GOV 2001 Replication Paper

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Abstract

This is our really good abstract.

1 Introduction

How does pre-colonial conlict shape contemporary economic and political development? Moreover, what are the mechanisms of persistence? In a recent paper, Besley and Reynal-Querol (2014) explore these questions in the context of Africa by assembling and analyzing a new national and subnational dataset of pre-colonial conflict in Africa. While much of the existing scholarship on African political economy points to the pernicious role of colonial institutions and practices in perpetuating economic and political underdevelopment, Besley and Reynal-Querol (2014) provide evidence that some of these roots of underdevelopment may actually lie long before the era of colonization (Nunn, N.d.; Nunn and Wantchekon, 2011; Michalopoulos and Papaioannou, Forthcoming).

Though Besley and Reynal-Querol (2014) provide an important substantive contribution to the literatures on African political economy, the persistence of historical events, and conflict, we argue that there are several avenues through which their piece can be improved to further enrich our understanding of the relationship between historical conflict and contemporary economic and political development. First, we argue that the authors of the original article are susceptible to the problem of overadjustment for covariates (Schisterman, Cole and Platt, 2009). Second, we maintain that the authors fail to utilize all of the information that they have in their data by assuming that historical conflict has constant effects across all units–an assumption that is generally implausible in most studies. Third, we argue that when the authors do investigate their mechanisms, their strategy of controlling for post-treatment covariates opens their estimates up to unexpected biases. Fourth and finally, we posit that the authors should have also utilized further data in their individual-level survey results that speak directly to their proposed mechanisms of persistence.

In this research note, we provide solutions to each of these in a principled and systematic way.

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2 Overview

3 Effect Heterogeneity and Variable Selection

3.1 Effect Heterogeneity and Variable Selection

Besley and Reynal-Querol (2014) sketch the contours of mechanisms through which the broad relationship in their study - between pre-colonial conflict and modern day conflict - is realized. They argue that historical conflict affects modern outcomes through its consequences on subsequent economic, political and social outcomes. However, it remains to assess which of these mechanisms matter when and the authors demonstrate only that this pre-colonial conflict correlates with some indicators of trust and certain measures of local economic development.

There are several feasible ways to parse the mechanisms through which pre-colonial conflict matters for modern development outcomes, both theoretical and empirical. In this section, we discuss an automated variable selection method using the lasso algorithm (Tibshirani, 1996). The basic idea behind such variable selection approaches is simple: given a set of candidate independent variables, what combination of them best explains the observed variance in the outcome variable?

The intuition behind lasso (the least absolute shrinkage and selection operator) is that we run a series of models and penalize the absolute size of the regression coefficients. In so doing, we constrain the sum of regression coefficients to be below a certain threshold (which we specify using cross-validation, as explained below), and if this threshold is exceeded then we penalize particular parameters by setting them to zero. The basic process is to sequentially add parameters to the model in the order of their bivariate correlation with the outcome variable, and gradually increase the coefficients associated with these variables until they are no longer the most strongly correlated with the outcome. Then, introduce additional explanatory variables until no other variables can be introduced into the model which are better correlated with the outcome subject to the coefficient size constraint.

In all models, we use cross-validation to select the optimal number of coefficients to keep in the model. Cross-validation randomly selects a subset of the overall dataset as a training set, then fits a model and assesses its performance on the rest of the dataset (the validation data). If the model predicts out-of-sample observations with a relatively low mean-squared error then it is selected. This enables us to select the optimal lasso-generated set of independent variables.

We argue that using the lasso is useful in the context of Besley and Reynal-Querol (2014) for two distinct applications:

1. When the order of candidate independent variables is a similar order to the number of observations in a dataset, and including all of them would badly overfit the model.

2. When we believe that the way key explanatory variables interact with others is important for the underlying mechanism, but it is theoretically hard to predict which deserve focus.

These two applications allow us first to select variables in models that are otherwise overdetermined, and secondly to detect effect heterogeneity that the authors do not explore.

3.1.1 Cross-country analysis

Regarding the first application, we apply the lasso to the cross-country regressions the authors describe in Table 2 of their paper, which show that the number of years a given African country has been in civil war since independence is highly correlated with the number of wars in that territory between 1400-1700.

