven by this systematic bias. These include testing for the effects of ethnic divisions on perceptions of other aspects of school quality and of national-level governance issues, as well as holding school-level characteristics constant in order to analyse variation in the error component alone. I also offer an explanation for why the mechanism at play in the Indonesian setting is unlikely to be applicable in this context.

This analysis contributes to the literature in three ways. First, it provides new evidence of a significant determinant of teacher absenteeism that can partially explain such high rates in poor and ethnically divided areas. Second, it introduces a new measure of ethnic divisions that is consistent with the heterogenous effects of ethnic diversity on a variety of outcomes found in the literature. Moreover, the 'constructivist' component of the measure leaves room for a policy response. Finally, it presents evidence that ethnic divisions do not affect absenteeism through formal sanctioning institutions or discriminatory altruism; instead, it is the erosion of social capital between teachers within a school that appears most likely to undermine the provision of public education. This casts a new light on the study of teacher incentives in developing countries.

The paper is organised as follows. In the next section I discuss briefly the analysis of ethnic diversity in the literature, including methodological challenges. I then introduce the data and discuss measurement issues, before presenting the reduced form estimation results for both the multi-country and Ugandan analyses. I subsequently offer an explanation for the reduced form results by testing for competing mechanisms. I finally conclude.

2 Analysing Ethnic Diversity

Scholars have long highlighted the deleterious impact of ethnic diversity on economic and political development, particularly in poor and institutionally weak countries (Easterly and Levine, 1997; Alesina et al., 2003; Alesina and La Ferrara, 2005). The cross-country evidence that characterized the early stages of the literature have been complemented since by a series of micro-level studies that have made progress in uncovering the channels through which ethnic diversity affects particular outcomes.

Of particular importance for this study are analyses that increase our understanding of how divisions lead to collective action problems in sub-saharan Africa. Miguel and Gugerty (2005) provide evidence that parents in Kenya contribute to school funding more in homogeneous areas due to the credible threat of social sanctions for non-cooperation. In a seminal paper, Habyarimana et al. (2007, 2009) provide laboratory evidence for this social sanctioning channel amongst residents of Kampala, Uganda. It is an especially compelling explanation in these settings, where people are more reliant on within-group networks to organise the provision of public goods that effective governments would otherwise provide.[13] However, Hjort (2012) also points to a 'taste' based discriminatory mechanism, showing that floriculture plant workers in Kenya weight the utility of coethnics ahead of non-coethnics. He finds that non-coethnics were even willing to incur a cost to display this discrimination amid the heightened ethnic tensions associated with the 2007 presidential election.

This wave of micro-level studies has also shed light on the conditions under which ethnic diversity may not have the expected effect on certain political and economic outcomes. Miguel (2004), for example, shows that ethnic diversity has heterogenous effects on school funding and water well maintenance in districts that straddle either side of the Kenya-Tanzania border. In Kenya, moving from a homogeneous area to one with a mean level of diversity lowers local school fundraising by 25%; whereas in the neighbouring Tanzanian district, the same change has no significant effect. These contrasting outcomes are put down to the well-known nation-building efforts made in post-

[13] La Ferrara (2003) also analyzes the role of kin groups in the functioning of informal credit markets in Ghana.

independence Tanzania, characterized, amongst other policies, by the promotion of one common language (Kiswahili) and a strong emphasis on national unity throughout public school curricula. In Kenya, if anything, the opposite course was followed by a succession of politicians who were demonstrably willing to use ethnic diversity as a vehicle for their own political ends.[14] These divergent policies are set against a background of broadly similar colonial and historical characteristics, providing an empirical basis, also found in Hjort (2012), for the suggestion that the salience of ethnic diversity is politically malleable.

Direct evidence of this is presented by Eifert et al., (2010), who show using Afrobarometer data that the salience of ethnic identity, measured as the likelihood that respondents identify themselves along ethnic lines when faced with an open question on self identification, increases significantly with the proximity of competitive elections. Posner (2004a) also finds variation in the salience of ethnic cleavages across political contexts. Like Miguel (2004), he exploits the arbitrary determination of a national border—this time between Zambia and Malawi—and observes that the Chewa and Tumbuka groups are more likely to perceive each other as allies in Zambia than they are in neighbouring villages on the Malawian side of border, where they view each other with considerable antagonism and are less likely to inter-marry. This is explained by the political landscape in each country: in Zambia, neither group is large enough to form the basis of a viable political coalition; whereas in Malawi, by contrast, they each form large political blocs that vie for power.

Another example of the importance of context when analyzing the effects of ethnic diversity comes from Glennerster et al., (2012), who find that variation in ethnic diversity within Sierra Leone does not affect the provision of local public goods. This is despite being a poor and highly diverse country that has recently experienced major civil conflict. The authors explain the result by documenting Sierra Leone's unique combination of colonial history, tribal organization and language composition which together prevent the collective action failures one may expect to find in such settings. Similarly, Dunning and Harrison (2010) use an experimental approach to show that cross-cutting cleavages in the form of 'cousinge' dominate the role of ethnicity in the formation of political

[14]This culminated in a wave of violence following the disputed 2007 presidential elections.

preferences in Mali.

2.1 Methodological Concerns: Measurement

Taken together, these studies highlight the incontrovertible role for 'constructivist' explanations of ethnic identity, which stress the importance of context and time in shaping both the formation and salience of ethnic identification.[15] So what, if any, are the implications of these accounts for the measurement of ethnic diversity? Early cross-country studies used a measure of ethnolinguistic fractionalization that was calculated using the Herfindahl concentration formula on a dataset compiled by Soviet anthropologists in the *Atlas Narodov Mira* (1964). In a pointed critique, Laitin and Posner (2001) bemoan its once ubiquitous use in the cross-country economic literature, noting, for example, that it is akin to using the rate of inflation in 1945 as a measure for a country's prosperity today. This is because, firstly, it is a static measure of a changing phenomenon. Identities and cultures change over time in response to economic and political climates. They cite, for example, the reorganization of identities in Somalia since independence, where Isaaqs and Hawiyes would once have considered themselves part of a shared linguistic group. Today, Isaaqs conspicuously differentiate their speech in an attempt to justify attempts at secession. Second, the group categories on which the measure is based may have no discernible meaning in the context of political or economic cooperation. Ethnic identities have multiple dimensions in every country, and there is no way for a researcher to know ex-ante which ones are salient in which contexts. A third point rests with the concept of salience itself. As the literature above shows, ethnic identities in general may have very few implications for cooperation in some countries, while having a significant effect in others, be it at the dyadic level (Posner, 2004a) or in general (Miguel, 2004).

In response to these and similar critiques, several researchers have compiled new measures that incorporate better the multi-faceted nature of ethnic diversity. Alesina et al. (2003) create a new index that includes linguistic and religious fractionalization; Laitin (2000) and Fearon (2003)

[15] Chandra (2012) provides a contemporary discussion of constructivist theories of ethnicity.

create measures that incorporate the concept of linguistic 'distance' between groups; Posner (2004b) develops an index based on groups who engage in political competition, called the PREG index (for Politically Relevant Ethnic Groups); and Baldwin and Huber (2010) highlight the importance of accounting for economic inequality between groups.

In this paper, I use a new measure of ethnic *divisions* that overcomes the main pitfalls listed above. It consists of an interaction term between district level ethnic diversity, measured by applying the familiar variant of the Herfindahl concentration formula on the self-reported ethnicities of Afrobarometer respondents, and a district-level average of the respondents' answers to a question on the salience of their ethnic identity compared to their national identity. It is based on data that is concurrent with the outcome variable; it allows the subjects to choose their own ethnic identity; and it explicitly accounts for salience. A crucial added advantage is that it is measured at the district level, which allows me to control for regional (and, by implication, country) fixed effects throughout the analysis. The main implication, in light of the literature outlined above, is that it measures *relevant* diversity, and is thus a more accurate tool for identifying the types of problems that are synonymous with local heterogeneity in Africa and elsewhere.

2.2 Methodological Concerns: Estimation

While these constructivist findings have clear implications for the appropriate measurement of ethnic divisions, they also point to the need for a more careful approach to identifying valid estimation strategies. The ethnic divisions interaction term I use in this analysis is likely to be endogenous to a multitude of political and economic outcomes through factors as diverse as colonial history and current-day political competition. This calls for more comprehensive econometric specifications than those typically found in much of the early literature, which generally treats ethnic diversity as an exogenous phenomenon. Moreover, recent contributions from Ashraf and Galor (forthcoming), Aherlup and Olssen (2012) and Michalopoulos (2012) have provided empirical bases to 'evolutionary' theories, which describe diversity as a function of long term settlement patterns. Specifically, Ashraf and Galor (forthcoming) and Aherlup and Olssen (2012) show that the duration of human settlement

is a significant determinant of modern day diversity across countries. This is owing to cultural drift that happens over time in response to the need for peripheral groups to provide their own public goods. Michalopoulos (2012) provides more evidence of cultural drift, this time due to geographic variability—such as the variation in soil quality—which led to the development of non transferable human capital and, eventually, the formation of new linguistic groups.

Taken together, these strands of literature necessitate the inclusion of an extensive set of political, economic, geographic and historic controls in the analysis. I describe my data and estimation strategy in Sections 3 and 4 respectively.

3 Data

I use two main sources of data in the analysis. The first dataset comes from the 2005 round of Afrobarometer, a series of nationally representative surveys based on standardised interviews of a random sample of either 1,200 or 2,400 individuals in 16 sub-Saharan African countries: Benin, Botswana, Ghana, Kenya, Lesotho, Madagascar, Malawi, Mali, Mozambique, Namibia, Nigeria, Senegal, South Africa, Tanzania, Uganda, and Zambia. Figure 1 presents the location of every district in which interviews were conducted on a map of Africa. [16] The second dataset comes from Habyarimana (2010), and is a constituent dataset of the Chaudhury et al. (2006) survey of teacher absenteeism. It consists of data from two visits to each of almost 100 schools in 10 Ugandan districts, which are shown on a map in Figure 2. In each school, up to 20 teachers are selected at random from the roster, and their attendance is recorded at each visit. In addition, a rich set of characteristics for each teacher—present or otherwise—is recorded, as well as information on the head teacher, the school's facilities, its pupils and its structures of governance and management.

[16] I omit Cape Verde and Zimbabwe, as those respective samples do not have information on ethnicity and certain individual characteristics necessary for the analysis.

3.1 Data: Ethnic Divisions

Afrobarometer multi-country sample

For the Afrobarometer sample, I measure ethnic divisions as the product of ethnic salience and ethnic diversity. The measure for ethnic salience is recorded as the district-level mean of the following survey question:

> Let us suppose that you had to choose between being a [Ghanaian/Kenyan/etc.] and being a _____ [respondent's ethnic identity group]. Which of these two groups do you feel most strongly attached to?

I ascribe a value of 1 to respondents if the answer is "only [group]" or "more [group]," and 0 if the answer is "equal," "more [country]" or "only [country]".[17] In Table 1, I present some external validation that the question is in fact measuring the concept of salience that I discuss in the previous section. Recall that Posner (2004a) found Chewas and Tumbukas to be salient adversaries in Malawi, but not in Zambia. This was due to the political landscape in each country, as Chewas and Tumbukas were each large political groups vying for power in Malawi, whereas in Zambia they were too small to form the basis of any competitive coalition. In the top panel of Table 1, we can see that Chewas and Tumbukas are significantly more likely to identify themselves along ethnic lines in Malawi than they are in Zambia. While this is an imperfect test for their animosity towards each other, it is nonetheless illustrative of the fact that political competition can lead to salient sub-national identification.

In the second panel, we also see consistency with the findings from Miguel (2004). Recall again that ethnic diversity had adverse effects on local collective action in Kenya, but not in Tanzania. This was due to serious nation-building efforts in Tanzania that were designed to inculcate a sense

[17] Using the full five-point scale instead of this dichotomous interpretation does not qualitatively change the results. This is also the case when "equal" takes on a value of 1.

of common national identity ahead of sub-national ethnic attachments. Accordingly, ethnic salience is two and half times higher in Kenya than it is in Tanzania, despite similar levels of ethnic diversity and comparable colonial and precolonial backgrounds in both countries.

I measure ethnic diversity using the following Herfindahl concentration formula:

$$ELF_d = 1 - \sum_{g=1}^{n} s_g^2,$$

where s_i is the share of self-reported ethnic group $g \in (g \ldots n)$ in each of the 1207 sample districts d. It reflects simply the likelihood that two randomly drawn individuals in a district d report different ethnicities. In addition to the 2005 Afrobarometer sample, I include respondents to the 2008 round in order to increase the power of the Herfindahl statistic. The median district sample size for the variable is 47.[18]

I present non-parametric density functions of both interaction components in Figure 3, and a scatter plot of their country mean values in Figure 4. A cursory look at the scatter plot reveals very clearly the importance of accounting for both components in the analysis. By ignoring the salience of ethnic identities, researchers would erroneously conclude that highly heterogeneous Lesotho is more likely to suffer the consequences of ethnic divisions than relatively homogeneous (at the district level) Nigeria. This does not take into account, however, the cultural closeness of groups in Lesotho nor the history of ethnic violence in Nigeria, which may have contrasting effects on collective action. I argue that these are captured by the measure of ethnic salience.[19]

While I have thus far pointed to the clear need for including a 'salience' component of ethnicity in my measure of ethnic divisions, it is worth remembering that, in the context of local collective action, it is obviously necessary to include a measure of diversity as an interaction component, for it is unlikely that highly salient ethnic identification will lead to adverse public goods outcomes

[18]There is no measure of teacher absenteeism in the 2008 sample.

[19]This may be also reflected in the degree of residential sorting in each country. In Figure A1 in the appendix, I plot ethnic salience against diversity at the country level rather than the aggregated district level measure in Figure 4. The large difference between ELF at the district and country levels for Nigeria—and the relatively minute difference between them for Lesotho—suggests that coethnics may sort into districts in countries with high ethnic salience. This again highlights the importance of accounting for both diversity and salience, where otherwise highly diverse districts could be misinterpreted as highly divided districts.

within a homogeneous community.

Ugandan school visits

In the Ugandan sample, I use two measures of ethnic diversity. First, I match the district level Afrobarometer measure to all ten districts covered by the survey, namely: Arua, Bugiri, Bushenyi, Jinja, Kamuli, Kisoro, Luwero, Mpigi, Tororo and Yumbe. As this gives only ten data points, I also construct a value of ethnic divisions for each of the 94 schools in the sample. During the first random visit to each school, head teachers were asked to list the three most commonly spoken mother languages amongst the pupils, and to estimate the corresponding share of pupils for whom this is the case. Using these shares, I create another Herfindahl-based concentration index for each school and interact it with the district-level mean ethnic salience from Afrobarometer.

The kernel density function for school-level diversity is estimated in Figure 5. All equations described in Section 5 are estimated using both measures, which have a correlation coefficient of 0.48. In Section 6, I introduce a number of additional proxy measures based on the diversity of the teaching staff in each school.

3.2 Data: Teacher Absenteeism

Afrobarometer multi-country sample

In the multi-country Afrobarometer dataset, I base the measure of teacher absenteeism on responses to the following survey question:

> Have you encountered any of these problems with your local public schools during the past 12 months: Absent teachers?
>
> 0=Never, 1=Once or twice, 2=A few times, 3=Often, 7=No experience with public schools in the past twelve months, 9=Don't Know,

I code the responses on a four point scale from 0 to 3, omitting respondents who choose the remaining categories. This lowers the potential sample size from 21,598 to 14,100. Descriptive statistics are presented in Table 2, showing mean values for ELF_d, district-level ethnic salience, and a selection of individual and village level variables for each response category of the question.

As is frequently the case when variables are based on subjective opinions, the major concern in this part of the analysis is the potential for systematic bias caused by non-random measurement error. While it is likely that the survey question picks up at least some noise, so that $TA_{id} = TA^*_{sd} + u_i$, where TA_{id} is subjective teacher absenteeism reported by individual i in district d, TA^*_{sd} is actual teacher absenteeism at school s, and u_i is stochastic measurement error, the danger is that $TA_{id} = TA^*_{sd} + u_i + v_i$, where the error component v_i is correlated with ethnic diversity. If this is the case, the observed coefficient that describes the relationship between the outcome variable and ethnic divisions may be driven by the error component, rather than a fundamental association between ethnic divisions and true absenteeism. Olken (2009) suggests that this should be treated as a genuine concern. He finds that people in ethnically heterogeneous villages in Indonesia are more likely to overestimate the level of corruption associated with a road building project than villagers in homogenous areas.

He explains the findings by suggesting that feedback mechanisms over time have caused people in diverse areas to be wary of corruption in public projects, which in turn increases their scrutiny of public funds. However, the means through which scrutiny led to lower corruption in ethnically diverse villages for that particular project is linked to the disproportionately high rate of attendance at 'monitoring meetings' that were provided by the central government. In the absence of this exogenous facilitation of scrutiny, it is unclear whether or not diverse communities would cooperate better than homogeneous villages to minimise corruption. In any case, I include a wide set of falsification tests below that directly address this concern, and find it to be an unlikely driver of results.

Ugandan school visits

The measure of teacher absence in the Ugandan dataset is more straightforward. Enumerators recorded a teacher as absent if she was not present to teach a class that she was scheduled to teach. Over two visits, they collected the information up to 20 randomly selected teachers from the school's roster. In the cases where schools have less than 20 names on its roster, the enumerators collected information on all teachers.

In Figure 6, I plot the district mean values of each absenteeism variable. On the y-axis is the mean value for the four-point Afrobarometer scale; on the x-axis is the district mean for a teacher-level dummy variable indicating that a teacher was absent during a random school visit. I also include a linear fit, which confirms that the Afrobarometer measure contains significant information on actual teacher absenteeism. This provides some evidence for the validity of the multi-country analysis, which itself allows for a general interpretation of the results across 16 sub-Saharan African countries.

4 Estimation: Afrobarometer Multi-Country Sample

I begin the estimation section with a focus on the multi-country Afrobarometer survey data. As I note above, the two main challenges in this section relate to the potential endogeneity of salient ethnic divisions to actual teacher absence rates due to omitted variable bias, and also the possibility of a correlation between ethnic divisions and the error component v_i of the subjectively measured dependent variable. The basic equation I estimate takes the following form:

$$TA_{idr} = a + \Psi \sum_{i=1}^{n} \frac{ES_{id}}{n_d} + \lambda ELF_d + \beta(\sum_{i=1}^{n} \frac{ES_{id}}{n_d} * ELF_d) + \gamma X_{id} + \delta V_{id} + \eta R_r + e_{id}, \quad (1)$$

where TA_{idr} is perceived teacher absenteeism reported on a four-point scale by individual i in district d and region r; ES is ethnic salience; X is a vector of individual controls; V is a vector of village-level controls; and R represents regional fixed effects for 184 regions in 16 countries. The

individual controls include measures for age, age squared, level of education, gender, employment status, physical health, mental health, religion, individual ethnic salience,[20] access to food, water, medicine, fuel and income, as well as indicators for ownership of three assets: radio, television and a vehicle. The village level vector controls for whether or not a village—which is a sub-district level unit with a modal sample size of 8 respondents—contains each of the following services or facilities: a school, piped water, a sewage system, a health clinic, electricity, a police station, a post office, recreational facilities, a place of worship, community buildings and a tarred or paved road.

Given the incidental parameters problem, the equation is estimated initially using least squares with standard errors adjusted for two-way clustering within ethnicity groups and within districts (Cameron et al., 2011).[21] This method produces standard errors that are higher than those produced by either ethnicity- or district-level clustering alone. In addition, I run the equivalent ordered probit model, and report the relevant marginal effects in the robustness section below.

There is good reason to believe that this set of covariates controls for many of the potential sources of endogeneity that I explore in Section 2. In particular, the control for regional-level fixed effects at a stroke controls for country-level colonial and pre-colonial historical factors (Glennerster et al., 2012), post-colonial national policies (Miguel, 2004) and current day political competition (Eifert et al., 2010, Posner, 2004a), as well as the country-wide effects of macroeconomic policies that are associated with ethnic diversity (Easterly and Levine, 1997; Alesina et al., 2003). Moreover, the rich set of individual- and village-level controls accounts for variation in individual and local wealth, health and economic factors that could otherwise plausibly affect our interpretation of the coefficient of interest, β.

[20] This can be interpreted as controlling for the effects of an individual's deviation from the district mean value of ethnic salience. Omitting it does not have a significant effect on the results.

[21] The Stata command for this estimator is 'cgmreg'.

4.1 Results

In Figure 7, I present an illustration of the output from the most comprehensive specification estimated in this section.[22] I use a re-centering method to hold ethnic salience constant at a low level, which I define as the mean value minus one standard deviation (or 0.004), and at a high level, defined as the mean plus one standard deviation (or 0.33). The slope of ethnic diversity (ELF_d) at the low level (grey) is -0.14, and is statistically indistinguishable from zero; whereas the slope at the high level (red) is 0.29, or 0.26 standard deviations of perceived teacher absenteeism. The p-value for the interaction effect, which describes the statistical significance of the difference between the two slopes, is 0.005.

The results show clearly the importance of conditioning on salience when trying to ascertain the effects of ethnic diversity at the local level. In the absence of salience, ethnic diversity has no significant effect on teacher absenteeism.

In Table 3, I present the regression output for the most basic specification. In column (1), I omit the village-level controls, which could be affected themselves by ethnic divisions. While the independent effects of ethnic diversity (ELF_d) and ethnic salience do not affect perceived teacher absenteeism at traditional levels of statistical significance, their interaction has an impact that is both economically and statistically significant.

In column (2), I add the village-level controls described above. Although this inclusion increases the precision of the main estimate, while simultaneously reducing bias by accounting for some potentially endogenous factors, it also lowers the sample size from 13,468 to 12,240. In column (3), I highlight the importance of including the interaction term in the model. Its omission would lead us to erroneously conclude that it is only ethnic salience that reduces teacher absenteeism within a district, rather than a combination of salience and ethnic diversity. In column (4), I

[22] Specifically, I use the output from a specification based on Table 5, column (6), but without the pre-colonial fixed effects, which I describe in the next sub-section. The effect of diversity for any level of salience can be found simply by plugging in the desired level of salience to the relevant regression output function. Figure 7 is a graphical representation of the function $TA_{idr} = 1.71 - 0.151(ELF_d) + 1.33(\sum_{i=1}^{n} \frac{ES_{id}}{n_d} * ELF_d) + \Psi \sum_{i=1}^{n} \frac{ES_{id}}{n_d} + \gamma X_{id} + \delta V_{id} + \eta R_r + e_{id}$, where $\sum_{i=1}^{n} \frac{ES_{id}}{n_d} = 0.33, 0.004$. The black dots represent observations plotted by ELF_d on the x-axis and TA_{idr} on the y-axis.

present the most naïve representation of ethnic divisions, that is, ethnic diversity with no account for salience whatsoever. Again, though common in the literature, this measure fails to capture at all the significant effect of ethnic divisions on the outcome.

For the remainder of this section, I test the robustness of the association by (i) controlling for an additional range of factors that are plausibly correlated with ethnic divisions and teacher absenteeism; (ii) conducting a set of falsification tests to ensure that the results are not being driven by an error component in the measurement of the dependent variable; and (iii) presenting alternative specifications to ensure that the results are not driven by particularities in the survey sample.

4.1.1 Controlling for Observables

Cultural and institutional persistence Nunn and Wantchekon (2012) use Afrobarometer data to show how historical events can affect current behavior through culture, or, more specifically, the intergenerational transmission of norms within ethnic groups. They show that members of ethnic groups that were historically targeted by the slave trades have lower levels of trust in institutions and other people today. This is due to the nature of the slave trade, which often rewarded trickery and dishonesty by sparing from slavery those who provided other people for export. This led to a profusion of distrust amongst the kin of those who were sold for export, which in turn developed into a cost-saving heuristic that evidently survived over time. The implication for this analysis is simple: certain ethnic groups may display common traits that could affect the salience of their ethnicity and the development of local institutions.

In Table 4, I show how the omission of ethnicity-level covariates can lead to a biased estimate of β. The inclusion of three such variables in column (1) changes the size and statistical significance of the coefficient. The first variable is the natural log of the number of slave exports taken from the respondent's ethnicity group divided by the size of the area which it historically inhabited. It is taken directly from Nunn and Wantchekon (2012), who use Murdock (1959) to link current day ethnic group names to their pre-colonial ancestral groups. Historical slavery exports may affect current

day social capital, which could be manifested in more salient sub-national identities and lower levels of local cooperation. The second variable is taken from the *Ethnographic Atlas* (Murdock 1967) and coded by Nunn and Wantchekon (2012). It captures the political sophistication of each ethnicity's corresponding pre-colonial ancestral group by measuring the number of hierarchical layers in its power structure. This organisation of power could itself persist over time within ethnic groups to reflect better local coordination today. The third variable is a proxy for each ethnicity's historical wealth by indicating whether or not there was a city within its pre-colonial boundaries in 1400. It is taken from Chandler (1987) and again coded by Nunn and Wantchekon (2012), and is intended to reflect the probability of colonial plunder, which may negatively affect the persistent quality of institutions within groups over time.[23]

Slavery enters the model with no statistical significance, while the sophistication of pre-colonial institutions and the indicator for pre-colonial wealth enter significantly with the expected signs. Taken together, these results suggest that controlling for ethnicity-level variation in the response is a necessary step in establishing the robustness of the main finding. Accordingly, I include ethnicity fixed effects in column (2) and for the remainder of the analysis. I code ethnicity by country, in order to account for the variation in ethnic salience within ethnic groups that spill across country borders, as in Posner (2004a).

Although clearly a necessary inclusion, ethnicity fixed effects are not a sufficient means of controlling for variation in unobserved historical factors. Michalopoulos and Papaioannou (forthcoming) show that pre-colonial factors—in this case the jurisdictional hierarchy measure from column (1)—can also have persistent effects through local institutions. Indeed Nunn and Wantchekon (2012) present evidence of this channel that is independent of the cultural persistence discussed above. Both studies use information on the pre-colonial boundaries of ethnic groups from Murdock (1959) to link historical factors to current outcomes. In the case of Nunn and Wantchekon (2012), this is facilitated by recording the geographic coordinates of each Afrobarometer district in order to determine the ethnic group that inhabited the corresponding area in pre-colonial era. I use this information to create a vector that controls for historical fixed effects that vary at this level of

[23] Acemoglu et al (2001) provide some evidence on the colonial origins of institutional quality.

pre-colonial settlement areas.[24]

Conflict, sorting and settlement I now consider three more factors that could plausibly affect the main result. First, I address the possibility that armed conflict is associated with salient ethnic divisions and with perceived teacher absence. Montalvo and Reynal-Querol (2005) provide empirical evidence for the link between ethnic polarization and conflict, building on a seminal contribution from Horowitz (1985). It is not too far-fetched to consider that ethnic conflict and ethnic salience may be related; nor is it implausible to suggest that teacher attendance—or indeed perceptions of teacher attendance—could be affected by local conflict.

To account for this, I turn to the Armed Conflict Location and Event Dataset (ACLED), which contains data on over 60,000 fatal and non-fatal incidents of conflict throughout Africa, parts of Asia, and Haiti from 1997 to 2012.[25] The dataset also includes the geographic coordinates of each incident, which I use to measure its geodesic distance from the centroid of each Afrobarometer district.[26] The location of every recorded event is presented on a map in Figure 8. I combine various levels of spatial and temporal proximity to the number of armed conflict events and to the number of fatalities associated with each event. Specifically, I included all possible combinations between 20km, 10km, 5km and 1km, and 10 years, 5 years, 2 years, 1 year and six months. I find that only the number of conflict fatalities within 1 year and 1 kilometer from the centroid of each district has a significant impact on perceived teacher absenteeism. In columns (1) and (2) of Table 5, I show that the inclusion of both this measure and the corresponding measure of conflict events (fatal and non-fatal) has no qualitative effect on the main result.

Although potentially captured by the covariates already presented in the model, I include a measure of historical sorting in columns (3) and (4). Residential sorting amongst ethnic groups, as I discuss above, may reflect traits that could impact collective action outcomes. For example,

[24]Not every area could be linked to a precolonial group. I thus present results with and without these fixed effects for the remainder of these estimations.

[25]More information on the Acled dataset is available online at www.acleddata.com

[26]Sangnier and Zylberberg (2012) also combine Afrobarometer and Acled data using location coordinates.

it is possible that individuals from different ethnic groups who have no animosity toward outsiders may coexist in districts, which itself may perpetuate long-term cooperation and better local institutions. To measure sorting, I go back to the information on pre-colonial boundaries in Murdock (1959). I define historical assimilation as the percentage of current district residents whose ethnic ancestors were based elsewhere during the pre-colonial era. Adding this variable to the model has no discernible effect on the main results.

Like sorting, it is likely that correlates of the 'evolutionary' sources of ethnic diversity are already controlled for by the regional and pre-colonial fixed effects in the model. To see if this is the case, I include three proxies for human settlement that are discussed by Alehrup and Olsson (2012) and Michalopolous (2012) in columns (5) and (6). I first use the geodesic distance from each district to Addis Ababa, which is also shown by Ashraf and Galor (forthcoming), amongst others, to correlate highly with the duration of human settlement and, in turn, genetic diversity. In addition, I include distance to the equator (measured in degrees of latitude) and distance to the sea, which reflect two theories of early human migration patterns from East Africa between 150,000 and 200,000. As I mention above, I also include a binary variable for whether or not each village contains a tarred or paved road, which could be interpreted as a proxy for the ruggedness of land. None of the variables have a significant impact on the model.