However, in their baseline specification they fit 9 independent variables to their 49 observations, and in their secondary specification they fit 29 independent variables to the same sample size. This represents a clear case of overadjustment (Schisterman, Cole and Platt, 2009) and the resultant models are highly overfitted to the data, with many regressors sharing high covariance. So, we use the lasso to define the subset of these many variables which best explain variation in the dependent variable, then re-run the regression to assess how the coefficients of interest are affected.

Column 1 in Table **WHAT** replicates the baseline cross-country specification of the authors, and column 2 uses the same set of regressors, applies the lasso, then re-runs the regression with only the selected variables. Column 3 replicates their saturated specification, and column 4 applies the lasso to the larger set of independent variables and run-runs the regression accordingly. In column 3, most of the regressors are excluded for display purposes.

The results of the lasso process suggest that, even in spite of the overdetermined model, their key explanatory variable is explaining parts of variation in the outcome that the other variables - many of which are post-treatment - do not. This derives from the fact that the pre-colonial conflict variable is selected in both columns 2 and 4, and the coefficient size and significance is stable across specifications.

The procedure suggests that the only other variables that meaningfully explain variation are whether the country is in the west or east of Africa, and whether it was a French or Portuguese colony. All the other controls are shown to contribute little to the explanatory power of the model.

Table 1: Cross-country lasso

	Dependent variable:			
	Civil war incidence			
	(1)	(2)	(3)	(4)
WarPrevalence14001700	0.12**	0.13***	0.13**	0.14***
	(0.05)	(0.05)	(0.06)	(0.04)
f_french	−2.91	−2.60	−4.12	−1.19
	(2.40)	(1.90)	(3.32)	(1.30)
f_pothco	5.65	5.69*	9.96**	6.90**
	(3.62)	(3.35)	(4.68)	(3.37)
f_belg	1.04		−0.58	
	(2.99)		(3.99)	
f_italy	−3.45		−9.64*	
	(3.33)		(5.54)	
f_germ	−3.34	−3.26	−4.44	
	(2.96)	(2.60)	(3.55)	
region_nNUNN	−2.52		−15.74**	
	(3.29)		(5.55)	
region_sNUNN	−3.87		−3.08	
	(2.87)		(5.09)	
region_wNUNN	−5.07**	−1.54	−5.25	−3.00**
	(2.07)	(1.55)	(3.79)	(1.20)
region_eNUNN	0.32	3.92	13.22*	2.35
	(2.69)	(3.26)	(6.52)	(2.72)
region_cNUNN		3.65*		
		(2.08)		
Lasso	No	Yes	No	Yes
Specification	Baseline	Baseline	Secondary	Secondary
Variables omitted	No	No	Yes	No
Note:				*p<0.1; **p<0.05; ***p<0.01

3.1.2 Disaggregated analysis: Social attitudes

Regarding the second application of the lasso, in their more disaggregated analysis the authors use samples of a much larger size to demonstrate that historical conflict affects modern social attitudes but do not explore how the effect is moderated by any other factors. To try and get at the mechanisms through which pre-colonial conflict matters, we argue that looking at interaction effects between the key explanatory variable and other explanatory variables is an appropriate strategy.

For example, we may believe that pre-colonial conflict would affect the development of political institutions in a given country, which then affect the probability of civil wars (CITE SOMEONE). So, pre-colonial conflict may be expected to especially impact social outcomes in areas which subsequently became autocratic, or which were later exploited by the slave trade. However, given the number of possible interaction effects in their models, it is hard to choose *ex ante* which ones should be assessed.

The lasso approach is highly applicable here: we generate models based on their most saturated specifications of their key results, and interact every independent variable with the explanatory variable of interest, pre-colonial conflict. Then, using the lasso, we select the subset of interactions that together best explain variation in the outcome variable. While we cannot apply such an approach to the cross-country regressions due to power constraints, the Afrobarometer survey response, with $n > 17,000$, is more amenable to such approach.

The authors use this data to show that respondents who live in locations which suffered more pre-colonial civil wars display significantly lower levels of inter-group trust, significantly higher levels of ethnic identification, and significantly lower levels of national identification. In these regressions, they use 76 independent variables (including pre-colonial conflict) to control for omitted variables.