4.1.2 Falsification Tests

In this section, I address the potential effects of non-classical measurement error in the dependent variable. To recount, Olken (2009) shows that survey respondents in heterogenous Indonesian villages overestimated corruption in a road project more than those in homogeneous areas. The author suggests that this was caused by a higher level of skepticism in diverse villages that may have been triggered through a feedback mechanism from corruption in previous projects. As a result, community meetings designed to facilitate local monitoring and oversight of the road project were 22% more highly attended than meetings in homogeneous areas, which in turn led to a lower level of actual corruption. The implication for this study is that respondents from ethnically divided

areas may simply write-off the quality of all public services and collective action outcomes without regard to the true measure. This could lead to an upwardly biased β coefficient.

For the first set of falsification tests, I examine the impact of ethnic divisions on responses to alternative survey questions. In addition to absent teachers, respondents are also asked in the Afrobarometer survey whether they have encountered six other problems related to their local public schools in the previous 12 months. They are: "services are too expensive," "poor conditions of facilities," "overcrowded classrooms," "poor teaching," "lack of textbooks and other supplies," and "demands for illegal payments." The questions are framed in exactly the same manner as the way in which the dependent variable is framed, and all are sequenced together. If it is the case that residents of ethnically divided areas have a common proclivity to overstate problems with public goods provision, and if that is driving the main result of this section, then we should observe a similar effect of the interaction term on all—or at least some—of the other six variables.

In Table 6, I present the effects of ethnic divisions on all seven variables, each normalized to have a mean value of 0 and a standard deviation of 1 for comparison.[27] Using the most comprehensive specification presented thus far (from Table 5, column (6)), I show that district-level ethnic divisions only have a significantly positive effect on teacher absenteeism. This comprehensively rules out the possibility that a common error component of all seven measures is significantly correlated to ethnic divisions. The tests also suggest that the channel through which ethnic divisions ultimately affect teacher absenteeism does not apply to the other outcomes (a proposition corroborated in Section 6). The possible explanation for this may be reflected in the final row of the table, which shows that five of the six additional outcomes have higher within-country correlations than teacher absenteeism, albeit by small margins. This indicates that the organisation of these outcomes may take place at a more centralized level than teacher attendance.[28] As I discuss in the introduction, absenteeism is rarely sanctioned by official sources, and is thus likely to be affected by more local factors.

The next set of falsification tests follows a similar line of reasoning to a set presented by Olken (2009). It is based on a simple premise: if people in ethnically divided areas systematically overstate

[27] This does not affect the interpretation of the test results.

[28] The only outcome with a lower intra-country correlation, the demand for illegal payments, is positively affected by ethnic divisions in a specification with no pre-colonial fixed effects (not reported).

corruption, or any other metric representing the quality of public goods or collective action, then perceptions of common, national-level indicators should significantly differ between divided and undivided areas. If they do not overstate these measures, their responses should not significantly differ from those in undivided areas, as both groups are assessing the same phenomenon.

I run this test using six variables that measure responses to questions about national-level governance. The results are presented in Table 7. In columns (1) and (2), the dependent variables measure perceived corruption in the offices of government and the president respectively; in columns (2) and (3) the dependent variables measure the trust held by respondents in the ruling party and in the main opposition party respectively; and in columns (5) and (6) the dependent variables measure respondents' assessment of the manner in which the government is handling corruption and education respectively. All six dependent variables are measured on four point scales.

In every case, the responses of individuals in ethnically divided (or indeed ethnically diverse or ethnically salient) districts do not differ from the responses of those in undivided areas. It provides further evidence that the effect of ethnic divisions on perceived teacher absenteeism cannot be explained by this source of measurement error.[29]

In Table 8, I present the final set of tests for the robustness of the results to non-classical measurement error in the dependent variable. I first test the hypothesis that only minority group members in each district have higher perceptions of teacher absenteeism. I do this by including a binary variable that indicates whether or not an individual is a member of a non-modal group within their district. The result, shown in column (1), indicates that minority group members are not driving the main findings.

In columns (2) and (3) I present the results of a test which attempts to hold the true level

[29]Readers familiar with the Afrobarometer surveys will be aware of several questions that probe respondents for their opinion on a multitude of political and social issues. I chose questions that were most likely to elicit views on strictly national-level characteristics that plausibly affect individuals in diverse and homogeneous areas equally. Nevertheless, I could have presented alternative variables in each of the three categories shown in the Table 7 that arguably fit the criteria. Under corruption, respondents were also asked about judges and magistrates; under trust, respondents were also asked about parliament, the president, the national elections commission and courts of law; and under government performance, respondents were also asked about crime, health, water and food. I rerun the test with all of these alternatives, and find that the only question for which respondents in divided areas answered differently to others was on the government's handling of crime, which itself is likely to be influenced at least partially by local factors.

of teacher absenteeism constant, and therefore analysing only the variation in the individual error component. Recall that $TA_{id} = TA^*_{sd} + u_i$. If I hold TA^*_{sd} constant by controlling for school fixed effects, I can then observe the relationship between ethnic salience and the error component only.

As there are no school-level fixed effects in the dataset, I instead use village-level fixed effects. The village (or "primary sample unit") is the most granular level above the individual in the Afrobarometer. It has a modal sample size of 8 respondents. To the extent that all 8 refer to the same school in these surveys, controlling for village fixed effects will allow me to uncover the statistical relationship between the error component of the dependent variable and an assortment of individual characteristics.

In column (2) I provide strong evidence that individual ethnic salience is not related to the individual error component of the dependent variable. In column (3) I include an interaction term between individual salience and district level ELF. Although the inclusion of village fixed effects implies that district-level ethnic diversity is held constant, this is still a strictly better test than the one presented in column (2), as the interaction term gives a closer approximation to the true district-level interaction effect in a test without fixed effects. Again, the results suggest that there is no significant relationship between ethnic divisions and the error component of the dependent variable.

Finally, I show that the explanation put forward by Olken (2009) for the link between ethnic diversity and the overestimation of corruption is not applicable in this context. Recall that, in Indonesia, attendance rates at community oversight meetings were significantly higher in heterogeneous communities, which led to lower levels of actual corruption. A key part of that story lies in the fact that these meetings were facilitated as part of the nationwide road building project. It is unclear that heterogeneous communities would have monitored the project as effectively in the absence of this exogenous provision of community fora. I show in column (4) that, in this sample, members of ethnically divided communities do not attend community meetings more frequently than those in relatively undivided communities.[30]

[30] Respondents are asked if they attend community meetings. The dependent variable ranges on a four point scale from "no, would never do this" to "yes, often"

4.1.3 Other Robustness Checks: Sample Issues and Functional Form

In this sub-section, I present a final set of robustness tests for the multi-country analysis. In column (1) of Table 9, I use district-level averages for all variables to show that missing values for some covariates are not affecting the estimation of β.

In column (2), I run the analysis on a sub-sample of respondents who might be expected to have a better grasp of true teacher absenteeism TA^*_{sd}: mothers. Case and Ardington (2006) show using panel data that maternal deaths had a substantially more negative effect on a wide range of schooling outcomes than paternal deaths amongst a sample of Zulu children in South Africa, while paternal deaths had a larger impact on other socio-economic factors. This could be reflective of a higher maternal involvement in children's schooling. In such a case, the absence of a significant interaction effect in a sub-sample of women between the ages of 25 and 50 would cast some doubt on the validity of the results, as one would expect mothers to have a more accurate response to the question on perceived teacher absenteeism. The results show that the interaction effect is even larger, perhaps indicating that the rest of the population sample underestimates true absenteeism.

In columns (3) and (4), I provide evidence that the results are not driven by ELF measures that are calculated from small sample sizes, and thus have little statistical power. Indeed, as the table shows, the results are more robust for districts that have above-median sample sizes than districts with below-median sample sizes. This may have implications for establishing the channels of causation, which I discuss in Section 6.

In column (5), I present the results of an ordered probit model, given that (i) the steps between each response category in the dependent variable may not be constant; and (ii) the variable has a limited range. In order to facilitate the interpretation of the interaction term, I show in Table 10 the marginal effects of ethnic diversity on the probability of each response at a high level of ethnic salience (again, mean plus one standard deviation) and at a low level of ethnic salience (mean minus one standard deviation). The results show clearly that, at high ethnic salience, ethnic diversity significantly decreases the probability of a "Never" response, and significantly increases the probability of individuals reporting "Once or twice", "A few times" and "Often". At low ethnic

salience, ethnic diversity has no impact on the probability of any response. The results are consistent with the linear results presented throughout the section.

In summary, this section presents robust evidence that the statistical association between ethnic divisions and perceived teacher absenteeism in the Afrobarometer multi-country dataset is neither caused by omitted variables, an error component in the dependent variable nor the imposition of a linear functional form on the relationship. In the next section, I extend the results to a sample using objective data on recorded absenteeism in Uganda.

5 Estimation: Ugandan Dataset

Kremer et al. (2005) and Habyarimana (2010) analyse the determinants of teacher absenteeism using sub-samples of the Chaudhury et al. (2006) data collected during random, unannounced school visits in 2002 and 2003. Here, I use an almost identical empirical specification in order to establish the relationship between the probability of a teacher's absence and ethnic divisions in Uganda. The basic estimation equations take the following form:

$$Pr(TA_{jsd} = 1) = a + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd} \quad (2)$$

for the linear probability estimation, and:

$$Pr(TA_{jsd} = 1) = \Phi[a + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd}] \quad (3)$$

for the probit estimation, where ES_d is $\sum_{i=1}^{n} \frac{ES_{id}}{n_d}$ from the Afrobarometer sample, ELF is the either district-level ethnic diversity ELF_d, or school-level ethnic diversity ELF_s, as described in Section 3.1. Teacher-level characteristics, represented by X_{jsd}, include gender, age, marital status, education, place of birth, employment rank, experience, contract status, union status, and career training; S_{sd} is a set of school level characteristics, comprised of controls for institutional features,

such as the existence of parent teacher associations (PTAs), access and the quality of its facilities; T_{tdm} is three sets of fixed effects for the time, day and month of the visit. All covariates are described in more detail in the notes beneath Table 11.

5.1 Results

I present in Table 11 the estimation results for equations (2) and (3). In columns (1) and (2), I omit school-level characteristics, which are added in columns (3) and (4). All four specifications are estimated with a linear probability estimator. In each model, the interaction effect is large and significant. To illustrate, a one standard deviation increase in district-level ethnic diversity at a high level of ethnic salience (again defined as the mean plus one standard deviation) raises the probability of a teacher not turning up to a scheduled class by 9.3 percentage points. At a low level, the same increase of diversity actually decreases the probability of absence by 6.7 percentage points. An even larger interaction effect is present in the school-level diversity data: a one standard deviation increase in ELF_s at a high level of ethnic salience increases the probability of absence by 3.8 percentage points; while at a low level of salience the same change in diversity decreases the probability of absence by almost 17.7 percentage points.

In columns (4) and (5), I present results from the probit model. Ai and Norton (2003) highlight the dangers of misinterpreting the effects of an interaction term in non-linear models. They show how the marginal effect of an interaction term can have a different magnitude, sign and level of statistical significance than the true cross-partial derivative.[31] The results of their corrected method, interpreted as the average interaction effect across all observations, support the linear results.[32]

It is possible that these symmetrical effects, i.e., the negative effects of district- and school-level diversity on absenteeism where salience is low, reflect two forms of sorting mechanisms that are described respectively by Glennerster et al. (2012) and Miguel and Gugerty (2005). The first case

[31] I explain this issue in more detail in Appendix B.

[32] The Ai and Norton (2003) method requires that I drop the fixed effects for the time of day from the model. An equivalent linear model produces quantitively similar results, supporting the interpretation presented above. The remaining marginal effects are taken from the full model.

concerns residential sorting, whereby certain coethnics choose to live in clusters. By implication, the remaining individuals—those who do *not* cluster by ethnicity—form more diverse communities that are likely to have low levels of ethnic salience. Glennerster et al. (2012) find that 'non-sorters' in diverse areas tend to have higher levels of educational attainment, which I find in the analysis to be strongly linked with lower absenteeism. Moreover, we can see from Figures 4 and A1 that Uganda has one of the highest rates of sorting amongst the entire 16-country sample: the mean level of ethnic diversity by district is less than half the mean level of ethnic diversity for the country as a whole.

The symmetrical effect at the school-level may be further compounded by a more straightforward sorting mechanism described in Miguel and Gugerty (2005), whereby good schools (which are likely to have teachers who attend class) attract pupils from a wider radius, leading to a positive link between diversity and, in this case, teacher attendance. It is interesting to note also that teacher absenteeism is lower in homogeneous areas where people express a high sense of common ethnic identity, as implied by the significantly negative independent effect of ethnic salience. Again, sorting may explain the finding, as homogeneous communities formed from deliberate sorting may be better equipped for the type of collective action needed to provide local public goods than other homogeneous communities.

In any case, the impact of ethnic diversity on teacher absenteeism at a high level of ethnic salience is positive and significant in all specifications. Whether measured at the district level or at the school level, the effects of ethnic diversity on the probability of a teacher being absent from class is significantly higher in districts where individuals are more likely to identify themselves along ethnic lines.

6 Testing for Channels of Causality

In this section, I attempt to identify the channel or channels through which ethnic divisions affect teacher absenteeism using the Ugandan teacher-level data. As I discuss in the introduction, ethnic diversity can affect local cooperation and teacher behavior in different ways. Below, I consider the

three prominent theories given in the literature to explain why ethnic diversity undermines the provision of public goods in this context.

First, coethnics may have more concern for the utility of each other than for the utility of non-coethnics (Becker 1957, 1974; Hjort 2012). This could result in native teachers having a higher preference for increasing the wellbeing of pupils and parents than 'outsider' teachers, which may explain higher absenteeism rates in ethnically divided schools or districts.

A second, more broadly-supported theory concerns the credibility of the threat of social sanctions in ethnically diverse communities (Miguel and Gugerty, 2005; Habyarimana et al., 2007, 2009). In the absence of well functioning formal institutions, coethnics often rely on each other for public goods, credit or other services. Because of this, the costs of uncooperative behavior towards a coethnic are likely to be higher than the costs of uncooperative behavior towards a non-coethnic. In the case of teacher absenteeism, this could have two consequences: (i) diverse communities may lack the capacity for coordination needed to develop institutions of oversight for all teachers, such as effective parent teacher associations or other means of sanctioning; and (ii) 'outsider' (or non-native) teachers may not view the threat of sanctions from native (i.e. non-coethnic) parents, communities or head teachers as credible. Although any of these mechanisms could potentially explain the association between ethnic divisions and teacher absenteeism, recent evidence on teacher incentives in developing countries suggests strongly that official sanctions pose little threat to teachers, and, moreover, parents are unlikely to exert pressure or enforce attendance.

A third mechanism follows from Alesina and La Ferrara (2000), who find that participation rates in various social, professional and religious organizations in the USA can be explained partially by ethnic heterogeneity. They show that, conditional on individuals exhibiting a strictly positive preference toward socializing with coethnics, an increase in the heterogeneity of a population will decease the formation of and participation in social groups. The implication in this case is that teachers in divided areas may be less inclined to socialize together. This could affect attendance decisions in at least three ways. First, teachers who socialize together may develop an in-group altruism that directly increases the utility of attending school together. Second, the altruism may manifest itself in a concern for colleagues' potential obligations to mind unsupervised children in the

case of a teacher's absence. Third, group members are likely to pose a credible threat of sanctioning in the form of social ostracism that is not available to non-group members.

To investigate these possibilities, I use data on sanctioning institutions and the origins and social activities of teachers to test the following three channels:

- CHANNEL 1 *Teacher coethnicity*: teacher absenteeism is less probable if the teacher is 'native'. If this is rejected, i.e., if ϕ is not negative, we can say with some confidence that the 'taste' mechanism is unlikely to be driving the main result.

$$TA_{jsd} = a + \phi Native_{jsd} + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd} \quad (4)$$

- CHANNEL 2A *Sanctioning (homogeneous effect)*: teacher absenteeism is negatively determined by effective sanctioning institutions, i.e., φ is negative.

$$TA_{jsd} = a + \varphi Sanction_{sd} + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd}. \quad (5)$$

- CHANNEL 2B *Sanctioning (heterogeneous effect)*: teacher absenteeism is negatively determined by effective sanctioning institutions, conditional on the teacher being 'native', i.e., θ is negative.

$$TA_{jsd} = a + \phi Native_{jsd} + \varphi Sanction_{sd} + \theta(Native_{jsd} * Sanction_{sd}) + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd} \quad (6)$$

- CHANNEL 3 *Social networks between teachers*: teacher absenteeism is negatively determined by the extent to which teachers socialize together, i.e., ς is negative.

$$TA_{jsd} = a + \varsigma Social + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd}. \quad (7)$$

In each case, the extent to which the channel under investigation explains the main result depends on β, the interaction effect that describes the relationship between ethnic divisions and teacher absenteeism. If this interaction effect loses all statistical significance, it is likely that the relevant channel explains all of the relationship.

In all tests, I present linear probability models. Marginal effects derived from probit models produce qualitatively similar results.

6.1 Teacher Coethnicity

In this sub-section, I test the hypothesis described in Channel 1: that native teachers are less likely than 'outsider' teachers (or non-coethnics) to be absent from a class that they are scheduled to teach. If this is the case, it may be reflective of either of the first two theories: natives may have a higher degree of altruism (or 'other-regarding preferences') toward children and parents; or natives may view the threat of sanctioning more credibly. If I find no evidence of a statistically significant relationship, it implies that the 'taste' mechanism can be rejected as a unique explanation for the link between ethnic divisions and teacher absenteeism.

I use three variables to measure whether or not a teacher is native. The first is a dummy variable indicating whether or not a teacher speaks the local language natively. The second is a dummy variable which indicates that the teacher's ancestral home is in the same parish/city as the school. The third is a dummy variable which indicates that the teacher was born in the local county. In all specifications, I include as a control a categorical variable for where the teacher currently lives: the included categories are the local county and the local district; the omitted category is the local village.

In Table 12, I present the results using the district level and school level measures of ethnic diversity respectively. Firstly, it is important to note that the interaction effect representing ethnic divisions is large and statistically significant in all specifications, ruling out the possibility that the

full effect is explained by teacher-level ethnicity. In all specifications, native teachers are no more likely to attend school than non-natives. This indicates that teachers do not make decisions about attendance based on discriminatory altruism toward coethnics. Teachers who are natively fluent in the local language are significantly more likely to be *absent* from school, whereas those who are native by birth or by ancestry do not exhibit behavior that is statistically different from the rest of the sample. In an auxiliary specification (unreported), I test for the heterogeneous effects of coethnicity between ethnically divided and undivided districts/schools by including a triple interaction term. This is to ensure that the average effects presented in Table 12 are not masking significantly contrasting effects across districts or schools. The intuition is that non-native teachers in otherwise homogeneous areas may have selected into the district or school because they are not discriminatory. I also include triple interactions between the teacher's current home and the ethnic division components as controls. I find that 'outsider' teachers are no more likely to be absent than local teachers either in divided or undivided districts and schools. This strongly suggests that the 'taste' explanation does not account for the main result of the paper.

6.2 Sanctioning Institutions

The possibility remains that ethnic diversity may affect teacher absenteeism through its impact on either the effectiveness of sanctioning institutions (Channel 2a) or on the credibility of those institutions' threats in the eyes of 'outsiders' (Channel 2b). In Table 13, I show the effects of parent teacher associations (PTAs), school inspections and the previous sanctioning behavior of head teachers on teacher absenteeism. In columns (1) and (3), I include a dummy variable for the existence of a parent teacher association, a categorical variable to indicate its last meeting (omitted variable is "this month"), and a dummy variable to indicate that an inspection by the education ministry had occurred within the previous six months. In columns (2) and (4), I include a dummy variable to indicate that the head teacher has previously sanctioned a teacher for absence by either dismissing, suspending or transferring her. I present this in a separate set of specifications due to the obvious potential for reverse causality, as head teachers in schools with no absenteeism are not

required to sanction teachers.

The first point to note from the table is that the average effects of these institutions do not represent likely candidates for the channel of causation from ethnic divisions to teacher absenteeism. Across all four columns, the main interaction effect is positive, significant and stable, providing indirect evidence that the sanctioning variables are not associated with ethnic divisions.

The other point to note is that teachers in schools which have had very recent PTA meetings (the omitted group) are more likely to be absent than those who's annual meeting is perhaps approaching soon. There is evidence also that the sanctioning history of head teachers is significantly endogenous.

In Table 14, I present the effects of these sanctioning institutions conditional on whether or not a teacher is native by language (columns (1) and (4)), by ancestry (columns (2) and (5)) or by birth (columns (3) and (6)). To recount: the threat of sanctions by PTAs, local ministry officials or head teachers may be credible only to coethnic teachers, as non-coethnic teachers may be reliant on other groups for public goods. If this is the case, the lack of significance in the average effects presented in Table 13 may be masking significant heterogeneous effects.

Again, in all six specifications, the effect of ethnic divisions is positive, significant and stable, while no new patterns emerge. Taken together, these results indicate that ethnic divisions do not affect teacher absenteeism through the credibility of social sanctions.

6.3 Social Networks Between Teachers

To explore the possibility that social group participation may help to explain the main relationship in the analysis, I use a measure of social capital amongst teachers in each school that is based on answers given by the head teacher to the following survey question:

> When was the last time that the teachers in your school socialized with each other outside of school hours, gathering for a meal or party for example?

I let "never" equal 0, and all other responses equal 1. The responses almost split the sample evenly: 54% percent of head teachers report that teachers in their school never socialize together, while 46% report that they do. I present simple OLS covariates in columns (1) and (2) of Table A1 in Appendix A, which reveal that only ethnic divisions exhibit a statistically significant relationship with the measure across both specifications.[33] This can be interpreted as a necessary first-stage condition for the validity of this explanation.

In Table 15, I present the results for specification (6). Moving from a school where teachers never socialize to one in which they have socialized at least once in the memory of the head teacher decreases the probability of a teacher's absence by between 11.2 and 12.5 percentage points (or 19.2 and 21.7 percentage points based on marginal effects from a probit estimation). The inclusion of this variable in the model eliminates entirely the significance of ethnic divisions using the district-level measure, while also reducing substantially the magnitude and the significance of the effect of ethnic divisions as measured at the school level. This provides support for the explanation that ethnic divisions increase teacher absenteeism through the strength of social networks between teachers within schools.

In Table 16, I examine whether or not these effects depend on the ethnicity of the teacher. The average effect presented in Table 15 may be masking significant differences in the effects of social networks on attendance between native and non-native teachers. I find no significant heterogeneous effect when I proxy for coethnicity using variables based on birth or language, although when I use the ancestral definition I find a positive effect. In all cases, the main results are similar to those presented in Table 15.

Our ability to interpret these findings with certainty is limited by the data. Without knowing the extent to which social capital is endogenous in the model,[34] we cannot say with full confidence

[33] For this, I run a school-level regression of *Social* on the of the right-hand side variables included in empirical specification (2). Means values are taken where necessary.

[34] For example, it could be that high absenteeism creates animosity amongst colleagues, which may in turn reduce the likelihood of social participation.

how exactly these social networks are related to absenteeism. However, it is possible to conduct instructive falsifiability tests. If the causal channel is as mentioned, then we must expect to see a significant role for ethnic divisions *between teachers within schools.* Although the main analysis was conducted using measures based on the diversity of survey respondents within districts and of pupils within schools, there remains a number of useful proxies for the diversity of teachers within schools. If ethnic divisions amongst teachers are not significantly associated with higher absenteeism, we can immediately reject our interpretation of this channel.

In Table 17, I present the effects of fives measures of teacher divisions. In column (1), I use a Herfindahl concentration index based on the regional origins of each respondent;[35] in column (2), I use a Herfindahl concentration index based on the fluency of respondents in the local language[36]; in column (3) I use the share of non natively-fluent teachers within the school; in column (4) I use the share of non-native teachers by ancestry; and in column (5) I use the share of non-native teachers by birth. In each case, we see a significant and substantially positive effect of school-level divisions amongst teachers on absenteeism. In Table 18, I repeat the exercise with the inclusion of the measure for social networks, and find results analogous to those in Table 15. In further support of this interpretation, I run five additional school-level regressions of *Social* on each of the measures for teacher divisions in columns (3) to (7) of Table A1, and find that the effects of ethnic divisions is large, negative and, in all but two cases, statistically significant.[37] Across, a range of comprehensive specifications, higher ethnic divisions between teachers are associated with less social interactions; and less social interactions are associated with a higher probability of absenteeism.

Taken together, the evidence suggests that the source of variation in teacher absenteeism is not only ethnic divisions *per se*, but also the effect of ethnic divisions on the formation of social groups

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[35]The categories are North (19.86%), South (0.2%), West (19.75%), East (39.71%), Central (17.7%) and Sudan (2.77%). The share of respondents teaching in their native region in 67.16%. This is the preferred measure, as many of Uganda's strongest social cleavages are regional. The measures that follow do not necessarily distinguish between groups.

[36]Native fluency (65.93%), Fluent (14.05%), Very Good (5.97%), Good (5.92%), Functional (2.05%), Minimal (3.65%), Not able to speak well (2.43%).

[37]The two specifications in which the effect is not significant are based on arguably the two least precise measures of teacher diversity: share of non-native teachers by ancestry and birth.

amongst teachers. It is possible that the density of these social networks may in turn increase the social cost of absenteeism; or perhaps they may foster altruism between colleagues. We can say with confidence that the role of ethnic divisions in either the formation or the effectiveness of community monitoring institutions, such as parent teacher associations, or direct monitoring institutions, such as ministry inspections or the sanctioning behavior of head teachers, is inconsequential for teacher absenteeism; as is the direct effect of a teacher's ethnicity.

These findings serve as a clear invitation for experimental research in the field, where randomly generated variation in social activities for teachers (or in the composition of teachers within schools), combined with innovative measures of social capital could allow us to delve further into the relationship between ethnic divisions and teacher absenteeism.

7 Conclusion

In this paper I present robust evidence of a link between ethnic divisions and teacher absenteeism using sub-national data from two sources: a nationally representative series of random, unannounced school visits in Uganda; and a large opinion survey of citizens in 16 sub-Saharan African countries. The results are robust to a comprehensive set of individual, geographic, institutional and historical controls. I introduce a new measure of ethnic divisions which captures both ethnic diversity and the salience of ethnic identification. Using ethnic diversity alone, a practice common in the literature, would lead to a significant underestimation of the true effect. Across a range of specifications, and using various combinations of data, I find that ethnic diversity increases teacher absenteeism at high levels of ethnic salience; while, at low levels of salience, it either decreases teacher absenteeism or has no effect at all. I present suggestive evidence that the effect is unrelated to community monitoring institutions such as parent teacher associations, and may be explained better by the effect of ethnic divisions on within-school teacher networks. The analysis provides a partial explanation for the apparent existence of a large, non-pecuniary cost of teacher absence.

The results invite further experimental research in the field that could determine how social capital amongst teachers ultimately affects attendance decisions. Moreover, the demonstrable malleability of ethnic salience leaves room for direct policy responses to collective action failures in

ethnically divided areas, which could involve either fostering a common national identity or suppressing the attraction of ethnic electioneering. In all, this paper increases our understanding of high teacher absenteeism in poor, ethnically divided areas. In so doing, it points to new suggestions which could strengthen the link between educational investment and educational attainment.