From these 76 variables, we exclude all occupation and country-level fixed effects and interact the remaining 18 independent variables with the variable for pre-colonial conflict. Then, running the lasso algorithm on the entire model, we assess which interaction terms are selected by the lasso. The reason for excluding the fixed effects is that those interactions are hard to meaningfully interpret - we have no reason to believe that the effects of pre-colonial conflict should interact with the particular profession of the survey respondent, and looking at the interaction with country fixed effects just indicates which specific countries have had both pre-colonial conflicts and lower trust levels today.

Table **WHAT** presents the results, where 'Positive' means that the interaction of the variable listed (when interacted with pre-colonial conflict) is selected by the lasso and has a coefficient greater than zero, 'Negative' means the coefficient is less than zero, and an empty cell means the interaction is not selected by the lasso.

Table 2: Interaction effects selected by lasso (Afrobarometer)

Interacted variable	Inter-group trust	Ethnic identity	National identity
Age		Positive	Negative
Age squared	Negative		Negative
Male		Negative	Positive
Urban			Negative
Civil war incidence			
Log slave exports	Negative	Positive	Negative
Log pop density (1400)			Negative
GDP per capita			Negative
Latitude			Negative
Longitude	Negative		
Rainfall			Negative
Humidity			Negative
Temperature			
Log coastline area	Positive		
Islam		Positive	
Log gold per capita			
Log oil per capita	Positive		Positive
Log diamonds per capita			
Ruggedness			

Even though this is a fully automated approach to variable selection, the algorithm produces a number of interesting results. First, the only interaction term selected across the three dependent variables measures the exposure of that region to the slave trade. So, places with long histories of conflict and high amounts of slaves exported demonstrate lower levels of inter-group trust, higher ethnic identification, and lower national identification. This aligns strongly with eviden ce on the persistent impact of the slave trade on modern attitudes, as argued by Nunn and Wantchekon (2011).

Second, the interaction on oil reserves is selected in two of the models. This again makes sense: if we believe that pre-colonial conflict weakened institutional structures, then the presence of oil in that region ought to act as an exacerbator for conflict once the resource becomes valuable. A well-established literature on how institutions facilitate the resource curse in developing countries, which may impact social attitudes, leads credence to this heterogeneity (Mehlum, Moene and Torvik, 2006).

Third, that the interaction with civil war incidence is not selected in any of the models. This suggests, perhaps surprisingly, that there is no meaningful interactive effect between pre-colonial conflict and post-colonial conflict on modern social attitudes.

Other implications are less clear - that male respondents in areas with more history of conflict display stronger senses of ethnic identity and weaker senses of national identity may suggest something about the implications of conflict on gender norms, but it is hard to say much more.

3.1.3 Disaggregated analysis: Grid cell results

In their paper, the authors provide more granular evidence that the existence of pre-colonial conflict in a given 125 x 125 km grid cell is associated with more modern conflict in that grid cell, as well as significantly lower levels of night light intensity. As outlined in Henderson, Storeygard and Weil (2012), the use of night light density is argued to strongly proxy for subnational income indicators in developing countries - so, grid cells with more pre-colonial conflict have lower income today.

Here, we apply the same approach as to the survey data: we take the full set of 119 regressors from their from their most saturated models, then drop all the fixed effects for countries and economic activity in that grid cell. Then, with the remaining independent variables, we interact all of them with the central independent variable, apply the lasso, and assess the interaction terms that are selected as explaining important heterogeneity.

Table 3: Interaction effects selected by lasso (grid cell)

Interacted variable	Conflict	Light density
Distance to coast		
Average elevation		Positive
Ruggedness		
Average temperature	Positive	
Average precipitation		
Area		
Log pop density (1990)		Negative
City in cell in 1400		
More than one ethnicity in cell		Negative
Log slave exports		Negative
Capital in cell		Positive
Distance to capital 0-10 percentile		
Distance to capital 10-25 percentile		Negative
Distance to capital 25-50 percentile		
Distance to capital 50-75 percentile	Positive	Positive
Distance to capital 75-90 percentile		
Jurisdictional hierarchy		
Log night lights (1992)		
Mineral share		

While the selected interaction terms are less interpretable than those from the social attitudes data, it still provides some suggestive evidence on the mechanisms at work. For interactive effects on the presence of modern conflict, areas with pre-colonial conflict far from capital cities have more modern conflict, as well as those areas with higher average temperatures - which perhaps suggests a historical component to the large literature demonstrating a link between climate and violence (Hsiang, Burke and Miguel, 2013). Regarding local economic activity, more interactive effects appear important: again, the interaction with the slave trade is selected by the algorithm, as is the interaction with the extent of ethnic division in a given grid cell. Other interactions are harder to interpret.