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Figures

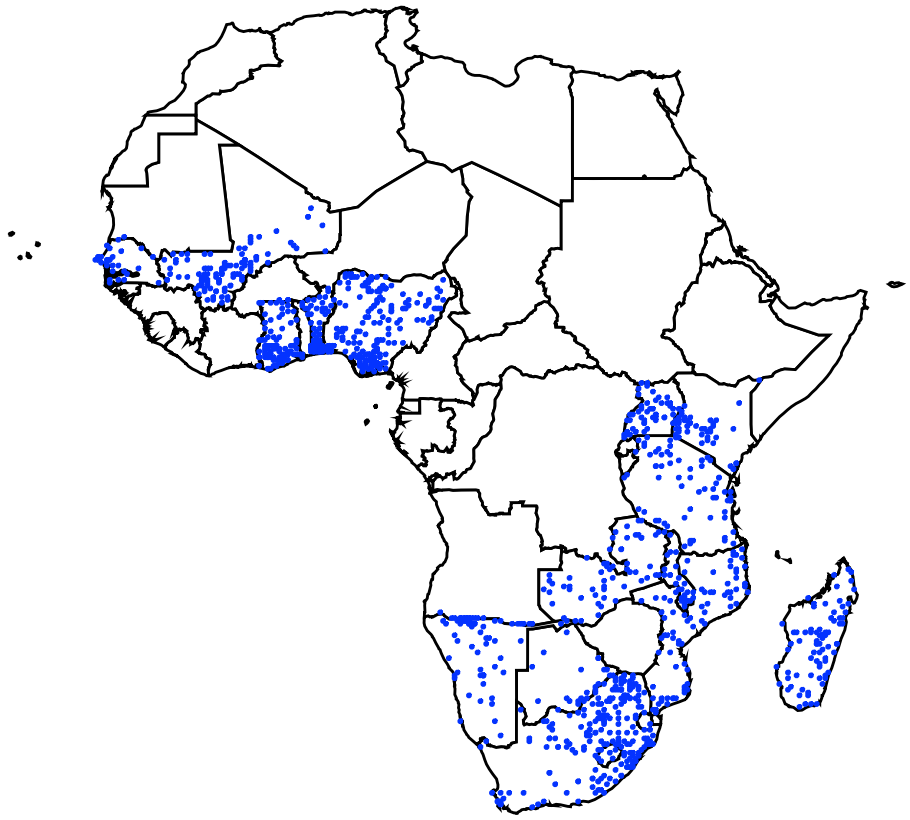

Figure 1: Location of Afrobarometer Districts

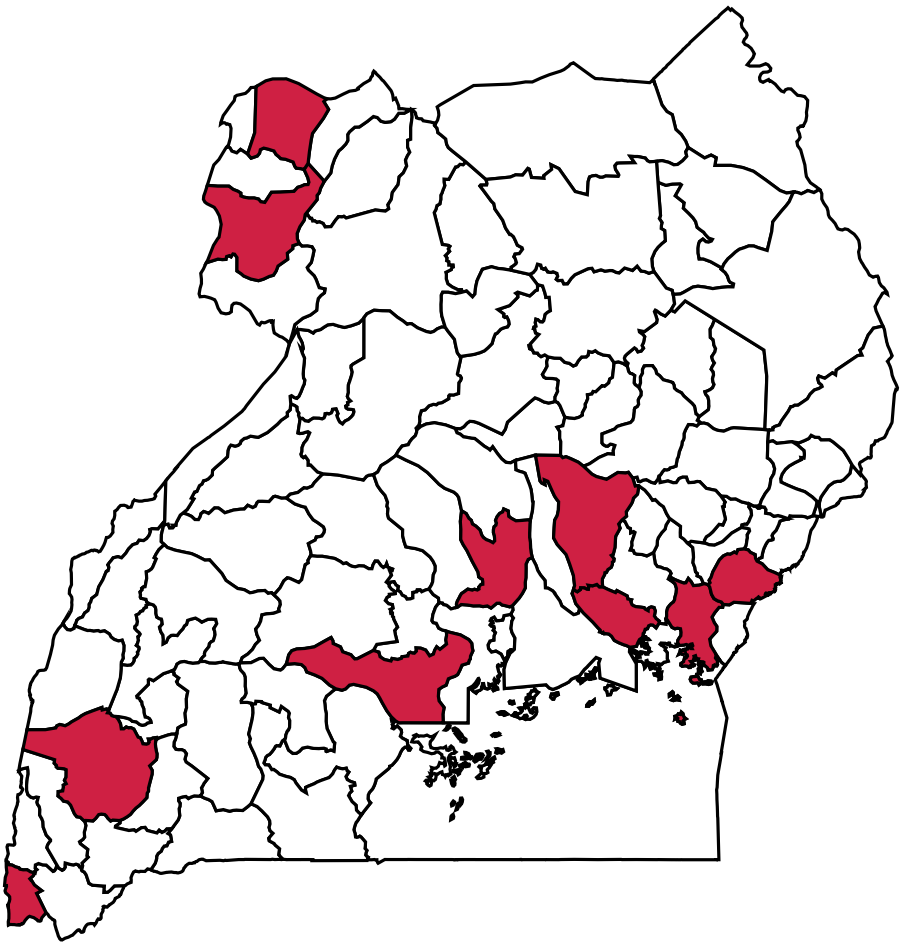

Figure 2: Location of Ugandan School Visits

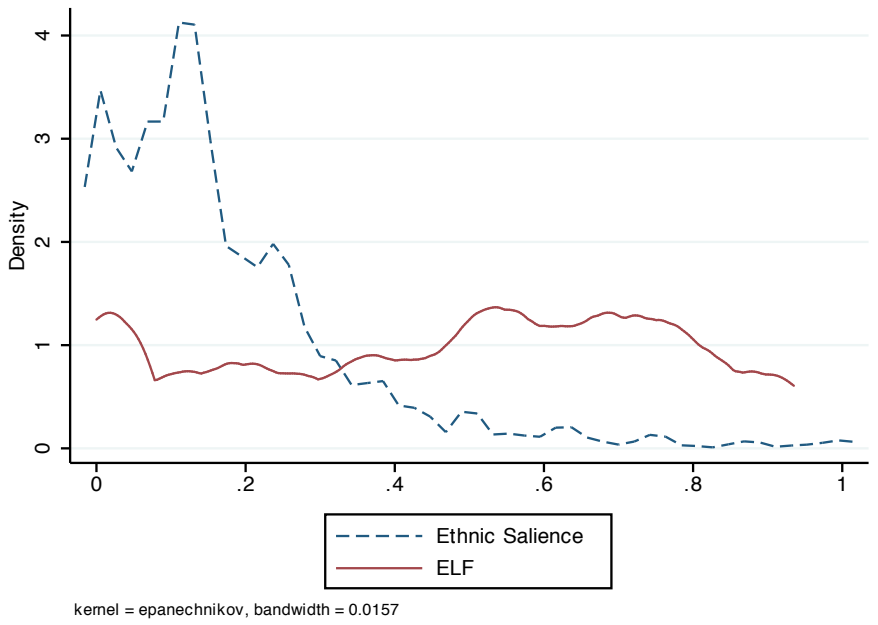

Figure 3: Kernel Density Functions: Ethnic Salience and ELF, Multi-Country

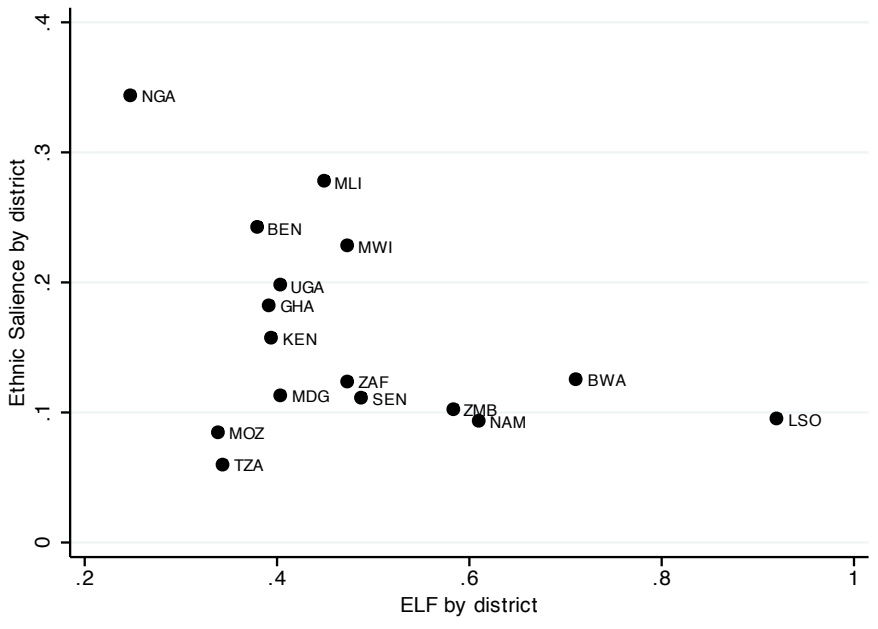

Figure 4: ELF and Ethnic Salience by District, Country Means

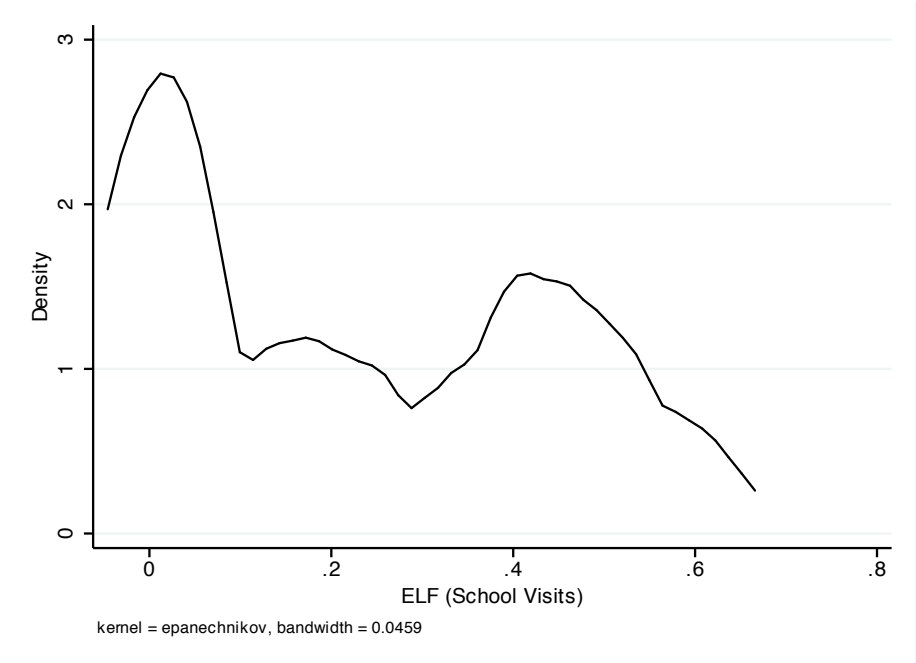

Figure 5: Kernel Density Function: ELF in Uganda (School Visits)

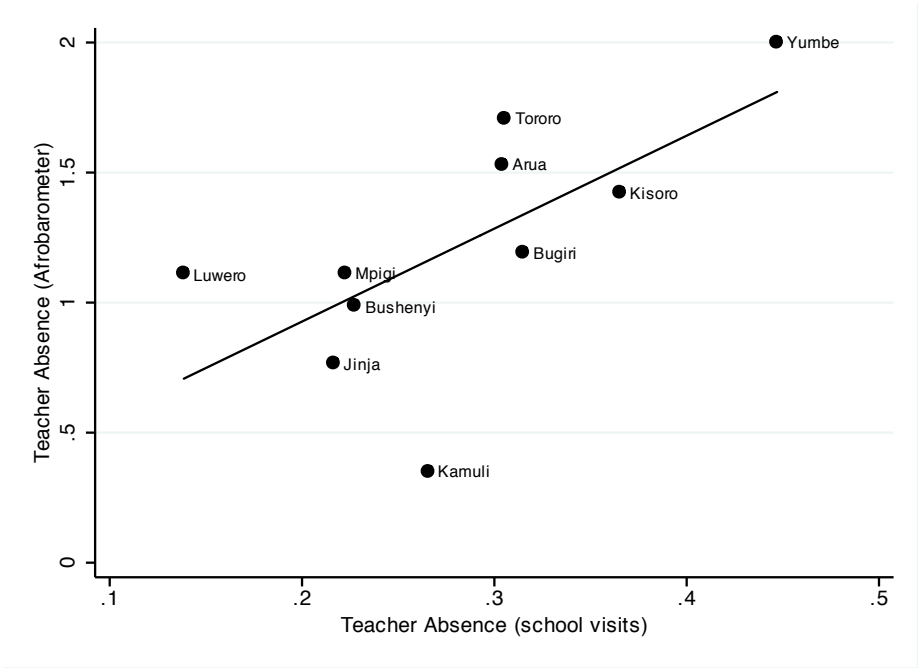

Figure 6: Absenteeism in Uganda: Afrobarometer vs. School Visits

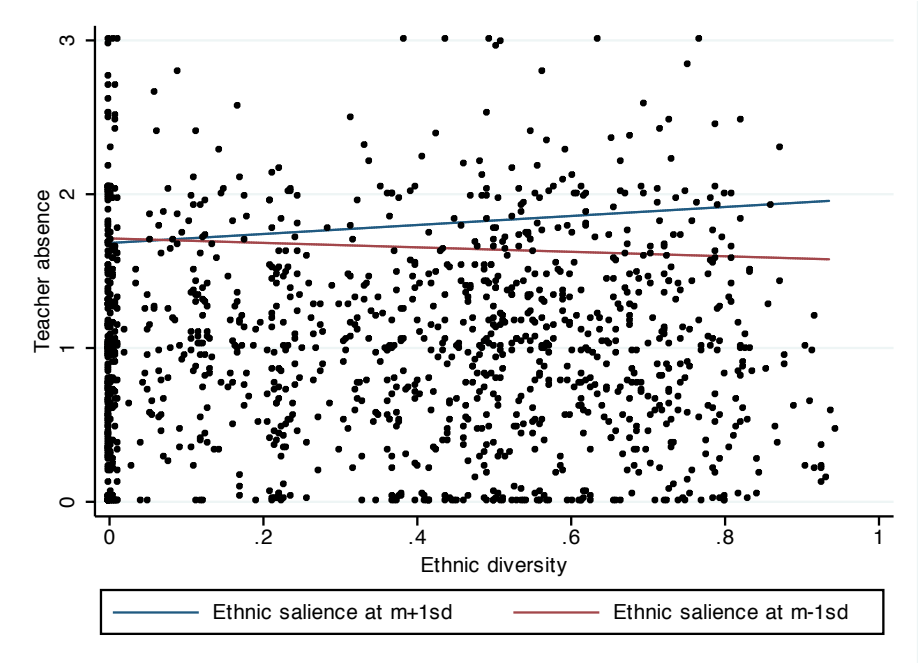

Figure 7: Teacher Absence and Ethnic Divisions

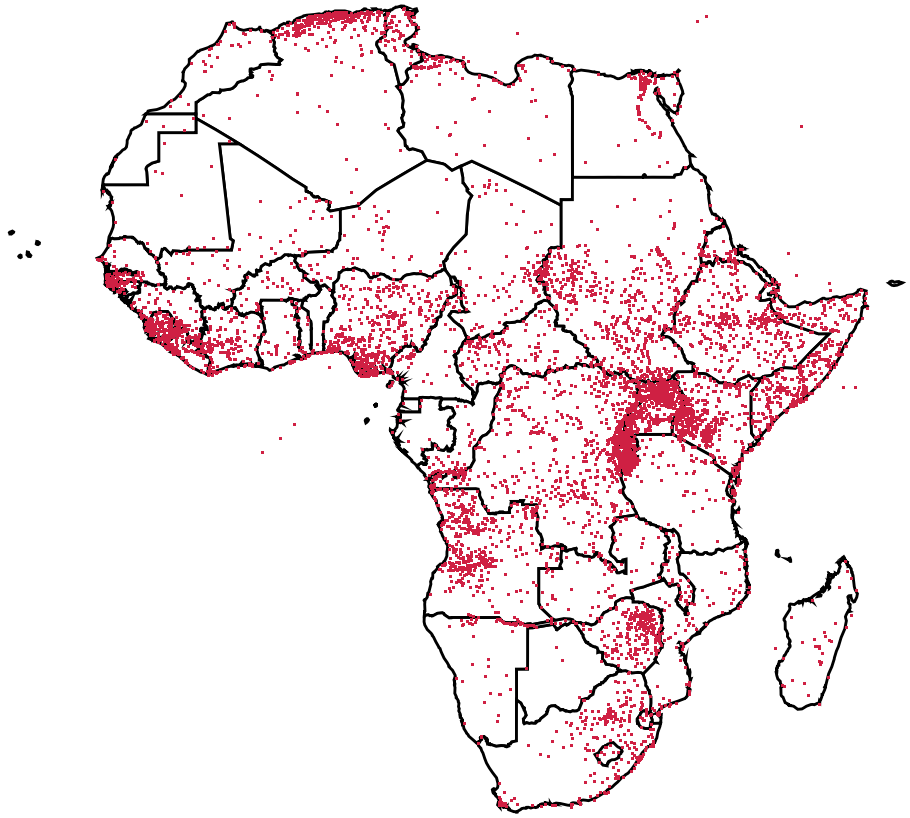

Figure 8: Location of Armed Conflict Events (Source: Acled)

Tables

Table 1: Ethnic Salience in the Literature

Mean Ethnic Salience			
Posner (2004) Test			
	Malawi	Zambia	Difference
Chewa	0.31	0.05	0.26***
Tumbuka	0.16	0.07	0.09*
Miguel (2004) Test			
	Tanzania	Kenya	Difference
	0.06	0.16	0.10***

Table 2: Descriptive Statistics

Teacher absence:	Never	Once/twice	A few times	Often	Full Sample
ELF_d	0.48	0.44	0.43	0.44	0.46
	(0.30)	(0.29)	(0.27)	(0.26)	(0.29)
Ethnic Salience	0.15	0.17	0.18	0.18	0.17
	(0.15)	(0.17)	(0.17)	(0.16)	(0.16)
Urban	0.35	0.39	0.38	0.32	0.38
	(0.48)	(0.49)	(0.49)	(0.47)	(0.47)
Village facilities: school	0.78	0.80	0.81	0.82	0.80
	(0.41)	(0.40)	(0.39)	(0.39)	(0.40)
Village facilities: water	0.53	0.52	0.47	0.43	0.51
	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)
Village facilities: electricity	0.52	0.58	0.52	0.47	0.54
	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)
Village facilities: health	0.46	0.50	0.52	0.47	0.49
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Village facilities: sewage	0.23	0.28	0.24	0.20	0.24
	(0.42)	(0.45)	(0.42)	(0.40)	(0.43)
Respondent characteristics					
Hardship	7.51	8.27	9.20	10.45	8.69
	(5.66)	(5.41)	(5.52)	(5.79)	(5.90)
Age	38.25	36.53	35.18	35.98	36.53
	(14.72)	(14.27)	(13.14)	(13.58)	(14.76)
Male	0.48	0.51	0.52	0.54	0.50
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Post-primary education	0.49	0.50	0.48	0.44	0.63
	(0.49)	(0.50)	(0.50)	(0.50)	(0.48)
Observations	6,755	2,521	2,791	2,033	21,598

Urban indicates the percentage of respondents surveyed in urban areas; Village facilities indicates the percentage of respondents surveyed in villages containing a school, piped water, electricity, a health clinic and a sewage system, respectively; Hardship is a composite variable ranging from 0-30, where 0 indicates that respondents never go without food, water, medical care, cooking fuel, a cash income, and school supplies like fees, uniforms or books, and 30 indicates that they always do. Post-primary education is the average of a dummy variable indicating that respondents have recieved any form of post-primary education.

Table 3: Teacher Absenteeism and Ethnic Divisions - Afrobarometer

	(1)	(2)	(3)	(4)
	Teacher absence: Afrobarometer			
ELF * Ethnic salience	1.008**	1.193***		
	(0.403)	(0.425)		
ELF	-0.002	-0.066	0.140	0.125
	(0.107)	(0.115)	(0.085)	(0.084)
Ethnic salience	-0.082	-0.073	0.319*	
	(0.166)	(0.178)	(0.187)	
Village controls	No	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	13,468	12,240	12,240	12,330
Number of clusters	318/1234	318/1234	318/1234	318/1234
R-squared	0.177	0.176	0.175	0.174

Standard errors are adjusted for two-way clustering within ethnic groups and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level. Regression equation: $TA_{idr} = a + \Psi \sum_{i=1}^{n} \frac{ES_{id}}{n_d} + \lambda ELF_d + \beta(\sum_{i=1}^{n} \frac{ES_{id}}{n_d} * ELF_d) + \gamma X_{id} + \delta V_{id} + \eta R_r + e_{id}$

Table 4: Cultural and Institutional Persistence

	(1)	(2)	(3)
	Teacher absence: Afrobarometer		
ELF * Ethnic salience	1.027**	1.306***	1.193**
	(0.474)	(0.465)	(0.533)
ELF	-0.018	-0.165	-0.153
	(0.129)	(0.116)	(0.134)
Ethnic salience	-0.049	-0.078	-0.075
	(0.184)	(0.202)	(0.229)
Slave exports	-0.025		
	(0.033)		
Pre-colonial juris. hierarchy	-0.061**		
	(0.026)		
Existence of city in 1400	0.091*		
	(0.047)		
Pre-colonial FE	No	No	Yes
Ethnicity FE	No	Yes	Yes
Village controls	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	10,772	12,240	11,593
Number of clusters	318/1234	318/1234	318/1234
R-squared	0.185	0.204	0.228

Standard errors are adjusted for two-way clustering within ethnic groups and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 5: Conflict, Sorting and Settlement History

	(1)	(2)	(3)	(4)	(5)	(6)
	Teacher absence: Afrobarometer					
ELF * Ethnic salience	1.299***	1.192**	1.307***	1.184**	1.344***	1.201**
	(0.462)	(0.532)	(0.463)	(0.527)	(0.481)	(0.529)
ELF	-0.157	-0.149	-0.154	-0.128	-0.176	-0.138
	(0.116)	(0.134)	(0.111)	(0.131)	(0.117)	(0.134)
Ethnic salience	-0.076	-0.077	-0.079	-0.077	-0.092	-0.067
	(0.201)	(0.228)	(0.200)	(0.227)	(0.205)	(0.226)
Armed conflicts within 1km & 1 year	-0.010	-0.008		-0.008		-0.008
	(0.010)	(0.007)		(0.007)		(0.007)
Conflict fatalities within 1km & 1 year	0.005**	0.004***		0.004***		0.004***
	(0.002)	(0.001)		(0.001)		(0.001)
Share of historical migrants			0.025	0.049		0.052
			(0.057)	(0.066)		(0.068)
Distance to Addis Ababa (km)					-0.000	-0.000
					(0.000)	(0.000)
Latitude					0.010	0.013
					(0.023)	(0.026)
Distance to sea (km)					-0.000	-0.000
					(0.000)	(0.000)
Pre-colonial FE	No	Yes	No	Yes	No	Yes
Ethnicity FE	Yes	Yes	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,240	11,593	12,240	11,593	12,044	11,593
Number of clusters	318/1234	318/1234	318/1234	318/1234	318/1234	318/1234
R-squared	0.204	0.228	0.204	0.228	0.204	0.228

Standard errors are adjusted for two-way clustering within ethnic groups and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 6: Falsification Tests - Other School Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Perceived school problems (normalized)						
	Teacher abs.	Expensive	Facilities	Crowding	Teaching	Materials	Bribes
ELF * Ethnic salience	1.073**	-0.105	-0.575	-0.131	0.127	-0.725*	0.383
	(0.473)	(0.382)	(0.374)	(0.389)	(0.375)	(0.387)	(0.395)
ELF	-0.123	0.012	0.235**	0.064	0.070	0.098	-0.138
	(0.119)	(0.098)	(0.096)	(0.101)	(0.110)	(0.101)	(0.108)
Ethnic salience	-0.060	0.206	0.223	0.051	0.044	0.390*	0.096
	(0.202)	(0.168)	(0.202)	(0.207)	(0.161)	(0.211)	(0.206)
Spatial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-colonial FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,593	12,071	11,589	11,634	11,479	11,754	11,568
Number of clusters	318/1234	318/1234	318/1234	318/1234	318/1234	318/1234	318/1234
R-squared	0.228	0.266	0.294	0.265	0.255	0.259	0.230
Intra-country correlation	0.077	0.092	0.122	0.118	0.103	0.088	0.074

Standard errors are adjusted for two-way clustering within ethnic groups and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 7: Falsification Tests - Governance Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Perceptions of country-level institutions					
	Corruption		Trust		Gov. performance	
	Government	President	Ruling party	Opposition	Corruption	Education
ELF * Ethnic salience	-0.093	-0.452	0.511	0.137	-0.452	0.081
	(0.386)	(0.343)	(0.403)	(0.358)	(0.391)	(0.273)
ELF	0.053	0.056	-0.102	0.023	0.141	-0.068
	(0.094)	(0.084)	(0.105)	(0.083)	(0.103)	(0.087)
Ethnic salience	-0.147	0.010	0.032	0.004	-0.247	-0.121
	(0.165)	(0.130)	(0.180)	(0.186)	(0.158)	(0.159)
Spatial controls	Yes	Yes	Yes	Yes	Yes	Yes
Pre-colonial FE	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity FE	Yes	Yes	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,324	13,943	16,595	16,126	15,857	17,051
Number of clusters	318/1234	318/1234	318/1234	318/1234	318/1234	318/1234
R-squared	0.221	0.266	0.294	0.167	0.226	0.257

Standard errors are adjusted for two-way clustering within ethnic groups and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 8: Other Falsification Tests

	(1) Teacher absence	(2) Teacher absence	(3) Teacher absence	(4) Community meetings
ELF * Ethnic salience (district)	1.348**			-0.102
	(0.549)			(0.365)
ELF	-0.175			0.075
	(0.139)			(0.112)
Ethnic salience	-0.110			0.139
	(0.636)			(0.232)
Minority	0.023			
	(0.597)			
ELF * Ethnic salience (individual)			0.830	
			(0.734)	
Ethnic salience (individual)	0.045	0.064	0.728	-0.098**
	(0.053)	(0.047)	(0.719)	(0.039)
Village FE	No	Yes	Yes	No
Spatial controls	Yes	N/a	N/a	Yes
Pre-colonial FE	Yes	N/a	N/a	Yes
Ethnicity FE	Yes	Yes	Yes	Yes
District controls	Yes	N/a	N/a	Yes
Individual controls	Yes	Yes	Yes	Yes
Region FE	Yes	N/a	N/a	Yes
Observations	11,000	12,974	12,974	17,359
Number of clusters	318/1234	289	289	318/1234
R-squared	0.225	0.396	0.396	0.255

Standard errors in column (1) and column (4) are adjusted for two-way clustering within ethnic groups and within districts. Standard errors in column (2) and column (3) are adjusted for clustering at the ethnicity level. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 9: Robustness - Data and Specification

	(1)	(2)	(3)	(4)	(5)
	Teacher absence: Afrobarometer				
	District average	Women 25–50	District sample size		Ordered Probit
			< Med.	> Med.	
ELF * Ethnic salience	1.218**	2.549***	0.657	3.668*	1.323**
	(0.564)	(0.816)	(0.610)	(2.101)	(0.429)
ELF	-0.126	-0.263	-0.142	-0.121	-0.172
	(0.194)	(0.220)	(0.157)	(0.472)	(0.116)
Ethnic salience	0.089	-0.807**	0.025	-0.933	-0.096
	(0.219)	(0.356)	(0.220)	(1.157)	(0.178)
Spatial controls	Yes	Yes	Yes	Yes	Yes
Pre-colonial FE	Yes	Yes	Yes	Yes	Yes
Ethnicity FE	Yes	Yes	Yes	Yes	Yes
Village controls	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	20,600	3,611	5,499	6,094	11,593
Number of clusters	318/1234	274/1149	254/1036	264/200	1055
R-squared	0.868	0.335	0.266	0.260	
Pseudo R-squared					0.105

Pre-colonial fixed effects, ethnicity fixed effects, and individual controls are included as district-level means in column (1). Standard errors are adjusted for two-way clustering within ethnic groups and within districts in columns (1) to (4), and for clustering at the district level in column (5). ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 10: Ordered Probit Marginal Effects

Teacher Absence		(1) Ethnic Salience	(2) Ethnic Salience
		Mean + 1 SD	Mean - 1 SD
$\frac{\partial(Pr(outcome))}{\partial(ELF)}$	Never	-0.089**	0.056
		(0.039)	(0.039)
	Once or twice	0.003**	-0.005
		(0.001)	(0.004)
	A few times	0.03**	-0.020
		(0.012)	(0.014)
	Often	0.057**	-0.031
		(0.026)	(0.021)

Marginal effects are calculated from the ordered probit regression presented in Table 9, column (5). ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 11: Teacher Absenteeism and Ethnic Divisions - Uganda School Visits

	(1)	(2)	(3)	(4)	(5)	(6)
	Teacher absence: school visits					
					Probit	
					Ai & Norton (2003) Interaction effect	
ELF (District) * Ethnic salience	4.410***		4.115***		2.36**	
	(1.477)		(1.429)		(1.019)	
ELF (Pupils) * Ethnic salience		4.901***		5.253***		2.43**
		(1.288)		(1.343)		(0.979)
					Marginal effects	
ELF (District)	-0.818***		-0.766***		-0.744	
	(0.272)		(0.287)		(0.463)	
ELF (Pupils)		-1.327***		-1.393***		-1.542**
		(0.338)		(0.349)		(0.722)
Ethnic salience	-2.229***	-2.145***	-1.966***	-2.127***	-1.392**	-1.644**
	(0.454)	(0.446)	(0.462)	(0.529)	(0.596)	(0.701)
Teacher demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Teacher rank FE	Yes	Yes	Yes	Yes	Yes	Yes
Teacher employment characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	No	No	Yes	Yes	Yes	Yes
School and location controls	No	No	Yes	Yes	Yes	Yes
Time of day FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,686	1,686	1,594	1,594	1,400	1,400
Number of clusters	94/10	94/10	94/10	94/10	83	83
R-squared	0.248	0.253	0.252	0.256	0.223	0.230

Teacher demographic controls include: gender, age, marital status, a dummy variable indicating completion of A-levels (high school final exams), and a dummy variable indicating place of birth (this district or another district); Teacher's rank is a categorical variable indicating the following ranks: deputy head, head of department, permanent teacher, private teacher, temporary teacher, volunteer teacher, and 'other'. The omitted category is head teacher. Teacher's employment characteristics include: duration of teaching career; duration of tenure at current school, and dummy variables indicating full-time status, membership of a union, and attendance of a teacher training program in the previous year. Institutional controls include dummy variables indicating the existence of a Parent Teacher Association (PTA), a categorical variable indicating the time lapsed since the last meeting, and dummy variables indicating an official inspection in the previous six months and the existence of a local means of recognition for good teachers. School and location controls include a set of dummy variables to indicate the existence of the following facilities: covered classrooms, non-dirt classroom floors, a toilet/latrine, drinking water and electricity; as well as the pupil-teacher ratio, average education levels of parents, and dummy variables indicating that the school is public, that it practices multi-grade teaching, whether it is within five kilometres of a paved road and whether it is in a rural location. Column (5) and (6) present marginal effects from a Probit regression. Standard errors in columns (1) to (4) are adjusted for two-way clustering within schools and within districts. Standard errors in column (5) and column (6) are adjusted for clustering at the school level. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level. Regression equation: $TA_{jsd} = a + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd}$