3.1.4 Summary

The results of the variable selection analysis demonstrate two points. First, that in spite of the specification issues of their coarse cross-country regressions, the incidence of pre-colonial conflict appears to explain variation in modern conflict distinct from their set of plausibly overfitted set of independent variables. And second, that the process detects intuitive interactive effects in their data that the authors do not explore in their analysis - that the effect is especially magnified by subsequent exposure to the slave trade and the existence of oil, which supports the academic literature pointing to the central importance of historical institutional development in determining modern outcomes.

4 Assessing the Mechanisms of Persistence

4.1 Linking the Past to Present

While a recent wave of scholarship systematically and quantitatively documents the impact of historical events on contemporary political and economic phenonemon, one of the main shortcomings of this literature is that the causal mechanisms that attribute to the persistence of historical events or institutions largely remain in a "black box" (Imai et al., 2011; Acharya, Blackwell and Sen, Forthcoming). Given that the authors estimate effects that persist over hundreds of years, this concern is especially acute for understanding how historical conflict shapes contemporary conflict and cooperation. In their paper, the authors lay out several paths through which the effects of pre-colonial conflict might persist until today and, to their credit, they test several of the observable implications. The primary empirical challenge, however, is to systematically analyze the degree to which the effects of pre-colonial conflict in Africa flow through certain hypothesized mechanisms. In this section, we address this shortcoming by estimating the Average Controlled Direct Effect (ACDE) of historical conflict on contemporary outcomes as a strategy to rule out certain causal pathways that explain the persistence of pre-colonial conflict on African political economy.

Before laying out the assumptions needed to identify the ACDE of pre-colonial conflict as well the procedure to consistently estimate this quantity of interest, we first present Besley and Reynal-Querol (2014)'s preferred causal mechanisms in greater detail. In general, Besley and Reynal-Querol (2014) argue that the presence of historical conflict at both the national and subnational level enervates political and economic development. Particularly, the authors highlight two mechanisms:

> ...conflicts can affect the evolution of subsequent economic, political, and social outcomes which have a bearing on contemporary conflict. For example, historical conflicts could promote distrust among social groups which affect attitudes and identities. They could also have an economic legacy, making regions poorer and could also influence the choice of political institutions. (Besley and Reynal-Querol, 2014, pg. 321).

While the authors present a number of empirical tests for these mechanisms in Tables 4 and 5 in their paper, there are a number of problems in the approach that they take. First when the authors estimate the effect historical conflict on contemporary levels of trust, ethnic identity, and national identity, they include a number of post-treatment confounders that both could be biasing their estimates as well as obscuring the actual mechanisms driving their results. For example, the historical conflict may shape contemporary social identities, but this effect only runs through the ways in which adverse economic development or political institutions shape social identity. By conditioning on variables such as contemporary levels of conflict and economic development, the authors leave themselves open to the possibility of post-treatment bias in estimating the effect of historical conflict on identity and trust. In essence, contemporary economic and development and conflict are themselves potential mediators for the effect of pre-colonial conflict on identity politics.

Second, the authors attempt to make empirical claims about the subnational effects of historical conflict on contemporary conflict and development. Again, the authors condition on a post-treatment confounder–the grid-level population density in 1990–which itself is also likely to be a product of historical conflict since population density is a proxy for development in agricultural economies. Since simply conditioning on post-treatment variables is not enough to determine the direct effect of a variable, it is unclear as to the magnitude of the direct effect of pre-colonial conflict on contemporary conflict and development. In the rest of this section, we present the identifying assumptions needed to estimate the ACDE of pre-colonial conflict in addition to estimating this quantity of interest using Sequential-G estimation (Joffe and Greene, 2009; Vansteelandt, 2009; Acharya, Blackwell and Sen, Forthcoming).

4.2 Estimating the Average Controlled Direct Effect

Intuitively, the ACDE is the direct effect of the treatment variable of interest (historical conflict) holding some mediator (economic development for example) fixed at a certain value. The advantage of this quantity of interest is that it represents the effect of historical conflict independent of a particular causal channel. As Acharya, Blackwell and Sen (Forthcoming) point out, this can help researchers rule out whether certain causal mechanisms drive a certain set of results, which can help adjudicate between competing theories of politics. In this case, the authors are interested in two sets of ACDEs. First, the authors want to be able to assess whether pre-colonial conflict in Africa has a direct effect on identity and trust net of its effect on economic development and conflict. Second, the authors aim to make an empirical claim that historical conflict shapes contemporary economic development and politics independent of its demographic consequences on population density.