Table 12: Channel 1 - Teacher Coethnicity

	(1)	(2)	(3)	(4)	(5)	(6)
	Teacher absence: school visits					
ELF (District) * Ethnic salience	4.330***	4.377***	4.378***			
	(1.460)	(1.461)	(1.460)			
ELF (Pupils) * Ethnic salience				5.552***	5.647***	5.647***
				(1.333)	(1.379)	(1.356)
ELF (District)	-0.798***	-0.814***	-0.815***			
	(0.281)	(0.293)	(0.290)			
ELF (Pupils)				-1.436***	-1.478***	-1.478***
				(0.342)	(0.351)	(0.344)
Ethnic salience	-1.974***	-1.995***	-1.995***	-2.143***	-2.177***	-2.177***
	(0.469)	(0.479)	(0.478)	(0.521)	(0.535)	(0.528)
Native: language	0.051**			0.046**		
	(0.021)			(0.022)		
Native: ancestry		-0.005			-0.000	
		(0.045)			(0.049)	
Native: birth			0.042			0.042
			(0.035)			(0.037)
Teacher demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Teacher rank FE	Yes	Yes	Yes	Yes	Yes	Yes
Teacher employment characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes	Yes
School and location controls	Yes	Yes	Yes	Yes	Yes	Yes
Time of day FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,588	1,588	1,588	1,588	1,588	1,588
Number of clusters	94/10	94/10	94/10	94/10	94/10	94/10
R-squared	0.265	0.263	0.263	0.270	0.268	0.268

Standard errors are adjusted for two-way clustering within schools and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level. Regression equation: $TA_{jsd} = a + \phi Native_{jsd} + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd}$

Table 13: Channel 2a - Sanctioning Institutions

	(1)	(2)	(3)	(4)
	Teacher absence: school visits			
ELF (District) * Ethnic salience	4.098***	4.061***		
	(1.430)	(1.376)		
ELF (Pupils) * Ethnic salience			5.285***	5.417***
			(1.333)	(1.151)
ELF (District)	-0.766***	-0.751***		
	(0.287)	(0.274)		
ELF (Pupils)			-1.411***	-1.460***
			(0.342)	(0.297)
Ethnic salience	-1.966***	-1.956***	-2.141***	-2.163***
	(0.465)	(0.434)	(0.529)	(0.458)
PTA	0.032	0.047	0.030	0.054
	(0.104)	(0.101)	(0.102)	(0.096)
Last PTA meet: last month	0.022	0.018	-0.015	-0.024
	(0.115)	(0.115)	(0.102)	(0.102)
Last PTA meet: < six months	-0.118	-0.121	-0.139*	-0.145*
	(0.085)	(0.084)	(0.078)	(0.078)
Last PTA meet: < one year	-0.164**	-0.169**	-0.165**	-0.173**
	(0.065)	(0.066)	(0.068)	(0.069)
Last PTA meet: > one year	-0.053	-0.061	-0.046	-0.058
	(0.081)	(0.084)	(0.082)	(0.083)
Recent inspection	0.029	0.031	0.053	0.059
	(0.048)	(0.047)	(0.045)	(0.043)
Head teacher has sanctioned		0.078		0.121**
		(0.067)		(0.053)
Teacher demographic controls	Yes	Yes	Yes	Yes
Teacher rank FE	Yes	Yes	Yes	Yes
Teacher employment characteristics	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes
School and location controls	Yes	Yes	Yes	Yes
Time of day FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	1,588	1,588	1,588	1,588
Number of clusters	94/10	94/10	94/10	94/10
R-squared	0.260	0.261	0.266	0.267

Standard errors are adjusted for two-way clustering within schools and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level Regression equation: $TA_{jsd} = a + \phi Sanction_{sd} + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd}$

Table 14: Channel 2b - Sanctioning Institutions by Coethnicity

	(1)	(2)	(3)	(4)	(5)	(6)
	Teacher absence: school visits					
ELF (District) * Ethnic salience	3.904***	3.570***	3.971***			
	(1.268)	(1.364)	(1.431)			
ELF (Pupils) * Ethnic salience				5.363***	5.130***	5.462***
				(0.949)	(1.202)	(1.345)
ELF (District)	-0.735***	-0.650**	-0.728**			
	(0.230)	(0.276)	(0.290)			
ELF (Pupils)				-1.427***	-1.422***	-1.477***
				(0.263)	(0.307)	(0.344)
Ethnic salience	-1.931***	-1.797***	-1.898***	-2.185***	-2.054***	-2.137***
	(0.386)	(0.449)	(0.464)	(0.416)	(0.471)	(0.504)
PTA	0.144**	0.035	0.036	0.150***	0.044	0.045
	(0.062)	(0.081)	(0.088)	(0.058)	(0.078)	(0.083)
Last PTA meet: last month	-0.054	-0.006	-0.020	-0.080	-0.048	-0.059
	(0.112)	(0.112)	(0.104)	(0.104)	(0.101)	(0.090)
Last PTA meet: < six months	-0.151	-0.130	-0.157*	-0.173*	-0.158*	-0.182**
	(0.107)	(0.091)	(0.091)	(0.090)	(0.085)	(0.082)
Last PTA meet: < one year	-0.249***	-0.161***	-0.182***	-0.257***	-0.164**	-0.186***
	(0.064)	(0.060)	(0.067)	(0.064)	(0.064)	(0.068)
Last PTA meet: > one year	-0.118	-0.040	-0.081	-0.116	-0.037	-0.077
	(0.093)	(0.095)	(0.086)	(0.089)	(0.094)	(0.084)
Recent inspection	0.014	0.012	0.015	0.024	0.039	0.042
	(0.048)	(0.053)	(0.051)	(0.043)	(0.047)	(0.046)
Head teacher has sanctioned	0.156**	0.039	0.056	0.199***	0.083	0.101**
	(0.068)	(0.065)	(0.060)	(0.055)	(0.054)	(0.047)
Native by:	Language	Ancestry	Birth	Language	Ancestry	Birth
Native	0.204*	-0.245***	-0.154	0.176*	-0.252***	-0.148
	(0.106)	(0.091)	(0.145)	(0.103)	(0.091)	(0.142)
Native*PTA	-0.171	0.078	0.131	-0.166*	0.074	0.110
	(0.109)	(0.135)	(0.149	(0.100)	(0.136)	(0.142)
Native*Recent inspection	0.040	0.094	0.096	0.064	0.094	0.116
	(0.037)	(0.092)	(0.108)	(0.040)	(0.095)	(0.107)
Native*Head teacher has sanctioned	-0.142*	0.209**	0.146	-0.142*	0.197**	0.146*
	(0.076)	(0.101)	(0.102)	(0.077)	(0.090)	(0.086)
Native*Last PTA meet: last month	-0.090*	-0.039	-0.196	-0.086*	-0.042	-0.186
	(0.048)	(0.284)	(0.178)	(0.046)	(0.289)	(0.178)
Native*Last PTA meet: < six months	0.011	0.170	0.029	-0.004	0.150	0.021
	(0.077)	(0.115)	(0.157)	(0.082)	(0.116)	(0.148)
Native*Last PTA meet: < one year	-0.065	0.156*	0.071	-0.066	0.160*	0.084
	(0.056)	(0.089)	(0.085)	(0.049)	(0.086)	(0.080)
Native*Last PTA meet: > one year	0.076	-0.030	-0.176	0.083	-0.045	-0.169
	(0.056)	(0.136)	(0.117)	(0.055)	(0.130)	(0.108)
Teacher demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Teacher rank FE	Yes	Yes	Yes	Yes	Yes	Yes
Teacher employment characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes	Yes
School and location controls	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,588	1,588	1,588	1,588	1,588	1,588
Number of clusters	94/10	94/10	94/10	94/10	94/10	94/10
R-squared	0.267	0.270	0.267	0.273	0.277	0.274

Standard errors are adjusted for two-way clustering within schools and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level. Regression equation: $TA_{jsd} = a + \phi Native_{jsd} + \varphi Sanction_{sd} + \theta(Native_{jsd} * Sanction_{sd}) + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd}$

Table 15: Channel 3 - Social Networks Between Teachers

	(1)	(2)
	Teacher absence: school visits	
ELF (District) * Ethnic salience	2.434	
	(1.823)	
ELF (Pupils) * Ethnic salience		3.420**
		(1.726)
ELF (District)	-0.316	
	(0.364)	
ELF (Pupils)		-0.917**
		(0.406)
Ethnic salience	-1.427***	-1.585***
	(0.493)	(0.498)
Social	-0.125**	-0.112**
	(0.050)	(0.053)
Teacher demographic controls	Yes	Yes
Teacher rank FE	Yes	Yes
Teacher employment characteristics	Yes	Yes
Institutional controls	Yes	Yes
School and location controls	Yes	Yes
Time of day FE	Yes	Yes
Day FE	Yes	Yes
Month FE	Yes	Yes
Observations	1,476	1,476
Number of clusters	94/10	94/10
R-squared	0.264	0.263

Standard errors are adjusted for two-way clustering within schools and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level. Regression equation: $TA_{jsd} = a + \phi Social_{sd} + \Psi ES_d + \lambda ELF + \beta(ES_d * ELF) + \gamma X_{jsd} + \delta S_{sd} + \eta T_{tdm} + e_{jsd}$

Table 16: Test for Heterogeneous Effects of Social Networks

	(1)	(2)	(3)	(4)	(5)	(6)
	Teacher absence: school visits					
ELF (District) * Ethnic salience	2.094	2.133	2.138			
	(1.750)	(1.772)	(1.773)			
ELF (Pupils) * Ethnic salience				3.230*	3.266*	3.390**
				(1.655)	(1.718)	(1.719)
ELF (District)	-0.272	-0.258	-0.276			
	(0.352)	(0.361)	(0.355)			
ELF (Pupils)				-0.860**	-0.868**	-0.909**
				(0.390)	(0.402)	(0.404)
Ethnic salience	-1.410***	-1.399***	-1.403***	-1.564***	-1.549***	-1.582***
	(0.486)	(0.488)	(0.483)	(0.491)	(0.505)	(0.494)
Social	-0.156***	-0.139***	-0.128**	-0.144***	-0.129**	-0.118**
	(0.043)	(0.050)	(0.050)	(0.050)	(0.053)	(0.052)
Social * Native: language	0.050			0.045		
	(0.046)			(0.044)		
Social * Native: ancestry		0.123***			0.110**	
		(0.044)			(0.045)	
Social * Native: birth			0.044			0.040
			(0.054)			(0.054)
Native: language	0.031			0.030		
	(0.031)			(0.032)		
Native: ancestry		-0.103**			-0.087*	
		(0.045)			(0.049)	
Native: birth			-0.005			-0.003
			(0.037)			(0.036)
Teacher demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Teacher rank FE	Yes	Yes	Yes	Yes	Yes	Yes
Teacher employment characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes	Yes
School and location controls	Yes	Yes	Yes	Yes	Yes	Yes
Time of Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,476	1,476	1,476	1,476	1,476	1,476
Number of clusters	94/10	94/10	94/10	94/10	94/10	94/10
R-squared	0.263	0.263	0.261	0.266	0.265	0.264

Standard errors are adjusted for two-way clustering within schools and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 17: Teacher Absenteeism and School-level Ethnic Divisions Among Teachers

	(1)	(2)	(3)	(4)	(5)
	Teacher absence: school visits				
ELF (Teachers: regional origin) * Ethnic salience	5.043***				
	(1.510)				
ELF (Teachers: native fluency) * Ethnic salience		3.846***			
		(0.905)			
(Share of non-native teachers: language) * Ethnic Salience			2.768***		
			(0.663)		
(Share of non-native teachers: ancestry) * Ethnic Salience				8.386***	
				(1.989)	
(Share of non-native teachers: birth) * Ethnic Salience					9.336***
					(1.995)
ELF (Teachers: regional origin)	-1.427***				
	(0.338)				
ELF (Teachers: native fluency)		-1.218***			
		(0.222)			
Share of non-native teachers: language			-0.749***		
			(0.178)		
Share of non-native teachers: ancestry				-1.909***	
				(0.489)	
Share of non-native teachers: birth					-2.331***
					(0.475)
Ethnic salience	-2.226***	-2.184***	-1.989***	-8.127***	-8.836***
	(0.562)	(0.402)	(0.385)	(1.794)	(1.663)
Teacher demographic controls	Yes	Yes	Yes	Yes	Yes
Teacher rank FE	Yes	Yes	Yes	Yes	Yes
Teacher employment characteristics	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes
School and location controls	Yes	Yes	Yes	Yes	Yes
Time of day FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	1,588	1,588	1,588	1,588	1,588
Number of clusters	94/10	94/10	94/10	94/10	94/10
R-squared	0.267	0.271	0.266	0.261	0.267

Standard errors are adjusted for two-way clustering within schools and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Table 18: Teacher Absenteeism, School-level Ethnic Divisions and Social Networks Between Teachers

	(1)	(2)	(3)	(4)	(5)
	Teacher absence: school visits				
ELF (Teachers: regional origin) * Ethnic salience	2.722*				
	(1.511)				
ELF (Teachers: native fluency) * Ethnic salience		2.320**			
		(1.050)			
(Share of non-native teachers: language) * Ethnic Salience			1.415		
			(0.882)		
(Share of non-native teachers: ancestry) * Ethnic Salience				6.105***	
				(2.146)	
(Share of non-native teachers: birth) * Ethnic Salience					6.519***
					(1.952)
Social	-0.086*	-0.089*	-0.114**	-0.096**	-0.092*
	(0.046)	(0.053)	(0.053)	(0.048)	(0.047)
ELF (Teachers: regional origin)	-0.912***				
	(0.351)				
ELF (Teachers: native fluency)		-0.857***			
		(0.257)			
Share of non-native teachers: language			-0.401*		
			(0.215)		
Share of non-native teachers: ancestry				-1.083**	
				(0.480)	
Share of non-native teachers: birth					-1.527***
					(0.427)
Ethnic salience	-1.435***	-1.540***	-1.388***	-6.147***	-6.423***
	(0.530)	(0.448)	(0.416)	(1.798)	(1.658)
Teacher demographic controls	Yes	Yes	Yes	Yes	Yes
Teacher rank FE	Yes	Yes	Yes	Yes	Yes
Teacher employment characteristics	Yes	Yes	Yes	Yes	Yes
Institutional controls	Yes	Yes	Yes	Yes	Yes
School and location controls	Yes	Yes	Yes	Yes	Yes
Time of day FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	1,476	1,476	1,476	1,476	1,476
Number of clusters	94/10	94/10	94/10	94/10	94/10
R-squared	0.264	0.267	0.262	0.266	0.264

Standard errors are adjusted for two-way clustering within schools and within districts. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Appendix A