To estimate these sets of ACDEs, we need to make certain assumptions about the data-generating process. Primarily, we must make an assumption of *sequential ignorability* Robins (1997); Acharya, Blackwell and Sen (Forthcoming). That is, historical conflict is plausibly exogenous given a set of background covariates such as latitude, longitude, historic population density, etc. and that the proposed mechanism is plausibly exogenous conditional on both historical conflict and the background covariates. Most notably, Imai et al. (2011) also rely on this assumption to assess the Average *Natural* Direct Effect (ANDE) and the Average Natural Indirect Effect ANIE. Nonparametrically identifying these estimands relies on a further assumption of no intermediate confounders, which in most observational (and even experimental studies) is unlikely to hold. Thus, the ACDE can be identified under a weaker set of assumptions. The tradeoff, however, is that the ANDE and ANIE might be more suited to assessing competing mechanisms against each other.

For this paper, we utilize the Sequential-G estimation strategy discussed in Acharya, Blackwell and Sen (Forthcoming) and developed by Joffe and Greene (2009); Vansteelandt (2009). The basic intuition behind this estimation procedure is that we first estimate a regression including both historical conflict and the potential mediators (economic development and civil conflict) on the right-hand side. This is what Besley and Reynal-Querol (2014) do to assess the direct effect of pre-colonial conflict. The problem with only running this regression is that it induces bias of an unknown sign and magnitude (Acharya, Blackwell and Sen, Forthcoming). Instead, we take fitted values from that initial regression and "demediate" the outcome netting out the effects of these mediators on the outcome of interest and re-run a regression of the "demediated" variable on historical conflict. This approach, allows us to estimate the ACDE of historical conlict on the outcome of interest consistently.

To assess the direct effect of pre-colonial conflict on social identity, contemporary development, and civil conflict, we reanalyze the data used to produce the results for Tables 4 and 5 in the authors' main paper. First, we assess the direct effect of pre-colonial conlict on strength of ethnic identity, national identity, and intergroup trust by estimating the following sets of equations:

$$Y_i = \alpha + \beta \text{Historical Conflict}_i + \lambda \text{Log(GDP per Capita, 1960)}_i + \gamma \text{Civil War Incidence} + \phi X_i + \epsilon_i \quad (1)$$

$$Y_i - \widehat{\lambda} \text{Log(GDP per Capita, 1960)}_i - \widehat{\gamma} \text{Civil War Incidence} = \alpha + \beta \text{Historical Conflict}_i + \phi X_i + \eta_i \quad (2)$$

Y_i represents the outcome of interest indexed by each respondent i. In this case, it is either whether the Afrobarometer respondent identifies more with his or her own ethnicity over other possible identities, identifies more with his or her national identity, and whether the respondent trusts members of other ethnic groups. The main coefficient of interest is β, which represents the ACDE of historical conflict. The coefficients λ and γ represent the effects of the mediators contemporary development and civil conlict respectively. Finally, the matrix X_i represents the set of pre-treatment controls and fixed effects while ϵ_i and η_i represent Gaussian error terms.

We estimate a similar set of equations in our reanalysis of Table 5, which investigates the direct effect of historical conflict on subnational economic and political development at the grid-cell level. Thus, we estimate the following set of equations:

$$Y_g = \alpha + \beta \text{Historical Conflict}_g + \kappa \text{Log(Population Density, 1990)}_g + \phi X_g + \epsilon_g \quad (3)$$

$$Y_g - \widehat{\kappa} \text{Log(Population Density, 1990)}_g = \alpha + \beta \text{Historical Conflict}_g + \phi X_g + \eta_g \quad (4)$$

For these estimating equations, Y_g represents the incidence of conflict or the light density (proxy for development) at the grid-cell level g. X_i represents the authors' specified set of pre-treatment control variables. Finally, both equations have Gaussian error terms ϵ_g and η_g respectively.