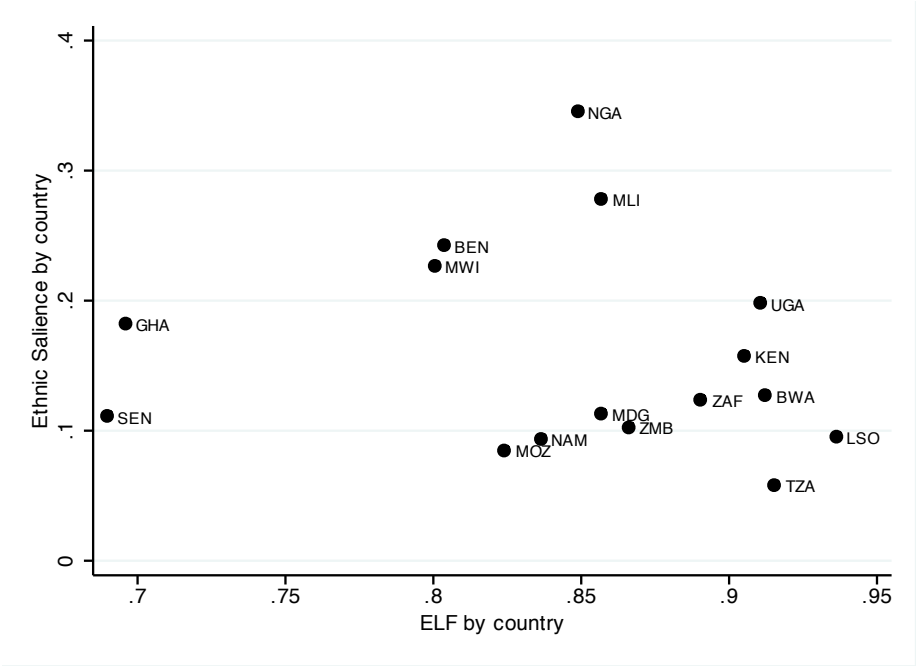

Figure A 1: ELF and Ethnic salience by country

Table A1: Social Networks Between Teachers - OLS Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable: Social						
ELF measured by:	District	Pupils	Teachers:		Share of non-native teachers by:		
			Region	Language	Language	Ancestry	Birth
ELF * Ethnic salience	-6.997*	-5.527*	-5.574*	-6.692**	-4.110**	-2.752	-1.632
	(3.732)	(2.833)	(2.801)	(2.682)	(1.606)	(3.400)	(3.349)
ELF	1.160*	0.723	1.909**	1.755***	0.604*	0.416	0.607
	(0.608)	(0.683)	(0.719)	(0.610)	(0.356)	(0.691)	(0.753)
Ethnic salience	1.058	0.730	0.379	1.590	1.252	1.634	0.513
	(1.256)	(0.969)	(1.027)	(1.258)	(0.942)	(3.164)	(3.097)
PTA	-0.100	-0.127	-0.090	-0.040	-0.068	-0.118	-0.065
	(0.270)	(0.274)	(0.246)	(0.241)	(0.236)	(0.273)	(0.289)
Last PTA meet: last month	0.274	0.135	0.497*	0.379	0.165	0.194	0.299
	(0.280)	(0.303)	(0.274)	(0.275)	(0.273)	(0.305)	(0.314)
Last PTA meet: < six months	-0.029	-0.154	0.034	-0.017	-0.205	-0.165	-0.116
	(0.267)	(0.267)	(0.268)	(0.274)	(0.290)	(0.278)	(0.279)
Last PTA meet: < one year	0.465	0.528*	0.509*	0.485	0.484*	0.404	0.418
	(0.297)	(0.298)	(0.293)	(0.296)	(0.285)	(0.305)	(0.313)
Last PTA meet: > one year	0.010	-0.135	0.019	-0.027	-0.069	-0.142	-0.079
	(0.224)	(0.245)	(0.218)	(0.218)	(0.228)	(0.214)	(0.212)
Recent inspection	-0.112	-0.076	-0.142	-0.147	-0.146	-0.095	-0.125
	(0.178)	(0.170)	(0.178)	(0.178)	(0.184)	(0.189)	(0.182)
Female	0.433	0.316	0.596	0.425	0.542	0.618	0.531
	(0.464)	(0.447)	(0.455)	(0.443)	(0.441)	(0.469)	(0.480)
Age	-0.015	-0.006	-0.020	-0.016	-0.005	-0.017	-0.011
	(0.026)	(0.026)	(0.025)	(0.025)	(0.026)	(0.026)	(0.027)
Education	0.201	0.053	0.249	0.351	0.133	0.107	0.091
	(0.343)	(0.346)	(0.344)	(0.355)	(0.317)	(0.334)	(0.343)
Teacher training	-0.158	-0.086	-0.125	-0.156	-0.179	-0.126	-0.163
	(0.175)	(0.161)	(0.159)	(0.158)	(0.153)	(0.176)	(0.169)
Experience	0.002	0.003	0.000	0.002	0.002	-0.007	0.000
	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)	(0.029)	(0.032)
Experience at this school	-0.018	-0.025	-0.037	-0.029	-0.021	-0.036	-0.041
	(0.028)	(0.025)	(0.023)	(0.026)	(0.023)	(0.025)	(0.025)
Fulltime	-0.881	-0.829	-0.735	-0.851	-0.616	-0.397	-0.346
	(1.153)	(1.136)	(1.111)	(1.185)	(1.084)	(1.135)	(1.114)
Union	-0.171	-0.315	-0.161	-0.191	-0.281	-0.265	-0.249
	(0.228)	(0.214)	(0.223)	(0.222)	(0.211)	(0.231)	(0.238)
Married	0.404	0.453	0.265	0.338	0.447	0.385	0.405
	(0.294)	(0.276)	(0.290)	(0.290)	(0.281)	(0.310)	(0.307)
Recognition program	0.044	0.064	0.038	0.033	0.100	0.080	0.087
	(0.130)	(0.121)	(0.125)	(0.123)	(0.114)	(0.128)	(0.130)
Facilities: classroom	-0.283	-0.392	-0.171	-0.117	-0.135	-0.155	-0.241
	(0.601)	(0.653)	(0.544)	(0.544)	(0.476)	(0.586)	(0.585)
Facilities: floor	0.153	0.126	0.111	0.151	0.108	0.118	0.145
	(0.188)	(0.192)	(0.177)	(0.184)	(0.152)	(0.193)	(0.200)
Facilities: toilet	0.276	-0.110	0.163	0.330	0.318	-0.137	-0.117
	(0.668)	(0.699)	(0.733)	(0.678)	(0.725)	(0.681)	(0.630)
Facilities: water	-0.088	0.003	-0.182	-0.129	-0.082	-0.130	-0.167
	(0.139)	(0.137)	(0.128)	(0.128)	(0.126)	(0.138)	(0.142)
Facilities: electricity	0.110	0.093	0.073	0.108	0.166	0.126	0.093
	(0.200)	(0.201)	(0.187)	(0.188)	(0.183)	(0.205)	(0.205)
Rural	-0.064	-0.022	-0.105	-0.090	-0.058	-0.061	-0.045
	(0.126)	(0.133)	(0.124)	(0.125)	(0.126)	(0.130)	(0.127)
Access	0.009	0.089	0.001	0.007	-0.003	0.035	0.058
	(0.118)	(0.124)	(0.120)	(0.112)	(0.115)	(0.118)	(0.123)
Multi-grade	-0.002	0.048	-0.070	-0.049	0.252	-0.008	-0.013
	(0.234)	(0.257)	(0.217)	(0.238)	(0.249)	(0.305)	(0.320)
Pupil-teacher ratio	0.001	0.000	0.001	0.001	-0.001	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Parental education	0.018	0.024	0.015	0.015	0.009	0.019	0.019
	(0.018)	(0.016)	(0.018)	(0.017)	(0.016)	(0.017)	(0.018)
Public School	0.204	0.180	0.239	0.231	0.315	0.168	0.182
	(0.199)	(0.206)	(0.190)	(0.196)	(0.208)	(0.185)	(0.187)
Observations	86	86	86	86	86	86	86
R-squared	0.379	0.408	0.419	0.420	0.420	0.335	0.339

Robust standard errors in parentheses. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

Appendix B

In order to estimate the interaction effects in the probit models presented in Table 11, I turn to Ai and Tobin's (2003) well-known method of calculating the cross-partial derivative. They show that the marginal effect of an interaction term in non-linear models (i.e. $\frac{\partial \Phi(u)}{\partial (x_1 x_2)}$) can have a different magnitude, sign and level of statistical significance than the true cross-partial derivative (i.e., $\frac{\partial^2 \Phi(u)}{\partial x_1 \partial x_2}$).

Below, I show the interaction effects and z-statistics for the estimates presented in columns (5) and (6) respectively. The corresponding marginal effects are also presented for comparison. The plot of the z-statistics shows that every observation significantly different from zero is positive.

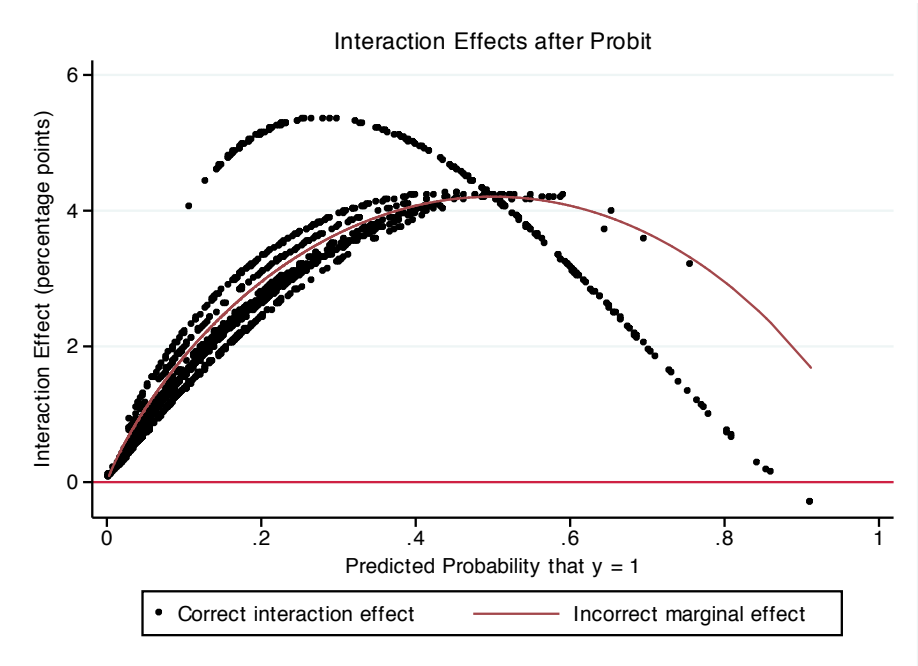

Figure A 2: Interaction effect with ELF at district level, probit

Figure A 3: z-statistics for interaction effect with ELF at district level, probit

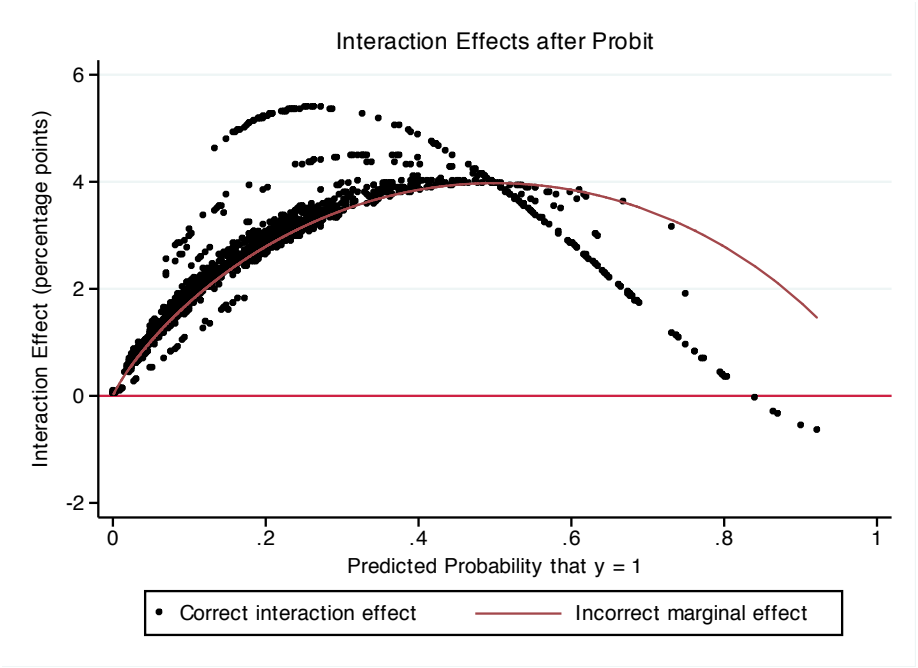

Figure A 4: Interaction effect with ELF at school level, probit

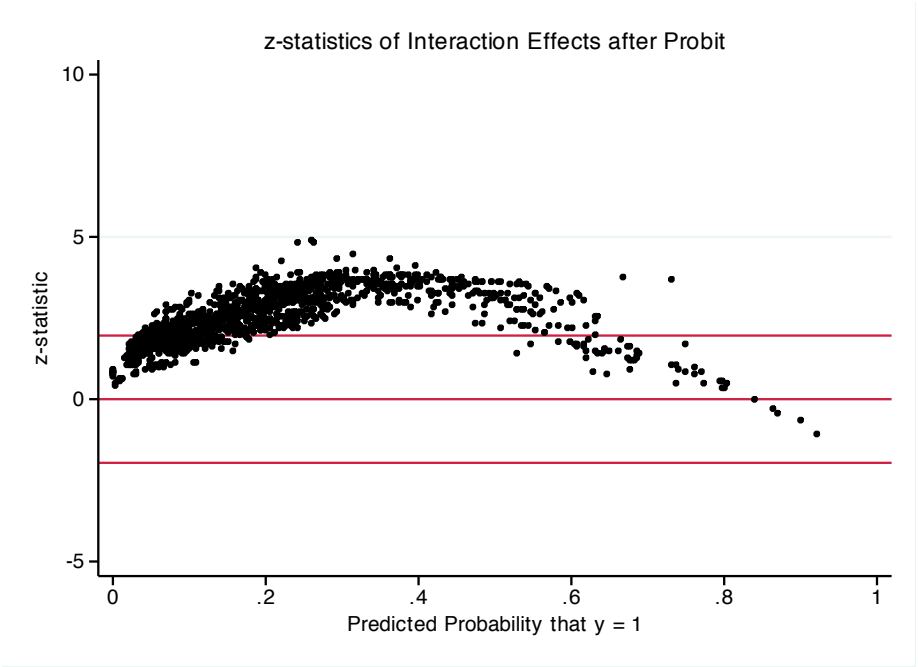

Figure A 5: z-statistics for interaction effect with ELF at school level, probit