4.3 Results

In the first set of results shown in Figure 1 we estimate the ACDE of historical conflict on ethnic identity, national identity, and intergroup trust and only demediate the outcome variables by the log of GDP per capita in 1960. We find that historical conflict seems to have a direct effect on social identity with the magnitudes of the effect in the same signs and magnitude as the specifications used in Table 4 of Besley and Reynal-Querol (2014). On average, a one unit increase in the ACDE of conflict seems to increase the salience of the respondent's ethnic identity by about 0.1 percentage points with the effect being just marginally insignificant at the $p < 0.05$ level, decrease the degree to which the respondent trusts individuals from other ethnic groups by about 1 percentage point, and decrease the degree to which the respondent identifies with his or her national identity by just over 2 percentage points. We find a similar pattern of results when we net out the effect of both contemporary development and contemporary civil conflict on social identity as shown in Figure 2.

These results speak to the authors' theory in a number of ways. It seems that the prevalence of precolonial conflict seems to operate independently of these economic and political channels hypothesized by the authors. Instead, the evidence suggests that pre-colonial conflict shapes social identity through cultural or institutional channels. These results, then, motivate further inquiry how the prevalence of pre-colonial conflict might shape the formation, amalgamation, or dissolution of various ethnic groups.

In the next part of the original paper, Besley and Reynal-Querol (2014) investigate the effects of pre-colonial conflict on *subnational* conflict and development. To do so, the authors utilize grid-cell level data on conflict and night light density (a commonly used proxy for development) as the dependent variables to be explained. Figure 3 provides evidence that pre-colonial conflict does have a direct effect on contemporary subnational conflict incidence net of the effect of conflict on population density in 1990 (a proxy for urbanization and development). This general finding is consistent with the authors' original findings on conflict in Table 5 of the main paper. Contrary to Besley and Reynal-Querol (2014), however, we find that pre-colonial conflict does not have a direct effect on contemporary levels of economic

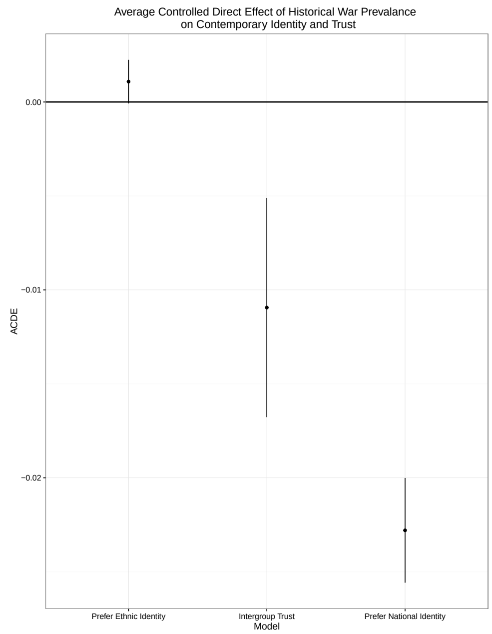

Figure 1: ACDE of historical conflict in Africa on ethnic identity, national identity, and intergroup trust netting out the effect of economic development in 1960. All models are estimated using the Sequential-G procedure described in Acharya, Blackwell and Sen (Forthcoming). Models include the original pre-treatment control variables.

development as proxied by night light density in 2007 independent of its effect on subnational urbanization at conventional levels of statistical significance.

Theoretically, the results from this set of tests suggest two main theoretical contributions. First, it seems that historical conflict at the subnational level seems to operate independently of its consequences on demographics. As a result, it could be the case that historical conflict shapes subnational politics through some sort of cultural or local institutional mechanism that operates independently of demographics and economic development. This evidence is consistent with our findings from the previous empirical test where we showed that the effect of pre-colonial conflict seems to operate independently of its effect on national economic development. Next, we find that subnational, historical conflict does not shape subnational economic development independent of its effect on demographics and urbanization. These results raise a puzzling tension for the authors' original theory that states that conflict historical conflict shapes contemporary development primarily through a mechanism where conflict begets conflict leaving areas in a sort of a conflict trap. Thus, the subnational results from this Sequential-G estimation strategy indicate that the channels through which pre-colonial conflict shapes contemporary economic development is quite different from the process through which pre-colonial conflict shapes contemporary conflict.

5 Extensions of the Analysis

Besley and Reynal-Querol (2014) argue that there may be evidence of pre-colonial conflict shaping current perceptions of ethnic versus national identity, and trust of members of different ethnic groups. In section 4.3 above, we provide further support that the demediated effect of pre-colonial conflict may shape social identity through cultural or institutional channels. If the mechanism of pre-colonial conflict holds, however, then only analyzing the effect of pre-colonial conflict on trust of outgroup members is an incomplete analysis of modern levels of trust. There is considerable evidence that, even in the absence

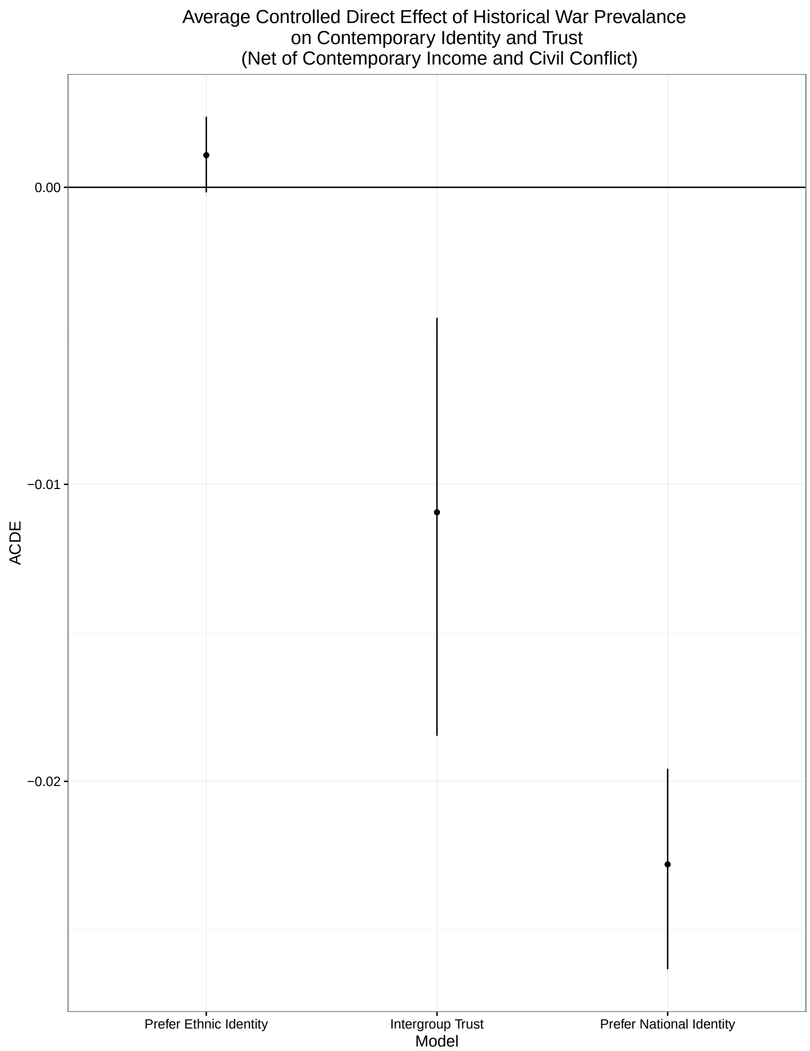

Figure 2: ACDE of historical conflict in Africa on ethnic identity, national identity, and intergroup trust netting out the effect of economic development in 1960. All models are estimated using the Sequential-G procedure described in Acharya, Blackwell and Sen (Forthcoming). Models include the original pre-treatment control variables.

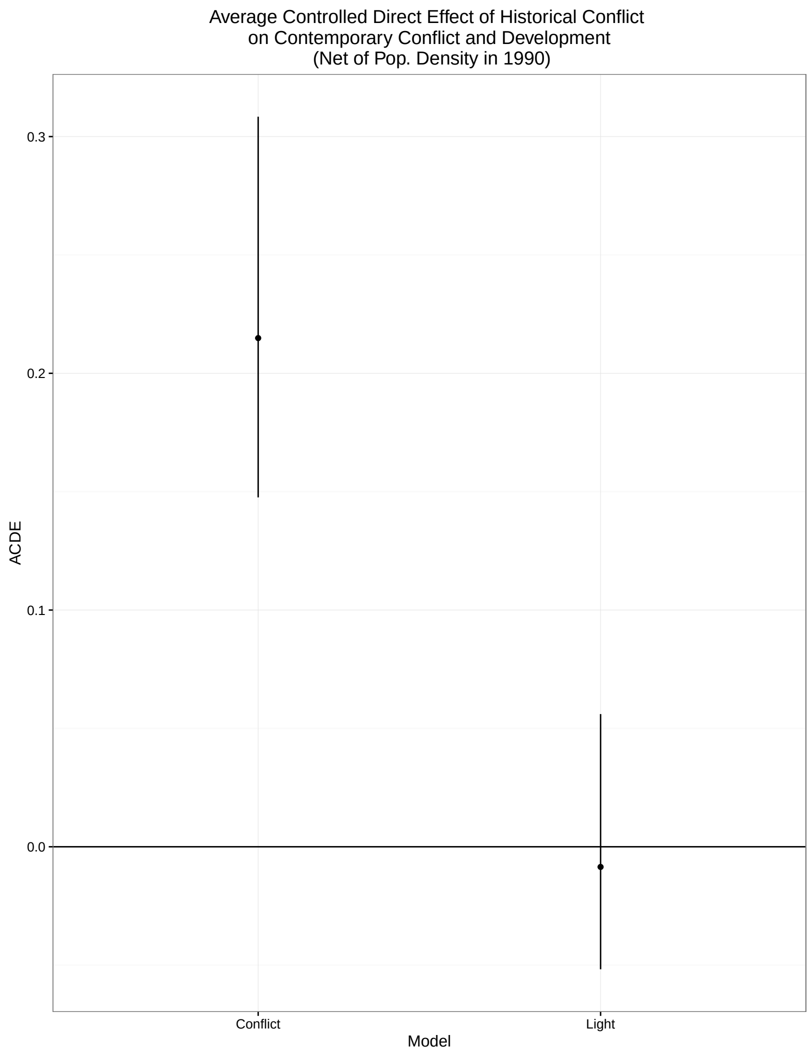

Figure 3: ACDE of historical conflict in Africa on contemporary conflict and light density at the grid-cell level netting out the effect of population density in 1990. All models are estimated using the Sequential-G procedure described in Acharya, Blackwell and Sen (Forthcoming). Models include the original pre-treatment control variables.

of conflict, individuals display higher levels of trust towards members of their own ethnic group than members of another ethnic group **??**. This has been experimentally proven as well **?**. We know less about situations in which an individual trusts neither group, or where baseline levels of trust are so low that it appears that trust is absent from any type of intergroup relations. In this section, we pair the data from Besley and Reynal-Querol (2014) to the original data from the Afrobarometer survey to compare respondents' trust of other institutions and individuals in areas with historical conflict with areas with no historical conflict.

We were able to successfully pair the data from Besley and Reynal-Querol (2014) with the responses from the original 2005 Afrobarometer survey. When running similar regressions to Table 4 in their paper, we find that individuals who hail from areas that have experienced historical conflict not only have greater levels of mistrust of other ethnic groups, but have greater levels of mistrust of the President, Parliament, local governments, political parties, the military, the police, and other political institutions.[1]. The coefficient for historical conflict, as in the Besley and Reynal-Querol (2014) analysis, is a negative and statistically significant predictor of trust at the $p < .01$ level.

The most interesting finding is the relationship between historical conflict and trust of coethnics, or members from your own ethnic group. Using the same regression models as Besley and Reynal-Querol (2014) of their Table 4, we find that the same survey respondents have even lower levels of intragroup trust compared to intergroup trust when controlling for colonial dummies, and the same low levels of intragroup trust as intergroup trust when controlling for civil war prevalence. The models of intergroup trust from Besley and Reynal-Querol (2014) are reprinted alongside our models of intragroup trust below in Table **??**.

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These results spark interesting questions for further research: does historical conflict reduce trust specifically between ethnic groups and cause individuals to experience more ingroup bias, or does it just reduce individuals' trust levels in all people? Table **??** suggests the latter. Instead of conflict affecting feelings towards particular groups as the original authors suggest, it is possible that conflict could cause individuals to trust no one and weaken social fabric both between similar individuals and different individuals.

A secondary question is about the relationship between low levels of trust and ethnic identity versus national identity. Does ethnic identity versus national identity matter when an individual trusts no one? Why does increased ethnic identity not translate to increased levels of ingroup trust?

[1] For brevity, these are not reported here, but `R` code can be found in the supplemental materials.

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